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Can the Nonlinear Present Value Model Explain the Movement of Stock Prices?

Shyh-Wei Chen
Department of Finance, Da-Yeh University
No 112, Shanjiao Rd, Dacun, Changhua 51591, Taiwan
E-mail: shyhwei.chen@gmail.com

Chung-Hua Shen
Department and Graduate Institute of Finance, National Taiwan University
No.1, Sec. 4, Roosevelt Rd., Taipei City 106, Taiwan
E-mail: chshen01@ntu.edu.tw

Abstract

This paper empirically investigates whether the nonlinear present value theory of stock price and dividend is able to explain the failure of its linear counterpart. Using two new econometric models, we extend Kanas' (2005) model. We replace ACE cointegration with rank cointegration to examine the contemporaneous relation between stock price and dividend, and we replace Hiemstra and Jones' (1994) method with that of Diks and Panchenko (2006) to implement the nonlinear causality test. When we employ the rank cointegration test, the nonlinear present value model is found to be suitable for the U.S., the UK and Germany but not for Japan. When we employ Diks and Panchenko's (2006) model, evidence of both linear and nonlinear causality from dividend to stock price is found for the U.S., the UK and Germany. However, neither linear nor nonlinear causality is found for Japan.

Keywords: Nonlinear cointegration, nonlinear Granger causality, present value model
JEL Classification Codes: G12, C12

1. Introduction

Economists have considerable interest in the present value (PV) model of stock price which argues that stock price is the present discount value of the future expected dividend. Empirical studies, however, have often reported substantial deviations between actual stock prices and theoretical stock prices derived from the linear present value model. For example, many studies find that U.S. stock prices are more volatile than those determined by the present value model. [1] A number of factors have been put forth to account for this substantial deviation, including noise traders (DeLong, Shleifer, Summers and Waldmann, 1990), fads (Shiller, 1981), varying discount rates (Campbell and Shiller (1988a, 1988b), West (1987, 1988), stochastic speculative bubbles (Blanchard and Waston, 1982; West, 1988; Flood

[1] For example, West (1987) found that there is a non-fundamental factor in stock prices. Chung and Lee (1998) found that the stock prices of Japan, Korea, Hong Kong and Singapore substantially deviated from those derived from the theoretical linear model.

and Garber, 1988; Diba and Grossman, 1988); and regime-switching in the dividend process (Driffill and Sola, 1998, Gutierrez and Vazquez, 2004).

A recent study by Kanas (2005) reports that the failure of the linear present value model can be attributed to nonlinearities in the stock price-dividend relation. To examine possible nonlinear relationships, he adopts three nonlinear methods. The first he uses is Granger and Hallman’s (1991) nonlinear cointegration test, which is known as the Alternating Conditional Expectations (ACE) method, to examine the contemporaneous relation. Next, he employs the nonlinear Granger causality (NLGC) of Baek and Brock (1992) and Hiemstra and Jones (1994, hereafter HJ) to test for nonlinearity in the dynamic stock price-dividend relation. Third, he uses the locally-weighted regression to obtain the nonlinear out-of-sample forecasts. Employing data for the U.S., the UK, Germany and Japan, Kanas (2005) finds that, whilst original stock price and dividend series are not linearly cointegrated and not Granger caused in the case of these four countries, there is significant evidence in support of their respective nonlinear forms.[2]

The aim of this paper is to revisit the work of Kanas (2005) by extending his first two methods. First, we use the more recent nonlinear cointegration test of Breitung (2001) to investigate cointegration between stock price and dividend. Proposing the use of rank transformation between two variables, Breitung (2001) claims his method is more powerful than its parametric competitors--for example, Granger and Hallman’s (1991) nonlinear cointegration test. Thus, it is interesting to determine whether Kanas’ (2005) conclusion still holds when a more powerful method is employed.

The second feature of this study is that we adopt Diks and Panchenko’s (2006, hereafter DP) nonlinear Granger causality test which conducts a more rigorous analysis. The reason is that Diks and Panchenko (2005) claim that, with Hiemstra and Jones’s (1994) model, the rejection probabilities under the null hypothesis tend to be one as the sample size increases. They, therefore, derive the exact conditions and propose a new test statistic which does not suffer from the problem of over-rejection. We further extend our sample period to include the most recent 2004:12, i.e. the time of writing this paper.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundation of a relation between a nonlinear stock price and dividend. Section 3 outlines the statistical methods used for testing nonlinearity. Section 4 discusses the data used and the empirical results. Section 5 compares our results with those from Kansa. Finally, section 6 concludes.

2. Theoretical Foundation

The theoretical framework described here is taken from Kansa (2005) and Campbell et al. (1997) (CLM). Stock return R_{t+1} is the sum of capital gain and dividend, i.e., $R_{t+1} = (P_{t+1} - P_t + D_{t+1})\ P_t\ /$, where P_t is stock price measured at the end of period t and D_{t+1} is dividend payment at time t +1. Under the assumption that expected stock return is constant, current stock price is related to the stock price and dividend of the next period, as shown in Eq. (1):

$$P_t = E\left(\frac{P_{t+1} + D_{t+1}}{1+R}\right) \tag{1}$$

When an efficient market is assumed and there is no arbitrage opportunity, then the constant expected stock return $E_t(R_{t+1}) = R_t$. Taking the expectation of Eq. (1) and solving it forward by repeatedly substituting out future stock prices, we have:

$$P_t = E\left[\sum_{i=0}^{\infty}\left(\frac{1}{1+R}\right)^i D_{t+1}\right] \tag{2}$$

[2] There is theoretical reasoning behind there being a nonlinear relation between stock price and dividend, for example, the fads model (Summers, 1986), the trigger strategies model (Krugman, 1987), the intrinsic bubbles model (Froot and Obstfeld, 1991), the psychology model (Cutler, 1991) and the model of market learning about managerial competence (Kiyotaki, 1990).

which expresses stock price as the expected present value of future dividends projected to the infinite future discounted at a constant rate. If we subtract a multiple of the dividend from both sides of Eq. (2), we obtain:

$$P_t - \frac{D_t}{R} = \frac{1}{R} E[\sum_{i=1}^{\infty} (\frac{1}{1+R})^i \Delta D_{t+1+i}] \tag{3}$$

If D_t follows a linear process with a unit root, stock price P_t also follows a linear process with a unit root. Since ΔD is a stationary process and *R* is constant, Eq. (3) also indicates that stock price and dividend are cointegrated. The rejection of cointegration between the two series is typically indicative of the rejection of the linear present value model (Campbell and Shiller, 1988a). Eq. (3) is based on the assumption that expected stock returns are constant. Though this assumption is analytically convenient, it contradicts empirical evidence showing that stock prices are hard to predict. When expected returns are time-varying, the relation between stock prices and returns becomes nonlinear. Employing a log-linear approximation to stock returns yields:

$$r_{t+1} \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t) = p_{t+1} - p_t + \log(1 + \exp(d_{t+1} - p_{t+1})), \tag{4}$$

where the subscripts denote the logs of the variables, i.e., $r_{t+1} = \log(R_{t+1})$. Using the first order Taylor expansion around the mean, Eq. (4) becomes:

$$r_{t+1} \approx k + \rho(p_{t+1}) + (1+\rho)d_{t+1} - p_t \tag{5}$$

where ρ and *k* are the parameters of linearization. Eq. (5) for the log stock price is analogous to Eq. (1) for the level of stock price under the assumption there are constant expected returns. Solving forward and imposing the terminal condition that $\lim_{j\to\infty} \rho^j p_{t+j} = 0$ in order to rule out rational bubbles, and then taking expectations into consideration, we have:

$$d_t - p_t = -\frac{k}{1-\rho} + E[\sum_{j=0}^{\infty} \rho^j [-\Delta d_{t+1+j} + r_{t+1+j}]] \tag{6}$$

This is the dynamic Gordon growth model, suggested by Campbell and Shiller (1988a, 1988b).

3. Econometric Methods

3.1. Nonlinear Causality

Baek and Brock (1992) proposed a nonparametric method for detecting nonlinear dynamic causal relations between two time series. They pointed out that the rejection of linear causality does not imply there is no non-linear causality because the conventional vector autoregressive (VAR) model only focuses on linear relations. Their method was soon modified by Hiemstra and Jones (1994) to allow for weak temporal dependence.

To define nonlinear Granger causality, assume there are two strictly stationary and weakly dependent scalar time series $\{X_t\}$ and $\{Y_t\}$. Define the *m*-lead vector of X_t as X_t^m and the *Lx*-length and *Lv*-length lag vectors of X_t and Y_t as X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly}, respectively; that is,

$$\begin{aligned} &X_t^m \equiv (X_t, X_{t-1}, X_{t+m-1}),\ m = 1,2,...,\ t = 1,2,..., \\ &X_{t-L_x}^{L_x} \equiv (X_{t-L_x}, X_{t-L_{x+1}}, ..., X_{t-1}),\ \ X_{L_x} = 1,2,...,\ t = L_{x+1}, L_{x+2}, ..., \\ &Y_{t-L_y}^{L_y} \equiv (Y_{t-L_y}, Y_{t-L_{x+1}}, ..., Y_{t-1}),\ Y_{L_y} = 1,2,...,\ t = L_{y+1}, L_{y+2}, ..., \end{aligned} \tag{7}$$

For the given value of *m*, L_x and $L_y \geq 1$ and e > 0, then the definition of nonlinear Granger non-causality is given by Eq. (8):

$$\begin{aligned} &\Pr(\left\| X_t^m - X_s^m \right\| < e \left\| X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x} \right\| < e, \left\| Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y} \right\| < e) \\ &= \Pr(\left\| X_t^m - X_s^m \right\| < e \left\| X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x} \right\| < e), \end{aligned} \tag{8}$$

where $\Pr(\cdot)$ and $\|\cdot\|$ denote probability and the maximum norm, respectively. In Eq. (8), the left-hand side is the conditional probability that two arbitrary *m*-length lead vectors of $\{X_t\}$ are within a distance *e* of each other provided that the corresponding *L*x-length lag vectors of $\{X_t\}$ and *L*y-length lag vectors of $\{Y_t\}$ are within the same distance *e* of each other. The right-hand side in Eq. (8) is the conditional probability that the corresponding *L*x-length lag vectors $\{X_t\}$ are within a distance *e* of each other..

A test based on Eq. (8) can be implemented by rewriting Eq. (8) in terms of the corresponding ratios of joint probabilities. Thus:

$$\frac{C_1(m+L_x,L_y,e)}{C_2(L_x,L_y,e)}=\frac{C_3(m+L_x,e)}{C_4(L_x,e)}, \tag{9}$$

where $C_1(m+L_x,L_y,e)/C_2(L_x,L_y,e)$ and $C_3(m+L_x,e)/C_4(L_x,e)$ are the correlation-integral estimators of the joint probabilities which are discussed in detail by HJ. For given values of m , L_x , and $L_y \geq 1$ and $e>0$ and under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$, then:

$$\sqrt{n}\left[\frac{C_1(m+L_x,L_y,e)}{C_2(L_x,L_y,e)}=\frac{C_3(m+L_x,e)}{C_4(L_x,e)}\right] \sim N(0,\sigma^2(m,L_x,L_y,e)), \tag{10}$$

where $\sigma^2(m,L_x,L_y,e)$ is the variance. We can also standardize the above equation as:

$$\sqrt{n}\left[\frac{C_1(m+L_x,L_y,e)}{C_2(L_x,L_y,e)}=\frac{C_3(m+L_x,e)}{C_4(L_x,e)}\right]\Big/\sqrt{\sigma^2} \sim N(0,1).$$

Diks and Panchenko (2006) claim that Eq. (8) is not generally compatible with the null hypothesis of Granger causality because it leads to over-rejection. They modify Eq. (8) as:

$$E\left[\frac{f_{X,Y,Z}(x,y,z)}{f_Y}-\frac{f_{X,Y}(x,y)}{f_Y(y)}\frac{f_{Y,Z}(y,z)}{f_Y(y)}\right]=0 \tag{11}$$

where $X=X_{t-L_x}^{L_x}$ $Y=Y_{t-L_y}^{L_y}$ and $Z=Y_t$ Under the null hypothesis of no Granger causality, the true relationship is:

$$\frac{E\left[f_{X,Y,Z}(x,y,z)\right]}{E\left[f_Y\right]}-\frac{E\left[f_{X,Y}(x,y)\right]}{E\left[f_Y(y)\right]}\frac{E\left[f_{Y,Z}(y,z)\right]}{E\left[f_Y(y)\right]}=0 \tag{12}$$

They show this equation as the starting point and construct the test statistic based on the functional form; thus, we have:

$$q=E\left[\left(\frac{f_{X,Y,Z}(x,y,z)}{f_Y}-\frac{f_{X,Y}(x,y)}{f_Y(y)}\frac{f_{Y,Z}(y,z)}{f_Y(y)}\right)g(x,y,z)\right] \tag{13}$$

DP point out that Eq. (12) is a special case of Eq. (13) under the condition q = 0. Let, $g(x,y,z)=f_Y^2(y)$ which refers to the corresponding functional, as follows:

$$\tilde{q}=E\left[f_{X,Y,Z}(x,y)f_Y(y)-f_{X,Y}(x,y)f_{Y,Z}(y,z)\right] \tag{14}$$

Note that for any small ε , $\tilde{q}$ as described above, is proportional to $(2\varepsilon)^{dx+2dy+dz}$. A natural estimator of $\tilde{q}$ is given by:

$$\tilde{q}_n=(2\varepsilon)^{dx+2dy+dz}\,T_n$$

where

$$T_n = \frac{1}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} \left(I_{ik}^{xyz} I_{ij}^{xy} - I_{ik}^{xy} I_{ij}^{yz} \right) \right],$$

and $I_{ij}^{W} = I(\|W_i - W_j\| < \varepsilon)$. Using the same approach as HJ (1994), DP (2006) obtain:

$$\sqrt{n}(\frac{T_n - (2\varepsilon)^m \tilde{q}}{S_n}) \sim N(0,1) \tag{15}$$

where S_n is the autocorrelation consistent estimator for variance and is described in Appendix A.3 of DP (2006).

3.2 Nonlinear Cointegration

In this section, we briefly describe the procedures involved in Breitung's (2001) rank tests for nonlinear cointegration. Consider two real-valued time series $\{x_t\}_1^T$ and $\{y_t\}_1^T$ that are nonlinearly related as $y_t = f(x_t) + u_t$, where y_t~I(1) and $f(x_t)$~I(1), i.e., each series is integrated of order one. Under the null hypothesis, u_t is I(1) which means y_t and x_t are not cointegrated. While the standard assumption is that $f(x_t)$ is a linear function, economic theory of course often gives rise to nonlinear relationships; thus, here it is assumed that $f(x_t)$ is a nonlinear function. Breitung (2001) shows that residual-based linear cointegrations are inconsistent for some classes of nonlinear function. To overcome this, Breitung (2001) proposes another set of tests based on a rank transformation of a time series.

Consider a slightly more general form with $u_t = g(y_t) - f(x_t)$, where $f(x_t)$ and $g(y_t)$ are I(1) and u_t is I(0). Breitung defines a rank series as $R_T(x_t) = \text{Rank[of } x_t \text{ among } x_1, \ldots, x_T]$ and $R_T(y_t)$. The rank statistics are constructed by replacing $f(x_t)$ and $g(y_t)$ with the ranked series, $R_T(x_t) = R_T[f(x_t)]$ and $R_T(y_t) = R_T[f(y_t)]$, respectively. We assume that $f(x_t)$ and $g(y_t)$ are two random walk series, and therefore, it follows that $R_T(x_t)$ and $R_T(y_t)$ behave like ranked random walks. The sequence of ranks is invariant to a monotonic transformation of the data. The advantage of a statistic based on a sequence of ranks is that the functions $f(\cdot)$ and $g(\cdot)$ need not know.

Breitung also proposes two "distance measures" between the sequences $R_T(x_t)$ and $R_T(y_t)$:

$$\kappa_T^* = T^{-1} \sup_t |d_t| / \hat{\sigma}_{\Delta d} \tag{16}$$

$$\zeta_T^* = T^{-3} \sum_t^T d_t^2 / \hat{\sigma}_{\Delta d}^2 \tag{17}$$

where $d_t =$ $R_T(y_t)$ - $R_T(x_t)$ and $\hat{\sigma}_{\Delta d}^2 = T^{-2} \sum_{t=2}^{T} (d_t - d_{t-1})^2$. The null hypothesis of no (nonlinear) cointegration between x_t and y_t is rejected if these testing statistics are small. The critical values of the testing statistics can be found in Breitung (2001, Table 1).

In general, it is not known whether $f(x_t)$ and $g(y_t)$ monotonically increase or decrease. For this situation, Breitung proposes a two-sided test:

$$\Xi_T^* = T^{-3} \sum_t^T \tilde{u}_t^R / \hat{\sigma}_{\Delta u}^2 \tag{18}$$

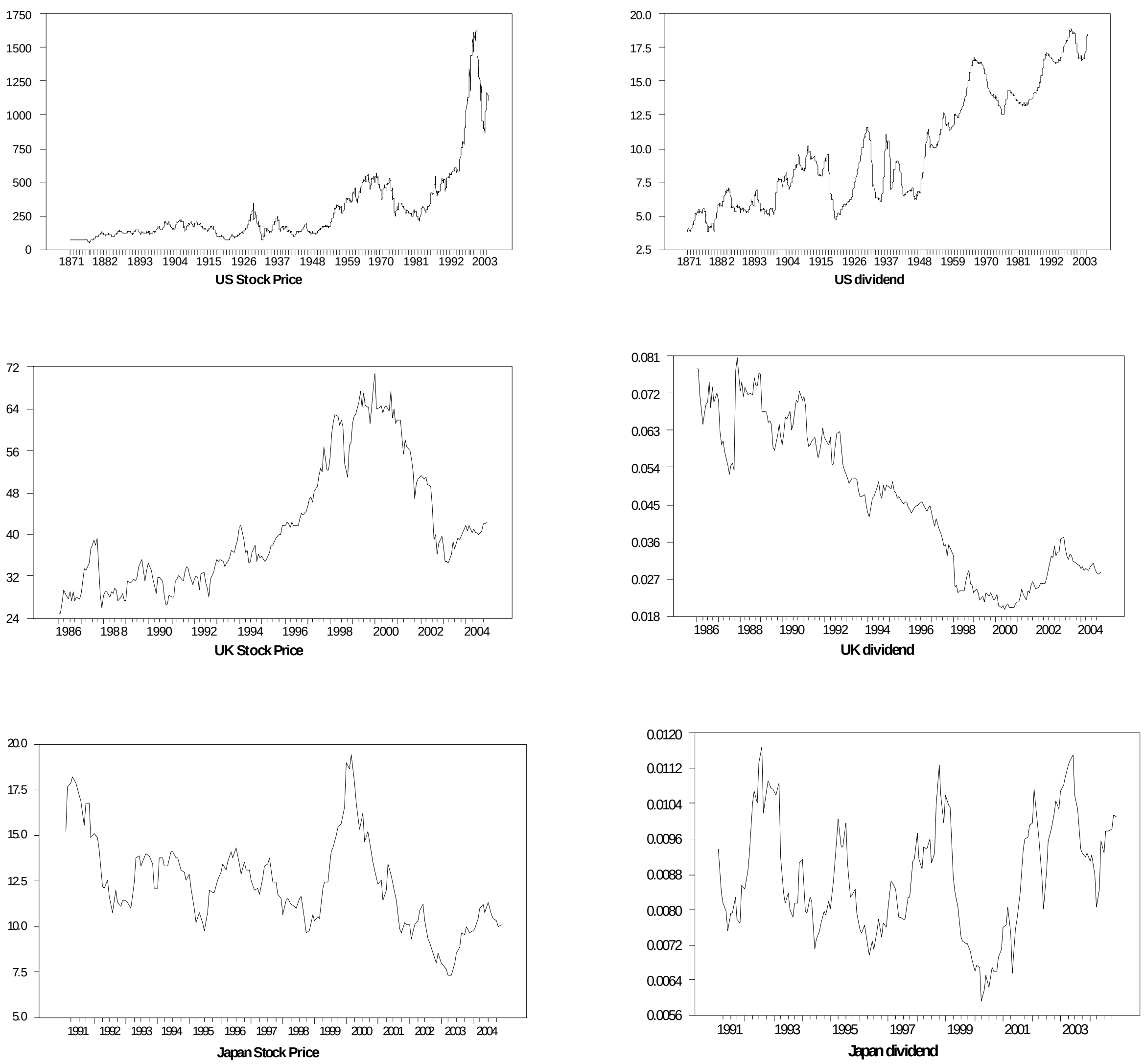
where $\tilde{u}_t^R$ is the least-square residual of the regression from $R_T(y_t)$ to, $R_T(x_t)$ and $\hat{\sigma}_{\Delta u}^2$ is the variance of $\tilde{u}_t^R$. The critical values for the test statistic Ξ_T^* are also presented in Table 1 of Breitung (2001).

4. Source of Data and Empirical Results

4.1 Source of Data

We select the same four countries as Kanas (2005), namely the U.S., the UK, Japan and Germany. The stock price indices we use are the Dow Jones Industrial Average 30 for the U.S., the Financial Times All Share index for the UK and *Datastream* total market indices for Japan and Germany. The dividend series are the corresponding dividend series for each stock price index. The dividend for the U.S. is from the Robert J. Shiller website, [3] while the dividends for the remaining three indices are from *Datastream*. We divide all variables by the consumer price index (CPI) of their respective country, and we use monthly data. Our sample period is 1871:1-2004:6 for the U.S., 1986:1-2004:12 for the UK, 1991:2-2004:12 for Japan and 1973:1-2004:12 for Germany. [4] See Figure 1 for the plots of the two series for each country.

Figure 1: Stock Price Indices and Dividends for the U.S., the UK, Japan and Germany



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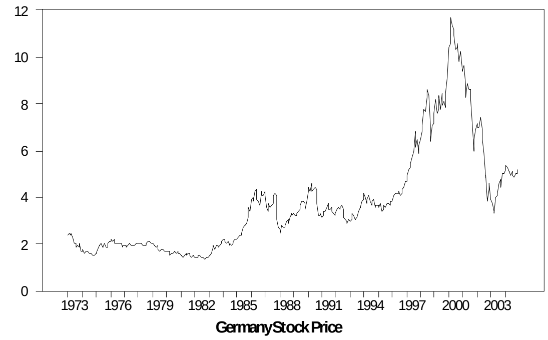
[3] The website of Professor Shiller is http://www.econ.yale.edu/~shiller/

[4] Our sample periods differ slightly from the sample period (1978:1-2002:5) used by Kanas (2005). First, we extend the sample period up to the time of writing this paper. Next, because we cannot trace the starting sample period used by Kanas (2005) for the UK, Japan and Germany, the starting periods for these countries vary slightly. This could also result in some estimation differences.



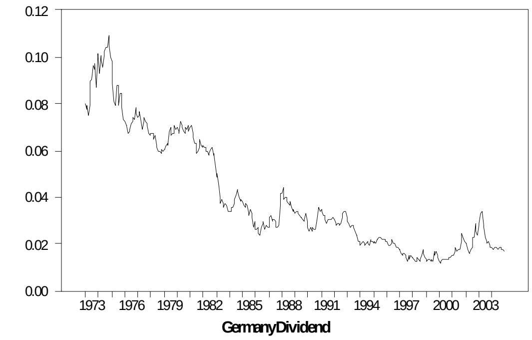


Table 1 reports the basic statistics of stock returns and dividends of the four countries. In the top panel, the mean of stock returns is around 0.002 for the U.S., the UK and Germany but around –0.002 for Japan. The standard deviation of stock returns range from 0.041 to 0.059 for the four countries. Except for Japan, the normality of the series based on the Jarque-Bera (JB) is rejected for all countries. We employ the Ljung-Box Q statistics (LB) test to check for autocorrelation and reject the null of no correlation for the U.S. and Germany but not for the UK and Japan. The ARCH effect exists in U.S. stock returns.

Table 1 : Basic Statistics of Stock Returns and Dividend Returns

	Country	Mean	S.D	SK	EK	JB	LB(24)	LBS(24)	ARCH(6)
Stock Returns	U.S.	0.002	0.041	-0.231	11.217	8403.296*	214.214*	480.044*	27.167*
	UK	0.002	0.050	-1.374	7.393	588.497*	18.19	8.790	0.241
	Japan	-0.002	0.058	0.195	0.083	1.103	19.791	28.404	0.539
	Germany	0.002	0.059	-0.691	2.385	121.407*	28.536	52.555*	2.886
Dividend	U.S.	10.001	4.206	0.441	-1.107	133.633*	36992.783*	37260.154*	842502.443*
	UK	0.046	0.018	0.149	-1.276	16.318*	4762.784*	4440.618*	818.169*
	Japan	0.009	0.001	0.185	-0.803	5.445	617.923*	579.086*	144.506*
	Germany	0.040	0.025	0.879	-0.358	51.538*	8441.582*	7784.107*	3715.730*

Note: * denotes significance at the 5% level; Mean is the average; SD denotes standard deviation; SK denotes skewness; EK denotes excess kurtosis; JB is the Jarque-Bera statistics; LB(24) is the Ljung-Box Q statistics with lag length 24; LBS(24) is the same as LB(24) except that the squared term is used; and ARCH is the autoregressive conditional heteroscedasticity with lag length 6.

As shown in the bottom panel of Table 1, the dividend ratio varies substantially across all four countries, with the highest for the U.S. (10.01) which is much higher than that for the UK (0.046), Germany (0.040) and Japan (0.009). The highest standard deviation, however, is also in the U.S. (4.206), much higher than that in Germany (0.025), the UK (0.018) and Japan (0.001). The estimated coefficients of skewness, excess kurtosis, normality and the ARCH effect are similar to those for stock returns. High autocorrelation is found for the U.S. as the LB statistics are highly significant.

4.2 Cointegration Tests
4.2.1 Conventional Linear Tests
Table 2 presents the results of three unit root tests: the ADF (Augmented Dickey Fuller), the PP (Phillips and Peron) and the KPSS tests. Because none of the tests can reject the null of a unit root in stock prices and dividends in the four countries, the two series are I(1) process in all four countries.[5]

[5] We reject the unit root when the difference form of the series is employed. The results are not reported here but are available upon request.

Table 2: Unit Root Test Results on Original Series

	ADF		PP		KPSS	
τ_τ	**Stock Price**	**Dividend**	**Stock Price**	**Dividend**	**Stock Price**	**Dividend**
U.S.	-2.25	-3.74*	-1.05	-2.01	3.09*	2.45*
UK	-1.21	-2.20	-1.31	-2.81	0.42*	0.34*
Japan	-2.30	-2.59	-2.64	-2.93	0.16*	0.20*
Germany	-2.31	-1.89	-2.25	-2.17	0.41*	1.23*
τ_μ	**ADF_P**	**ADF_D**	**PP_P**	**PP_D**	**KPSS_P**	**KPSS_D**
U.S.	0.89	-0.97	0.31	-0.36	16.52*	26.61*
UK	-1.28	-1.68	-1.61	-1.63	2.79*	4.12*
Japan	-2.03	-2.52	-2.29	-2.86	0.96*	0.29
Germany	-1.49	-3.43*	-1.38	-1.45	5.15*	6.58*

Note: ADF: Augmented Dickey Fuller test of the null of non-stationarity. PP is the Phillips and Perron test. KPSS examine the null of stationary. τ_μ is the unit root test with drift only, τ_τ and is the test with drift and trend. The notation * denotes significance at the 5% level.

Table 3 presents the estimated results of the conventional cointegration test using the Johansen maximum likelihood test of eigenvalues and tracing testing statistics. We start the model without intercepts and drifts and then gradually modify it to examine robustness. The results, however, do not change much. We test three null hypotheses, i.e., the null of no, of one and of two cointegration vectors. The estimated results cannot reject the number of cointegration vectors which is equal to zero (r=0) for the U.S., the UK and Japan regardless which testing statistics we use. Hence, the two series do not have a long-term relation in these three countries. As for Germany, both testing statistics reject the null of r=0 but cannot reject r=1. Accordingly, there is a long-term relation between the two series in Germany.

Table 3: Johansen Cointegration Test Results

Maximum Eigenvalue Test							
	H_0	H_1	**U.S.**	**UK**	**Japan**	**Germany**	**5% CV**
	r=0	r=1	9.82	3.04	9.12	17.38*	14.88
	$r \neq 0$	r=2	0.41	2.79	4.89	5.57	8.07
Cointegrated			No	No	No	Yes	
Trace Test							
	r=0	$r \neq 1$	10.23	5.83	14.01	22.96*	17.86
	$r \neq 0$	$r \neq 2$	0.55	2.79	4.89	5.57	8.07
Cointegrated			No	No	No	Yes	

*: significance at the 5% level. r is the number of cointegation vectors.

4.2.2 Nonlinear Cointegration Tests

Though linear cointegration is rejected for the U.S., the UK and Japan, it does not imply that the two series have no long-term relation because they may share a common nonlinear pattern. Even though one linear cointegration between the two series is found for Germany, there may still be a nonlinear cointegration. Table 4 presents the estimated results using the rank cointegration testing statistics, κ_T^*, ξ_T^* and Ξ_T^*. These three testing statistics overwhelmingly reject the null of no nonlinear cointegration regardless of the country. Thus, for the U.S., the UK and Japan, while there is no linear cointegration between stock prices and dividends, there is a nonlinear cointegration between the two series. By contrast, there are both linear and nonlinear relationships for Germany.

Table 4: Nonlinear Cointegration Test Results

Statistics	U.S.	UK	Japan	Germany	5% CV
κ_T^*	0.0277*	0.1043*	0.1043*	0.0693*	0.3635
ξ_T^*	0.0001*	0.0926*	0.0019*	0.0009*	0.0188
ξ_T^*	0.0002*	0.0019*	0.0026*	0.0011*	0.0197
Nonlinear Cointegration	Yes	Yes	Yes	Yes	

*: significance at the 5% level.

4.3 Causality Tests
4.3.1 Linear Causality Test
Table 5 presents the estimated results of the (linear) Granger causality test using the *F* test. Because the two series of the U.S., the UK and Japan are not cointegrated, we use the difference form. But, we use the error correction model in the case of Germany (see Engle and Granger, 1987). As regards the null that dividend does not Granger cause stock price, the *F* statistics are significant for the U.S., the UK and Germany but not for Japan. As for the null that stock price does not Granger cause dividend, the *F* statistics are significant for the U.S. and Germany but not for the UK and Japan. In short, there is bidirectional causality in the stock price-dividend relation for the U.S. and Germany, one way Granger causality from dividend to stock price for the UK but no causality between the two series for Japan.

Table 5: Granger Causality Test Results

Null hypothesis: Dividend Does Not Cause Stock Price				
	U.S.	**UK**	**Japan**	**Germany**
F-statistic	1.62[0.05]*	13.78[0.00]*	0.70[0.40]	1.67[0.03]*
Causality	Yes	Yes	No	No
Null hypothesis: Stock Price Does Not Cause Dividend				
	U.S.	**UK**	**Japan**	**Germany**
F-statistic	3.23[0.00]*	1.16[0.30]	0.01[0.93]	1.54[0.06]*
Causality	Yes	No	No	Yes

4.3.2 Nonlinear Granger Causality Tests
Tables 6 to 9 present the estimated results using the nonlinear Granger causality tests for the four countries, respectively. The left- and right-hand side of each table report the results from the HJ and DP models, respectively. In Table 6, for the U.S., because the *t* statistics obtained from HJ's method are overwhelmingly smaller than the critical value of 1.65 regardless of the null hypotheses of no causality from stock price to dividend or from dividend to stock price, we cannot reject the null. Thus, when we employ HJ's model, there is no nonlinear causality between the two series in the case of the U.S. The results change dramatically, however, when we employ DP's model. Except when the lag length is one, the two nulls are overwhelmingly rejected for the remaining seven lag lengths. Because DP's method has better appropriate size and power than HJ's method, there is in fact bidirectional nonlinear causality in the case of the U.S.. The implication here is that caution must be taken when interpreting the results from HJ's method.

Table 6: Nonlinear Granger Causality Test Results－U.S.

Hiemstra and Jones (1994) test		Diks and Panchenko (2006) test	
H_0: **Dividend Does Not Cause Stock Price**			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	0.50[0.31]	1	1.14[0.13]
2	0.63[0.26]	2	1.83[0.03]*
3	1.00[0.16]	3	3.14[0.00]*
4	1.00[0.16]	4	3.38[0.00]*
5	0.87[0.19]	5	3.57[0.00]*
6	0.69[0.24]	6	3.69[0.00]*
7	0.89[0.19]	7	3.78[0.00]*
8	0.87[0.19]	8	3.61[0.00]*
H_0: **Stock Price Does Not Cause Dividend**			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	0.64[0.26]	1	2.31[0.01]*
2	0.85[0.20]	2	2.70[0.00]*
3	1.04[0.15]	3	3.31[0.00]*
4	1.10[0.13]	4	3.19[0.00]*
5	1.02[0.15]	5	3.51[0.00]*
6	0.86[0.20]	6	3.20[0.00]*
7	0.97[0.16]	7	2.96[0.00]*
8	0.91[0.18]	8	2.59[0.00]*

*: significance at the 5% level.

Table 7 presents the mixed results based on UK data. With HJ's model, we cannot reject the null of no nonlinear causality from dividend to stock price when the lag lengths of dividend are 1, 2 and 4, but we reject it for the other lag lengths. Because the optimal lag length is 5 based on the Bayesian Information Criterion, we are prone to reject the null of the nonlinear causality from dividend to stock price. Similarly, there is nonlinear causality from stock price to dividend. The results, again, change substantially when we use the DP model. The *t*-values are overwhelmingly smaller than the critical values, a sign that we cannot reject the null. Thus, there is no nonlinear Granger causality between the two series in the UK.

Table 7: Nonlinear Granger Causality Test Results－ UK

Hiemstra and Jones (1994) test		Diks and Panchenko (2006) test	
H_0 : Dividend Does Not Cause Stock Price			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	0.33[0.37]	1	-0.73[0.23]
2	1.14[0.13]	2	0.47[0.32]
3	1.34[0.09]†	3	1.39[0.08]†
4	0.88[0.19]	4	0.65[0.26]
5	1.71[0.04]*	5	0.35[0.36]
6	2.27[0.01]*	6	1.07[0.14]
7	2.40[0.01]*	7	1.16[0.12]
8	1.82[0.03]*	8	1.29[0.10]†
H_0 : Stock Price Does Not Cause Dividend			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	0.88[0.19]	1	0.06[0.48]
2	1.13[0.13]	2	0.24[0.40]
3	1.27[0.10]†	3	-0.65[0.26]
4	0.81[0.21]	4	-0.60[0.27]
5	1.87[0.03]*	5	-0.08[0.47]
6	1.49[0.07]†	6	0.48[0.32]
7	1.10[0.14]	7	0.45[0.33]
8	0.99[0.16]	8	0.46[0.32]

*: significance at the 5% level.
†:significance at the 10% level.

Table 8 presents the estimated results in the case of Japan. The nulls of no nonlinear causality from either dividend to stock price or vice versa are rejected with all models we use. Accordingly, there is no nonlinear Granger causality between the two series of Japanese data. Because neither a linear nor a nonlinear relation exists for the two series, the present value model in either form is clearly not applicable to Japan.

Table 8: Nonlinear Granger Causality Test Results－ Japan

Hiemstra and Jones (1994) test		Diks and Panchenko (2006) test	
H_0 **: Dividend Does Not Cause Stock Price**			
$L_r = L_d$	**t-statistics [p-value]**	$L_r = L_d$	**t-statistics[p-value]**
1	-0.24 [0.60]	1	0.78[0.22]
2	-0.39 [0.65]	2	0.47[0.32]
3	-0.06 [0.52]	3	0.98[0.16]
4	0.39[0.35]	4	0.09[0.46]
5	0.29[0.39]	5	0.23[0.41]
6	0.20[0.42]	6	-0.56[0.29]
7	4.67[0.00]*	7	-0.17[0.43]
8	4.87[0.00]*	8	-0.16[0.44]
H_0 **: Stock Price Does Not Cause Dividend**			
$L_r = L_d$	**t-statistics [p-value]**	$L_r = L_d$	**t-statistics[p-value]**
1	0.27[0.39]	1	0.45[0.33]
2	0.11[0.46]	2	-0.60[0.28]
3	-0.01[0.51]	3	-0.38[0.35]
4	-0.02[0.51]	4	-0.28[0.39]
5	-0.15[0.56]	5	-0.21[0.42]
6	-0.28[0.61]	6	-0.99[0.16]
7	0.48[0.32]	7	-1.14[0.13]
8	NA	8	-1.05[0.15]

*: significance at the 5% level.
†:significance at the 10% level.
NA: Not Available.

Though it is not the main purpose of this paper to investigate the reasons for the failure of the PV model, a brief discussion about the applicability of the theory is enlightening. Chung and Lee (1998) also found that dividend cannot explain the movement of stock prices in Japan and suggested that there are a number of non-fundamental factors that affect prices, thereby causing theoretical stock price to deviate from the actual ones. In the case of Japan, since 1990, these non-fundamental factors could have included the lost-decade recession in the 1990s, the Kobe earthquake in 1995 and the Asian crisis in 1997-1999. Accordingly, the present value model may fail when there are many non-fundamental factors, continuously distorting stock price.

Table 9 presents the estimated results for Germany. When we employ HJ's model, there is no nonlinear causality in either direction. However, when we adopt DP's model, the null that dividend does not nonlinearly cause stock returns is rejected when the lag lengths are 4, 5 and 6. That is, we obtain mixed results. Furthermore, the null that stock return does not nonlinear cause dividend is rejected. Thus, there is nonlinear bilateral causality between the two series.

Table 9: Nonlinear Granger Causality Test Results－Germany

Hiemstra and Jones (1994) test		Diks and Panchenko (2006) test	
H_0 **: Dividend Does Not Cause Stock Price**			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	-1.45[0.93]	1	0.22[0.41]
2	-0.53[0.70]	2	0.66[0.26]
3	0.00[0.50]	3	0.34[0.37]
4	0.08[0.47]	4	-1.37 [0.08]†
5	0.20[0.40]	5	-1.28 [0.10]†
6	0.36[0.35]	6	-1.52 [0.06]†
7	5.92[0.00]*	7	-0.45 [0.33]
8	4.96[0.00]*	8	-0.64 [0.26]
H_0 **: Stock Price Does Not Cause Dividend**			
$L_r = L_d$	***t*-statistics [p-value]**	$L_r = L_d$	***t*-statistics[p-value]**
1	0.20[0.42]	1	0.63[0.26]
2	0.02[0.49]	2	-0.41 [0.34]
3	-0.19 [0.58]	3	-0.77 [0.22]
4	0.18[0.43]	4	-2.70 [0.00]*
5	0.31[0.38]	5	-3.37 [0.00]*
6	0.48[0.32]	6	-3.00 [0.00]*
7	0.00[0.50]	7	-2.54 [0.01]*
8	NA	8	-2.77 [0.00]*

*: significance at the 5% level.
†:significance at the 10% level.
NA: Not Available.

5. Comparison with Previous Results

Table 10 compares our estimated results with those of Kanas (2005). As concerns cointegration, the two results are the same except in the case of Germany. For Germany, our findings are at complete odds with those of Kanas in that we find that there is linear cointegration between the two series. We conjecture that the sample length may have affected the estimated results since our sample period ranges from 1973:1 to 2004:12, unlike his which only cover 1978:1 to 2002:5. Because we both find nonlinear cointegration between the two series for all sample countries, differences in the investigation into nonlinear cointegration through either rank cointegration or ACE cointegration may merely be insignificant.

Table 10: Comparison of Granger Causality between HJ and DP

	Hiemstra and Jones (1994) test	Diks and Panchenko (2006) test
Does Dividend Cause Stock Price		
U.S.	No	Yes
UK	Yes	Yes
Japan	Yes	No
Germany	Yes	Yes
Does Stock Price Cause Dividend		
U.S.	No	Yes
UK	Yes	No
Japan	No	No
Germany	No	Yes

With regard to the estimated results with respect to causality, the differences between Kanas' results and those of the present study are much broader. Kanas finds that, though there is no linear causality, there is nonlinear causality for all sample countries. Our results stand in contrast to that since we find that both linear and nonlinear causalities exist for the U.S., the UK and Germany. Because the null of no nonlinear causality is overwhelmingly rejected by HJ but not by DP in our study, our results seem to confirm the position of Diks and Panchenko's (2006) vis-à-vis the problem of over rejection in HJ's model.

6. Conclusions

This paper investigates whether the nonlinear present value model has the capability to explain the failure of its linear counterpart. In particular, we extend Kanas' model by using two new econometric models. Our results are highlighted in the following.

First, the estimated results for nonlinear cointegration via either rank coingration or ACE cointegration do not differ significantly. In other words, both methods are seemingly valid when it comes to investigating nonlinear cointegration. The nonlinear Granger causality test results, however, are measurably different when we use the two different methods, i.e., the Diks and Panchenko (2006) and the Hiemstra and Jones (1994) methods. In light of its being better in the statistical sense, our empirical conclusions are based on the former method.

Next, linear cointegration fails to exist when we use data for the U.S., the UK and Japan but not Germany. Employing rank cointegration to examine the nonlinear present value model, however, is successful for the U.S., the UK and Germany but not Japan. Thus, the assertion that nonlinearity can account for deviations in the linear model is particularly suitable for the U.S. and the UK model. The failure with Japanese data may be attributed to there being too many non-fundamental shocks. For Germany, the nonlinear part can add more explanatory power to the linear one, but for Japan, neither model is valid. Future research could further pursue the failure in the case of Japan.

Finally, evidence of both linear and nonlinear causality from dividend to stock price is found for the U.S., the UK and Germany. However, neither linear nor nonlinear causality exists for Japan. On the other hand, evidence of linear and nonlinear causality from stock price to dividend is only found for the U.S. and Germany. In the case of the UK and Japan, there is neither.

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