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Nonlinearity in the stock price–dividend relation

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Abstract

We provide empirical evidence of nonlinearities in the present value (PV) model of stock prices. We test for nonlinearity both in the contemporaneous and in the dynamic stock price–dividend relation for the UK, the US, Japan, and Germany. We employed three nonlinear nonparametric techniques, namely nonlinear cointegration, locally-weighted regression, and nonlinear Granger causality tests. Whilst there is no evidence of linear cointegration and Granger causality for any country, there is significant evidence of nonlinear cointegration and nonlinear Granger causality for all four countries. Furthermore, out-of-sample forecasts obtained from the locally-weighted regression are more accurate than out-of-sample forecasts obtained from the linear model for the UK, the US, and Japan. These results are robust to sub-period analysis. The results are in line with empirical evidence that expected stock returns are time-varying.

JEL classification: G12

Keywords: Present value model; Nonlinear cointegration; Locally-weighted regression; Nonlinear Granger causality; Stock prices; Dividends

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1. Introduction

Following the failure of the linear present value (PV) model to explain the behaviour of stock prices, significant interest was shed on possible causes to which this failure can be attributed. Such causes include the constant discount rate and rational expectations. Allowing a variable discount rate (Campbell and Shiller, 1988a, 1988b; West, 1987, 1988) led to little positive empirical evidence (Flood and Hodrick, 1986; Campbell and Shiller, 1988a). Furthermore, incorporating speculative bubbles into the PV model (Blanchard and Watson, 1982; Flood and Garber, 1980) also led to inconclusive empirical results (West, 1987; Diba and Grossman, 1988).

This article examines whether the failure of the linear PV model can be attributed to nonlinearities in the stock price–dividend relation. We test the hypothesis that nonlinear extensions of the PV model perform significantly better than the existing (linear) model in explaining the behaviour of stock prices as a function of dividends. Importantly, we test for nonlinearity in both the contemporaneous and the dynamic stock price–dividend relation. Nonlinearity in the contemporaneous relation is tested for using nonlinear cointegration tests (Granger, 1991; Granger and Hallman, 1991), and the locally-weighted regression (LWR) approach. The nonlinear cointegration approach is used to examine whether there is a long-run nonlinear relation between stock prices and dividends. The LWR approach is utilised to obtain nonlinear out-of-sample forecasts, which are compared against linear (OLS-based) out-of-sample forecasts in terms of forecast accuracy. Nonlinearity in the dynamic stock price–dividend relation is tested for using the nonlinear Granger causality (NLGC) test of Baek and Brock (1992), and Hiemstra and Jones (1994). The latter test can uncover significant nonlinearity in the dynamic interrelationship between two variables, and can reveal whether dividend changes have a nonlinear predictive power for stock returns. All three techniques are nonparametric in the sense that they are not restricted to a particular nonlinear functional form.

The linear PV model is more tractable than its nonlinear version, and this accounts for its use in empirical work. However, as discussed in Campbell et al. (1997) (CLM), the linear PV model is based on the assumption of constant expected stock returns. This assumption is convenient, but it contradicts the empirical evidence discussed in CLM supporting the predictability and time-variation of expected stock returns. CLM illustrate that when expected stock returns are time-varying, the correct PV formula is nonlinear. In addition, several recent theoretical models have contended that the stock price–dividend relation is nonlinear. Such models include the fads model (Summers, 1986), the trigger strategies model (Krugman, 1987), the intrinsic bubbles model (Froot and Obstfeld, 1991), and the model of market learning about managerial competence (Kiyotaki, 1990). The statistical procedures used in this article are compatible with the nonlinearities relevant to the above theoretical models, but are much more general in the sense that they can be used to estimate structural models without the restrictions typically employed in empirical work.

We test for nonlinearity in the PV model for the UK, the US, Japan, and Germany, using monthly data for real stock index prices and real dividends. The importance of testing for nonlinearity is illustrated by our results. Whilst there is no evidence of linear cointegration, there is significant evidence of nonlinear cointegration for all four countries. Similarly, out-of-sample LWR-based forecasts are more accurate than OLS-based forecasts for the UK, the US, and Japan. With regard to the dynamic relation, there is evidence of nonlinear Granger causality for all four countries, and no evidence of linear Granger causality. The results are robust to different sub-periods within the full sample period. These findings indicate that incorporating nonlinearity into the PV model significantly improves the ability of this model to explain the behaviour of stock prices as a function of dividends.

The remainder of the paper is as follows. Section 2 reviews the theoretical foundations underlying a nonlinear relation between stock prices and dividends. Section 3 discusses the data used and provides a preliminary analysis. Section 4 outlines the statistical methods used for testing for nonlinearity and discusses the results. Finally, Section 5 concludes.

2. Theoretical foundations for a nonlinear stock price–dividend relation

The basic theoretical framework for the analysis of the PV model is analytically discussed in Campbell et al. (1997) (CLM). On the basis of the assumption that expected stock returns are constant, the current stock price is related to the next period's expected stock price and dividend as shown in Eq. (1):

$$P_t = E_t\left[\frac{P_{t+1} + D_{t+1}}{1+R}\right] \tag{1}$$

where P_t is the stock price measured at the end of period t, D_t is the dividend payment at date t, and R is the constant expected stock return ($E_t[R_{t+1}] = R$). Eq. (1) can be solved forward by repeatedly substituting out future prices. After solving forward K periods and assuming that the expected discounted value of the stock price K periods from the present shrinks to zero as the horizon K increases, CLM obtain Eq. (2) expressing the stock price as the expected present value of future dividends out to the infinite future discounted at a constant rate:

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

If D_t follows a linear process with a unit root, the stock price P_t will also follow a linear process with a unit root. In this case, the PV model reflected in Eq. (2) relates two unit-root processes for P_t and D_t. If we subtract a multiple of the dividend from both sides of Eq. (2), we obtain:

$$P_t - \frac{D_t}{R} = \left(\frac{1}{R}\right) E_t\left[\sum_{i=0}^{\infty}\left(\frac{1}{1+R}\right)^i \Delta D_{t+1+i}\right]. \tag{3}$$

The left hand side (lhs) of Eq. (3) reflects the difference between the stock price and $(1/R)$ times the dividend, and the right hand side (rhs) reflects the expected discounted value of the future changes in dividends. If changes in dividends are stationary, then the term on the lhs (difference between the stock price and $(1/R)$ times the dividend) should also be stationary. Thus, even though both the dividend and the stock price processes are nonstationary, there is a linear combination of prices and dividends which is stationary indicating they are cointegrated.

Eq. (3) is based on the assumption that expected stock returns are constant. This assumption is analytically convenient, but it contradicts empirical evidence suggesting that stock returns are predictable. When expected returns are time-varying, the relation between prices and returns, reflected in Eq. (1), and the PV relation reflected in Eq. (3) both become nonlinear. As is more difficult to work with (nonlinear) PV relations when expected returns are time-varying, a loglinear approximation is developed by CLM, and Campbell and Shiller (1988a, 1988b). The starting point of this loglinear approximation is the definition of log stock returns, i.e.

$$r_{t+1} = p_{t+1} - p_t + \log(1 + \exp(d_{t+1} - p_{t+1})) \tag{4}$$

where the lowercase letters denote the logs of the variables. Following CLM, the last term on the rhs of Eq. (4) is a nonlinear function of the log dividend–price ratio, $f(d_{t+1} - p_{t+1})$. Using a 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 parameters of linearisation. Eq. (5) for the log stock price is analogous to Eq. (1) for the level of stock price under the assumption of 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, leads to Eq. (6):

$$p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j \left[(1-\rho)d_{t+1+j} - r_{t+1+j}\right]. \tag{6}$$

Taking expectations of Eq. (6), noting that $p_t = E_t[p_t]$, and simplifying yields:

$$p_t = \frac{k}{1-\rho} + p_{dt} - p_{rt} \tag{7}$$

where p_{dt} is the expected discounted value of $(1-\rho)$ times future log dividends, and p_{rt} is the expected discounted value of future log stock returns. As Eq. (7) is in terms of the log stock price, it can be rewritten in terms of the log dividend–price ratio as follows:

$$d_t - p_t = -\frac{k}{1-\rho} + E_t\left[\sum_{j=0}^{\infty} \rho^j \left[-\Delta d_{t+1+j} + r_{t+1+j}\right]\right]. \tag{8}$$

Eq. (8) is used when the dividend follows a loglinear unit-root process, so that log dividends and log prices are nonstationary. In this case, changes in log dividends are stationary, and from Eq. (8) the log dividend–price ratio is stationary provided that the expected stock return is stationary. In this case, log stock prices and dividends are cointegrated. According to CLM, this simple approach '…makes the loglinear model easier to use in empirical work than the linear cointegrated model' in Eq. (3).

CLM present empirical evidence on stock return predictability, using dividend–price ratios and interest rates as forecasting variables. Evidence of stock return predictability contradicts the assumption of constant expected stock returns and thus, is against the linearity of the PV model. Using stock prices and dividends on the value-weighted CRSP index of stocks traded on the NYSE, the AMEX, and the NASDAQ, CLM run long-horizon regressions of log real stock returns on the log of the dividend–price ratio over various holding horizons for the period 1927–1994, and for the sub-samples 1927–1951 and 1952–1994. The results indicated that the log dividend–price ratio had a significant ability to predict stock returns over long forecast horizons in the full sample and in the prewar sub-sample, and over both short-run and long-run horizons in the postwar sub-sample. Further evidence which suggests that long-horizon stock returns are predictable is provided by Campbell and Shiller (1988b), and Fama and French (1988).

In addition, several recent theoretical models have explicitly introduced nonlinearities in the PV model. Summers (1986), and Cutler et al. (1991) proposed the fads model according to which, investors perceive 'psychological' barriers to upward movements in stock prices. When a stock price barrier is reached, a group of noise traders might either enter the market, in which case a new barrier is established, or exit ('profit taking'). Speculation by rational investors would, in this setting, establish a nonlinear relation between stock prices and dividends.

Krugman (1987) introduced the trigger strategies model, which establishes a concave (nonlinear) relation between stock prices and dividends. Trigger strategies are followed by private investors participating in portfolio insurance schemes who commit themselves to buying or selling when the stock price reaches a pre-determined level. Assuming that the fundamental follows a discrete random walk, Krugman (1987) derives the relation between stock prices and dividends depicted in Fig. 1. In this setting, the market is characterised by two regimes, the one regime being that portfolio insurers are still in the market and the other being that portfolio insurers drop out. Under static expectations, as long as the portfolio insurers are still in the market, the stock price will move along line E_3. Once the portfolio insurers drop out, the stock price moves along E_2. Under rational expectations, which take into account the effects of portfolio insurance schemes on future stock prices, the stock price–dividend relation is given by the schedule labeled E_1C. In the regime where insurers have not yet sold out, the stock price–dividend relation is tied down by the fact that when the price falls below the trigger level, there is a transition to the other regime. Eventually, random walking of the dividend will bring the market to C, leading insurers to drop out. After that point, the market's behaviour is described by the schedule labeled E_2.

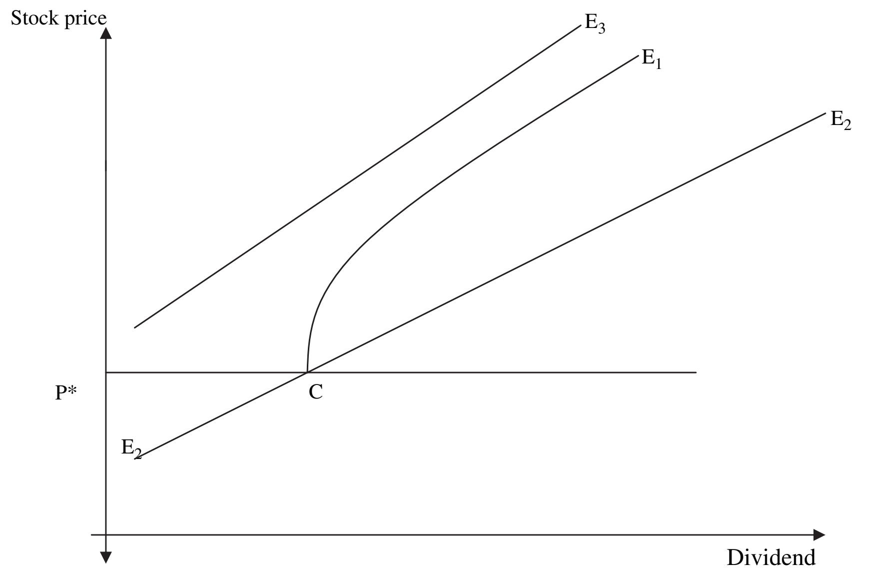

Fig. 1. The stock price–dividend relation in the trigger strategies model. *Note*: P^*: the pre-determined trigger stock price.

Kiyotaki (1990) derives a nonlinear relation between a firm's stock price and the fundamental in a model of market learning about managerial competence. In this model, nonlinearity is due to the uncertainty attached to the quality of the manager. People know whether the manager is replaced, but they do not know how good the manager is; they gradually learn about it by observing the changes in the fundamental under the current manager. Kiyotaki shows that if the manager is good, people become more and more optimistic about the manager and the stock price tends to increase more rapidly than the fundamental stock price. This optimism disappears with sudden retirement of the manager, and the stock price then equals the fundamental price. In this setting, the stock price follows a bubble-like behaviour, and is nonlinearly related to the fundamental.

Froot and Obstfeld (1991) introduced a type of rational stock price bubbles known as 'intrinsic bubbles'. Froot and Obstfeld show that the linear PV model should be expanded to include a term due to the intrinsic bubble which is a nonlinear function of dividends. This term results in the PV relation being nonlinear. They also provide empirical evidence in favour of the existence of intrinsic bubbles for the US stock market.

3. Data and preliminary analysis

We focus on four developed economies, namely the UK, the US, Japan and Germany, and obtain monthly nominal stock index prices and dividends for each country.[1] The stock price indices used are: the Dow Jones Industrial Average (30) for the US, the Financial Times All Share index for the UK, and the Datastream total market indices for Japan and Germany.[2] The dividend series are the corresponding dividend series for each stock price index. All data series are obtained from Datastream. For all four countries, the data span the period January 1978–May 2002 (1978:1–2002:5). To control for the stock market crashes of October 1987 and 1989, these two months are excluded from the sample, giving a sample of 291 observations. Nominal stock prices and dividends were expressed in real terms using the Consumer Price Index (All Items). Real stock price and dividend series were expressed in natural logarithms, and monthly real stock index returns were calculated as the first difference of two consecutive real monthly stock index prices.[3]

As a preliminary step in our analysis, we follow CLM and explore whether long-horizon stock returns for the UK, the US, Japan, and Germany can be predicted using forecasting variables other than past returns themselves. Evidence of predictability of long-horizon stock returns would contradict the assumption of constant expected stock returns and thus, the linearity of the PV model. To test for predictability, we estimate the model $r_t = b(d_t - p_t) + e_t$, where r is the log real return on the stock index of the respective country, and $(d - p)$ is the log dividend–price ratio (CLM, page 269). The time horizon of stock returns is 12 months. The results are reported in Table 1. This table shows that the estimated coefficient $\hat{b}$ is statistically significant for all four countries over the period 1978:1–2002:5, thereby suggesting that the log dividend–price ratio has some ability to predict the 12-month stock returns for each country. This evidence suggests that departures from the linear PV model should be expected for all four countries over this period.

We also performed structural stability (Chow) tests for the long-horizon regressions in Table 1. In these tests, the breakpoint month was taken to be 1989:12, approximately in the middle of the full sample, yielding two sub-periods with approximately equal number of observations, i.e. 1978:1–1989:12 (142 observations) and 1990:1–2002:5 (149 observations). The results from these tests are also reported in Table 1. As shown in this table, the results are rather mixed

[1] Previous papers testing for cointegration between stock prices and dividends employed either annual or monthly data. Given that for most of the countries considered in this study, annual data going back to the early-1900s are not available, we opted for monthly data. We did not use higher frequency (i.e. weekly) data in order to be consistent with previous studies, and due to considerations regarding the power of cointegration tests. As stated in Mills (1993b), the power of these tests only marginally increases using data sampled more frequently, the increase becoming negligible as the sampling interval is decreased. DeJong et al. (1992) provide Monte Carlo evidence supporting this argument.

[2] For Germany and Japan, we preferred the stock price indices constructed by Datastream to the FAZ and Nikkei indices, respectively, as the corresponding dividend series for FAZ and Nikkei were only available for a relatively short period, yielding a relatively small sample. Having a small sample would not be consistent with Timmermann (1995), who found that in small samples, cointegration tests for present value models are unlikely to reject the null of no cointegration even if the present value model is valid.

[3] We tested for seasonal effects in the data and failed to find any. Mills (1993b) reached a similar conclusion for UK data. Van Norden and Schaller (1993) also used seasonally un-adjusted data.

Table 1
Long-horizon regressions of log stock returns on the log dividend–price ratio

	UK	US	Germany	Japan
Full sample: 1978:1–2002:5				
$\hat{b}$	−0.01*	−0.01*	−0.012*	−0.008*
t-stat ($\hat{b}$)	−6.41	−8.39	−5.04	−3.40
Chow stability test (Break point: 1989:12)	14.77* [0.00]	0.18 [0.66]	0.99 [0.32]	85.37* [0.00]
Sub-sample: 1978:1–1989:12				
$\hat{b}$	−0.017*	−0.01*	−0.017*	−0.031*
t-stat ($\hat{b}$)	−6.49	−3.53	−3.62	−11.14
Sub-sample: 1990:1–2002:5				
$\hat{b}$	−0.005*	−0.01*	−0.011*	0.008*
t-stat ($\hat{b}$)	−3.28	−8.30	−3.61	2.47

Notes: The estimated model is: $r_t = b(d_t - p_t) + e_t$, where r is the log real return on the stock index of the respective country, $(d - p)$ is the log dividend–price ratio. The time horizon of stock returns is 12 months. Regressions are estimated using OLS, with heteroscedasticity consistent (White, 1980) standard errors. * Denotes statistically significant coefficient at the 5% level.

across the four countries. In accordance with CLM, we next proceed to estimate the long-horizon regressions over the two sub-periods. As shown in Table 1, the forecasting power of the log dividend–price ratio is maintained in both sub-periods and for all four countries. The fact that the Chow stability test was significant for two countries (the UK, and Japan) is attributed to changes in the value of $\hat{b}$ and not to changes in its statistical significance. Thus, the previous conclusion that stock returns are predictable is robust to different sub-periods within the full sample period.

We next examine the time series properties of real stock price indices, real stock index returns, real dividends, and real dividend changes for all countries, by testing for a unit root over both the full sample and the two sub-periods (1978:1–1989:12, and 1990:1–2002:5). The augmented Dickey–Fuller (ADF) unit-root test is used. Table 2 reports the results. This table shows that all real stock prices and real dividend series are found to be $I(1)$, while all real stock returns and real dividend changes series are found to be $I(0)$ over both the full sample and the two sub-samples.

4. Testing for nonlinearity

4.1. Nonlinearity in the contemporaneous stock price–dividend relation

4.1.1. Nonlinear cointegration

Nonlinear cointegration was introduced by Granger (1991), Granger and Hallman (1991), and Meese and Rose (1991). The series y_t and x_t are said to be nonlinearly cointegrated if there are nonlinear measurable functions $\theta(\cdot)$ and $\phi(\cdot)$

Table 2
Unit-root tests on original series

Variable	Full sample 1978:1–2002:5	First sub-sample 1978:1–1989:12	Second sub-sample 1990:1–2002:5
UK real stock price index	−1.14 (0)	−1.59 (0)	−1.96 (0)
UK real stock index returns	−17.28 (2)*	−13.19 (0)*	−11.25 (0)*
UK real dividends	−1.90 (0)	−2.28 (0)	−2.14 (0)
UK real dividend changes	−17.60 (2)*	−13.79 (0)*	−11.10 (2)*
US real stock price index	−2.43 (0)	−0.89 (0)	−1.65 (0)
US real stock index returns	−18.06 (0)*	−12.71 (0)*	−13.29 (0)*
US real dividends	−2.15 (0)	−1.30 (0)	−1.93 (0)
US real dividend changes	−17.50 (1)*	−12.11 (0)*	−12.64 (1)*
German real stock price index	−2.15 (1)	−1.34 (0)	−1.94 (0)
German real stock index returns	−16.36 (0)*	−12.17 (0)*	−111.51 (0)*
German real dividends	−2.45 (4)	−2.24 (0)	−2.36 (0)
German real dividend changes	−17.37 (3)*	−12.24 (0)*	−12.30 (0)*
Japan real stock price index	−0.57 (1)	−1.15 (0)	−3.16 (4)
Japan real stock index returns	−15.80 (0)*	−10.56 (0)*	−11.97 (0)*
Japan real dividends	−1.41 (0)	−1.50 (0)	−3.12 (4)
Japan real dividend changes	−15.97 (0)*	−10.95 (0)*	−11.80 (0)*

Notes: The table reports the ADF test of the null of nonstationarity. The numbers in brackets report the number of lags in the ADF regressions, determined on the basis of the Akaike Information Criterion (AIC). * Denotes rejection of the null of nonstationarity at the 5% level. The 5% critical value of the ADF test is −3.36.

such that $\phi(y_t)$ and $\theta(x_t)$ are both $I(1)$, and a linear combination of $\phi(y_t)$ and $\theta(x_t)$ is $I(0)$. Thus, linear cointegration among nonlinearly transformed variables is characterised as nonlinear cointegration among the raw variables. Hallman (1991) has shown that nonlinear transformations of nonstationary series may be cointegrated while the raw series are not linearly cointegrated. Thus, it is of interest to determine whether tests of nonlinear cointegration identify long-run behaviour that escapes linear analysis.

Granger and Hallman (1991), Meese and Rose (1991), and Chinn (1991) employed the nonparametric Alternating Conditional Expectations (ACE) algorithm to obtain nonlinear transformations of the variables. ACE relies on extremely weak distributional assumptions, and can handle a wide variety of nonlinear transformations of the data; hence, it is a nonparametric algorithm. ACE is a method of estimating data transformations ($\theta(\cdot)$ and $\phi(\cdot)$) so as to minimise the expected mean squared error of the regression $\phi(y_i) = \gamma\theta(x_i) + \varepsilon_i$. The essence of the methodology is a simple algorithm that estimates a series of alternating conditional expectations (hence the method is known as the "ACE" algorithm). $\theta(\cdot)$ is estimated conditionally for a given choice of $\phi(\cdot)$; then $\phi(\cdot)$ is estimated conditioning on the estimate of $\theta(\cdot)$. ACE operates iteratively; the transformations of all of the variables except one are treated as fixed, and the optimal transformation for the variable in question is estimated with a nonparametric data smooth technique. The algorithm next proceeds to the next variable. Iterations continue until the equation mean squared error has been minimised. Intuitively, this technique unravels the transformations that make the relationship between $\phi(y)$ and $\theta(x)$ as linear as possible, using the mean squared-residual-error as a measure of departure from linearity. Breiman and Friedman (1985) show that the ACE algorithm provides transformations which asymptotically converge to the optimal transformations. A possible consequence of this algorithm is that it may cause an original $I(1)$ series to become $I(0)$ after transformation (Granger and Hallman, 1991). Thus, prior to testing for cointegration among the transformed variables, one needs to confirm that these variables are $I(1)$. The detailed procedure for testing for nonlinear cointegration involves two stages (Granger and Hallman, 1991; Meese and Rose, 1991). Firstly, the ACE-transformed variables are tested as to whether the nonstationarity is maintained by using unit-root tests with bootstrapped critical values. Secondly, if the ACE-transformed variables are $I(1)$, cointegration tests are applied to the ACE-transformed variables.

Turning to the empirical results, we first examine whether there is linear cointegration between the original real stock prices and real dividends. As the number of cointegrating vectors is at most one, we consider residual-based, as opposed to system-based, tests (Baillie and Bollerslev, 1994). To ensure robustness of results, two alternative tests are considered, i.e the Engle–Granger test, and the P_z multivariate test (Phillips and Ouliaris, 1990).[4] For both tests, the null hypothesis is that of no cointegration; the null cannot be rejected if the computed test statistic is lower than the critical value. The linear cointegration tests are conducted for both the full sample period and the two sub-periods. The results are reported in Tables 3 and 4 (Engle–Granger tests and P_z tests, respectively). As shown in Table 3, applying the Engle–Granger test to the regression $P_t = a_0 + a_1 D_t + u_t$ over the full sample period, yields an ADF test statistic with two lags [ADF(2)] without trend of −3.02 for the US, −1.37 for the UK, −1.41 for Japan, and −1.86 for Germany, with a 5% critical value of −3.36.[5] Thus, the Engle–Granger test indicates that the null of no cointegration cannot be rejected for all four countries over the full sample period.[6] The sub-period results reported in this table lead to exactly the same conclusion. Furthermore, as shown in Table 4, all P_z test statistics are lower than the 5% critical value of 55.2202, suggesting that the null of no cointegration cannot be rejected for any country for the full sample period and the two sub-periods. Overall, both tests indicate that there is no evidence of linear cointegration between real stock prices and real dividends. This result is in line with previous evidence for the US by Phillips and Ouliaris (1986) (using annual data for the period 1872–1985), Campbell and Shiller (1987) (using annual data for the period 1871–1986), Froot and Obstfeld (1991) (using annual data for the period 1900–1988), Timmermann (1995) (using annual data for the period 1871–1986), and Dwyer and Hafer (1990) (using monthly data for the period April 1973–December 1987), and with evidence for the UK,

[4] Another test, which could potentially be used, is the Phillips and Hansen (1990) method. However, we use the Engle–Granger test here on the basis of the Monte Carlo evidence provided by Timmermann (1995).

[5] Critical values for the Engle–Granger and P_z tests are from Phillips and Ouliaris (1990).

[6] Similar results are obtained if a trend is included in the ADF tests.

Table 3
Linear cointegration tests: Engle–Granger tests

	UK	US	Germany	Japan
Full sample: 1978:1–2002:5				
Engle–Granger test statistic	−1.37	−3.02	−1.86	−1.41
Sub-sample: 1978:1–1989:12				
Engle–Granger test statistic	−1.13	−1.28	−0.88	−2.03
Sub-sample: 1990:1–2002:5				
Engle–Granger test statistic	−1.39	−2.95	−1.28	−1.80

Notes: The table entries are the Engle–Granger test statistics based on the normalisation $P_t = a_0 + a_1 D_t + u_t$. The reported statistics are the augmented Dickey–Fuller (ADF) statistics calculated using the estimated residuals from the previous normalisation, with two lags (ADF(2)) without trend. The choice of two lags in the ADF tests was based on likelihood ratio tests. Alternative lag structures led to qualitatively similar results. Furthermore, the inclusion of trend did not change the results. The 5% critical value of the Engle–Granger test is −3.36. Similar results were obtained under the Engle–Granger test with a trend in the ADF test statistic.

Japan and Germany by Dwyer and Hafer (1990) (using monthly data for the period April 1973–December 1987). Mills (1993a), using UK monthly data for the period 1965:1–1990:12, found that the null of no cointegration is rejected '…at around the 12.5 per cent level'.

We next turn to testing for nonlinear cointegration. Figs. 2 and 3 provide scatter plots between the ACE-transformed real stock price and real dividend series for the US and Japan, and reveal that the relation between these series appears to be linear.[7] We next proceed to test for a unit root in the ACE-transformed series, using the ADF test with bootstrapped critical values. The results for both the full sample period and the two sub-periods are reported in Table 5. As shown in this table, for the full sample period, all transformed real stock prices and dividend series are $I(1)$, and all real stock returns and dividend changes series are $I(0)$. Similar results are obtained for the two sub-periods. This result allows us to proceed to testing for cointegration among the transformed real stock prices and real dividends series.

Testing for cointegration among the ACE-transformed series using the Engle–Granger test requires that bootstrapped critical values for this test should be constructed, as the asymptotic distribution of this test is not free of nuisance parameters. In contrast, the P_z test has an asymptotic distribution that is not dependent upon nuisance parameters, indicating that for this test the critical values to be used are those reported in Phillips and Ouliaris (1990, Table IV). The results from applying the Engle–Granger tests for cointegration among the transformed real stock price and dividend series are reported in Table 6, Panels A (for the 1978:1–2002:5 period), B (for the 1978:1–1989:12 sub-period), and C (for the 1990:1–2002:5 sub-period). The results are for both normalisations of the

[7] The scatter plots for the UK and Germany look very similar to those of the US and Japan, and are not reported here to save space.

Table 4
Linear cointegration tests: P_z test

	UK	US	Germany	Japan
Full sample: 1978:1–2002:5				
P_z test	11.20	7.41	8.90	11.80
Sub-sample: 1978:1–1989:12				
P_z test	4.80	7.87	4.99	8.41
Sub-sample: 1990:1–2002:5				
P_z test	16.75	12.50	15.80	40.22

Notes: The P_z-statistic tests the null hypothesis of no cointegration, and is invariant to the normalisation of the cointegrating regression. To illustrate, consider the following cointegrating regression, $y_t = a + bx_t + z_t$, where z_t is the residual series of the cointegrating regression, and y_t and x_t are two variables. The P_z-statistic is calculated as $P_z = T$ trace $[\Omega_{\mathrm{p}} T^{-1} \Sigma_1^T X_t X_t']$, where $\Omega_{\mathrm{p}} = T^{-1} \Sigma_1^T z_t z_t' + T^{-1} \Sigma_1^{\mathrm{k}} w_{sk} \Sigma_{s+1}^T (z_t z_{t-s}' + z_{t-s} z_t')$ for some choice of lag window, T is the sample size, $X_t' = (y_t, x_t)$, and z_t are the residuals from estimating the above model with orthogonal regression. Using orthogonal regression, which is invariant to the formulation of the above regression, renders the P_z-statistic invariant to the normalisation of the cointegrating regression (Phillips and Ouliaris, 1990, page 172). Its asymptotic distribution is free of nuisance parameters. If the computed value of the P_z-statistic is lower than the critical value (55.2202, at the 5% level), then we cannot reject the null of no cointegration. The reported test statistics are based on a lag window of 2. Alternative lag windows yield qualitatively similar results.

cointegrating vector, i.e. $P_t^* = a + bD_t^* + u_t$ and $D_t^* = a' + b' P_t^* + u_t'$, where P_t^* and D_t^* are the ACE-transformed stock price and dividend series. The cointegration tests were based on bootstrapped critical values constructed under the null of no cointegration. Panel A shows that for the normalisation $P_t^* = a + bD_t^* + u_t$, the

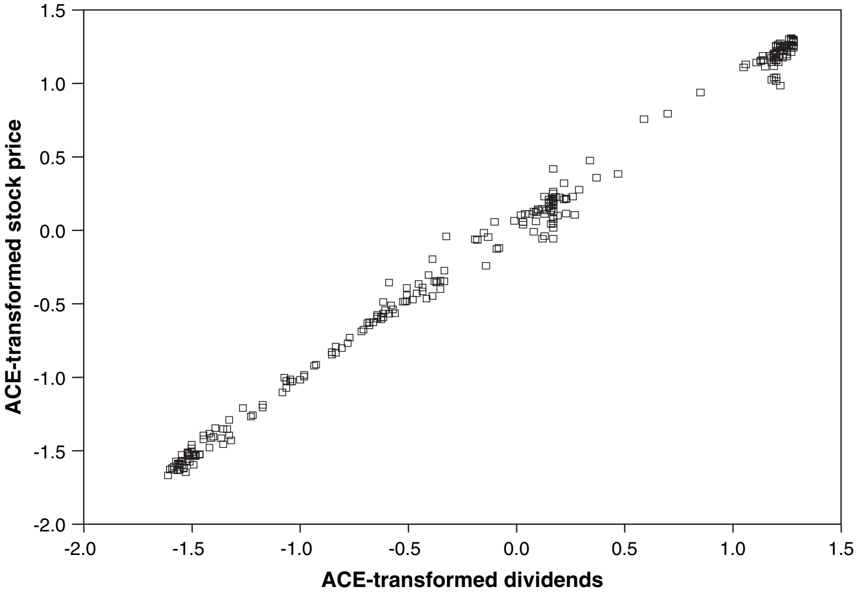

Fig. 2. US: ACE-transformed stock prices vs ACE-transformed dividends.

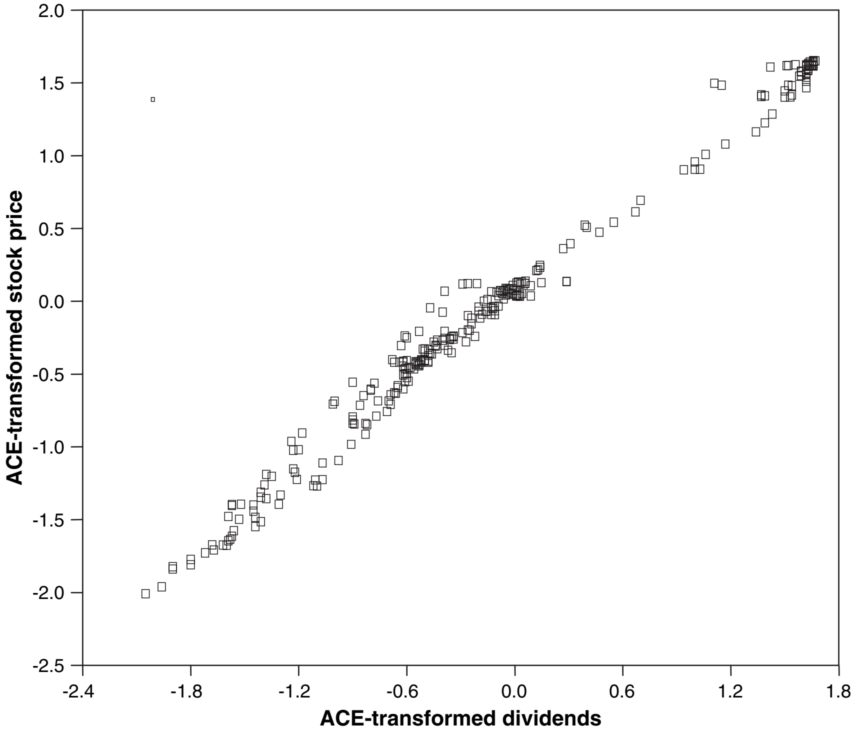

Fig. 3. Japan: ACE-transformed stock prices vs ACE-transformed dividends.

test statistics with trend are −3.79 (for the UK), −5.56 (for the US), −3.46 (for Germany), and −3.87 (for Japan), with corresponding 5% critical values of −3.28, −3.35, −3.36, and −3.44, respectively. As in all cases the test statistic is higher than the corresponding critical value, the null of no cointegration is rejected at the 5% level for all four countries. Exactly the same conclusion is obtained from the ADF statistics without trend (also reported in Panel A). Similarly, for the normalisation $D_t^* = a' + b' P_t^* + u_t'$, the test statistics with trend and without trend are higher than the corresponding 5% critical values for all countries, thereby indicating that the null of no cointegration is also rejected. The same conclusion is obtained from the sub-period test results reported in Panels B and C. Thus, on the basis of the Engle–Granger cointegration test, the null of no cointegration is rejected at the 5% level in favour of the alternative of cointegration among the ACE-transformed series for all four countries.

We next turn to the nonlinear cointegration results from the P_z test. The results for the full sample period and the two sub-periods are reported in Table 7. As shown in this table, for the full sample period, the test statistic with and without trend is higher than the 5% critical value for all countries, thereby suggesting that the null of no cointegration is rejected. Similar results are obtained for all countries for both

Table 5
ADF unit-root tests on ACE-transformed series

Variable	Full sample 1978:1–2002:5		First sub-sample: 1978:1–1989:12		Second sub-sample: 1990:1–2002:5	
	Test statistic	Bootstrap critical value	Test statistic	Bootstrap critical value	Test statistic	Bootstrap critical value
UK real stock prices	−2.44 (0)	−11.10	−2.61 (0)	−8.25	−1.85 (0)	−11.15
UK real stock returns	−15.88 (0)*	−11.13	−10.80 (0)*	−8.20	−11.56 (0)*	−11.15
UK real dividends	−2.95 (0)	−11.14	−2.54 (0)	−8.22	−2.55 (0)	−11.14
UK real dividend changes	−17.33 (0)*	−11.15	−11.98 (0)*	−8.18	−12.38 (1)*	−11.10
US real stock prices	−2.64 (0)	−11.03	−1.68 (0)	−8.26	−1.84 (0)	−11.14
US real stock returns	−17.09 (0)*	−11.12	−9.60 (0)*	−8.23	−15.75 (0)*	−11.14
US real dividends	−2.48 (0)	−11.21	−1.93 (2)	−8.20	−1.46 (0)	−11.12
US real dividend changes	−11.53 (1)*	−11.10	−10.98 (2)*	−8.18	−12.76 (1)*	−11.12
German real stock prices	−3.30 (1)	−11.02	−2.16 (1)	−8.22	−2.68 (0)	−11.14
German real stock returns	−14.45 (0)*	−11.05	−9.25 (0)*	−8.14	−11.97 (0)*	−11.14
German real dividends	−3.49 (2)	−11.12	−2.35 (0)	−8.20	−3.40 (2)	−11.12
German real dividend changes	−17.28 (1)*	−11.23	−11.12 (0)*	−8.20	−13.68 (0)*	−11.12
Japan real stock prices	−1.24 (0)	−11.10	−2.06 (1)	−8.15	−3.50 (2)	−11.12
Japan real stock returns	−15.43 (0)*	−11.10	−9.94 (0)*	−8.18	−12.68 (2)*	−11.15
Japan real dividends	−1.26 (0)	−11.01	−2.16 (0)	−8.20	−3.30 (3)	−11.15
Japan real dividend changes	−15.68 (0)*	−11.05	−10.81 (0)*	−8.20	−11.87 (2)*	−11.10

Notes: The null hypothesis is that of nonstationarity. The number in the parenthesis next to the test statistic reports the number of lags in the ADF test. * Denotes that the null of nonstationarity is rejected at the 5% level.

sub-periods, with the exception of Germany for which the test statistic without trend for the period 1990:1–2002:5 is marginally insignificant at the 5% level.

Overall, both the Engle–Granger and the P_z tests suggest that there is significant evidence of nonlinear cointegration between stock prices and dividends for all four countries, and no evidence of linear cointegration. These findings indicate that there is a nonlinear long-run relation between stock prices and dividends, and no linear long-run relation. If stock prices and dividends are appropriately nonlinearly transformed, then the PV model does imply the existence of a stationary relation between stock prices and dividends. In the absence of such nonlinear transformations, the stock price–dividend relation is nonstationary. Thus, the poor performance of the linear PV model in explaining the long-run properties of stock prices in the UK, the US, Japan and Germany can be attributed to the lack of appropriate nonlinear transformations of the variables.

Table 6
Testing for nonlinear cointegration: Engle–Granger test

	Cointegrating regression $P_t^* = a + bD_t^* + u_t$		Cointegrating regression $D_t^* = a' + b'P_t^* + u_t'$	
	Trend	No trend	Trend	No trend
Panel A: Full sample: 1978:1–2002:5				
UK				
Test statistic	−3.79* (2)	−3.73* (2)	−3.84* (2)	−3.68* (2)
5% Bootstrapped critical value	−3.28	−2.77	−3.44	−2.87
US				
Test statistic	−5.56* (2)	−5.55* (2)	−5.55* (2)	−5.57* (2)
5% Bootstrapped critical value	−3.35	−2.90	−3.43	−2.84
Germany				
Test statistic	−3.46* (2)	−3.39* (2)	−3.52* (2)	−3.53* (2)
5% Bootstrapped critical value	−3.36	−2.84	−3.44	−2.85
Japan				
Test statistic	−3.87* (2)	−3.54* (2)	−3.72* (2)	−3.51* (2)
5% Bootstrapped critical value	−3.44	−2.88	−3.40	−2.86
Panel B: Sub-sample: 1978:1–1989:12				
UK				
Test statistic	−4.12* (2)	−4.15* (2)	−4.13* (2)	−4.14* (2)
5% Bootstrapped critical value	−3.39	−2.90	−3.45	−2.89
US				
Test statistic	−3.61* (2)	−3.82* (2)	−3.62* (2)	−3.86* (2)
5% Bootstrapped critical value	−3.44	−2.89	−3.39	−2.89
Germany				
Test statistic	−4.39* (0)	−4.31* (0)	−3.51* (0)	−3.54* (0)
5% Bootstrapped critical value	−3.43	−2.86	−3.43	−2.88
Japan				
Test statistic	−3.51* (1)	−3.08* (1)	−3.51* (1)	−3.08* (1)
5% Bootstrapped critical value	−3.42	−2.99	−3.44	−2.87
Panel C: Sub-sample: 1990:1–2002:5				
UK				
Test statistic	−3.00 (2)	−2.97* (2)	−3.13 (2)	−3.00* (2)
5% Bootstrapped critical value	−3.45	−2.86	−3.44	−2.85

(*continued on next page*)

Table 6 (*continued*)

	Cointegrating regression $P_t^* = a + bD_t^* + u_t$		Cointegrating regression $D_t^* = a' + b'P_t^* + u_t'$	
	Trend	No trend	Trend	No trend
US				
Test statistic	−3.96* (2)	−3.85* (2)	−3.93* (2)	−3.93* (2)
5% Bootstrapped critical value	−3.42	−2.86	−3.40	−2.90
Germany				
Test statistic	−3.42* (0)	−2.90* (0)	−3.32 (0)	−3.33* (0)
5% Bootstrapped critical value	−3.40	−2.87	−3.43	−2.89
Japan				
Test statistic	−3.90* (0)	−3.70* (0)	−4.09* (0)	−3.84* (0)
5% Bootstrapped critical value	−3.45	−2.88	−3.44	−2.89

Notes: P_t^* and D_t^* are the ACE-transformed stock price and dividend series, respectively. The number in brackets next to the test statistic reports the number of lags in the ADF test. * Denotes that the null of no cointegration is rejected at the 5% level of significance.

4.1.2. Locally-weighted regression

We next focus on estimating the PV model using the nonlinear nonparametric technique of locally-weighted regression (LWR). LWR is a general technique for estimating regression surfaces in a moving average manner. As the method is nonparametric, a wide range of functions can be detected with this technique. This approach fits a curve to the data locally, so that at any point the curve depends only on the observations at that point and some specified neighbouring points. This method is attractive because it relies on the data to specify the form of the model. Because such a fit produces an estimate of the response that is less variable than the original observed response, the result obtained is called 'smoothing'. Let $y = f(x_t)$ be the real stock returns series and x the real dividend changes. Consider one point x (i.e. one

Table 7
Testing for nonlinear cointegration: P_z test

UK		US		Germany		Japan	
Trend	No trend	Trend	No trend	Trend	No trend	Trend	No trend
Full sample: 1978:1–2002:5							
140.33*	75.87*	149.20*	133.50*	103.80*	73.52*	88.51*	65.30*
Sub-sample: 1978:1–1989:12							
85.83*	68.87*	86.2*	77.15*	81.50*	57.00*	87.00*	56.80*
Sub-sample: 1990:1–2002:5							
89.20*	57.50*	89.10*	60.11*	90.75*	48.80	82.00*	59.80*

Notes: See notes in Table 4. * Denotes rejection of the null at the 5% level. The reported test statistics are based on a lag window of 2. Alternative lag windows yield qualitatively similar results.

value of the real dividend changes series), say x^*. The first step in the LWR-smoothing is to select a neighborhood of k points whose x_t are closest to x^*. The size of the neighborhood, k, is an adjustable parameter which determines how local the fitting is. Next, these points are weighted according to the distance of x^* from x_t, and a line is fit by weighted least-squares. This yields the value of the fitted function at point x^*, $\hat{f}(x_t^*)$. The procedure is repeated for all points x, thereby yielding the LWR-estimate of the response of real stock returns to real dividend changes (LWR-based fit).

A pictorial representation of the LWR-estimation of the response of real stock returns (LWR-based fit) for the full sample period is given in Figs. 4–7 (for the UK, the US, Germany, and Japan, respectively) together with the actual values of real stock returns. The impression from inspecting these figures is that the LWR-based fit is quite good for all four countries.[8] We next examine whether (nonlinear) LWR-based out-of-sample stock returns forecasts are more accurate than OLS-based out-of-sample forecasts. To carry out the forecasting experiments, we treat the last 48 observations of the full sample period (i.e. the observations for the period 1998:6–2002:5) as the out-of-sample period, and use the remaining period 1978:1–1998:5 as the in-sample period over which we estimate the model using OLS and LWR. On the basis of the 'in-sample' estimations, out-of-sample stock returns forecasts were created using the actually realised out-of-sample values of the contemporaneous dividend change for each country. We examine whether LWR-based stock returns forecasts are more accurate than OLS-based forecasts, using the Root Mean Squared Error (RMSE). Table 8 reports the results. For all four countries, the RMSE of the LWR-based forecasts [RMSE(LWR)] is smaller than the RMSE of the OLS-based forecasts [RMSE(OLS)]. To test whether the difference in the two RMSEs is statistically significantly different, we used the studentised version of the Wilcoxon's signed-rank test (Diebold and Mariano, 1995).[9] On the basis of this test, the difference in the RMSEs is statistically significant for the UK, the US, and Japan at the 5% level. Thus, nonlinearity is important in terms of improving the forecasting performance of the PV model. Overall, the results from nonlinear

[8] We also applied the F-statistic suggested by Cleveland and Devlin (1988), to test the null hypothesis that the OLS-fit is appropriate against the alternative of significant nonlinearities (reflected by LWR-estimation). The results, not reported here to save space, indicated that the LWR method provides a statistically significant improvement in fit compared to OLS.

[9] This test, proposed by Diebold and Mariano (1995), is used for testing the null hypothesis of no difference in the accuracy of the LWR- and the OLS-based forecasts. Forecast accuracy is measured by the RMSE. The alternative hypothesis is that the RMSE of the LWR forecasts is lower than the RMSE of the OLS forecasts (H_A: RMSE(LWR) < RMSE(OLS)). The test statistic, S_a, given by:

$$S_a = \frac{S - (T(T+1)/4)}{\sqrt{\frac{T(T+1)(2T+1)}{24}}} \sim N(0,1)$$

where $S = \sum_{t=1}^{T} I_+(d_t)\mathrm{rank}(|d_t|)$, d_t, $t = 1,\ldots T$, is a loss differential series, and T is the sample size. S is the sum of the ranks of the absolute values of the positive observations. On the basis of the alternative hypothesis (H_A: RMSE(LWR) < RMSE(OLS)), the one-tailed test is considered.

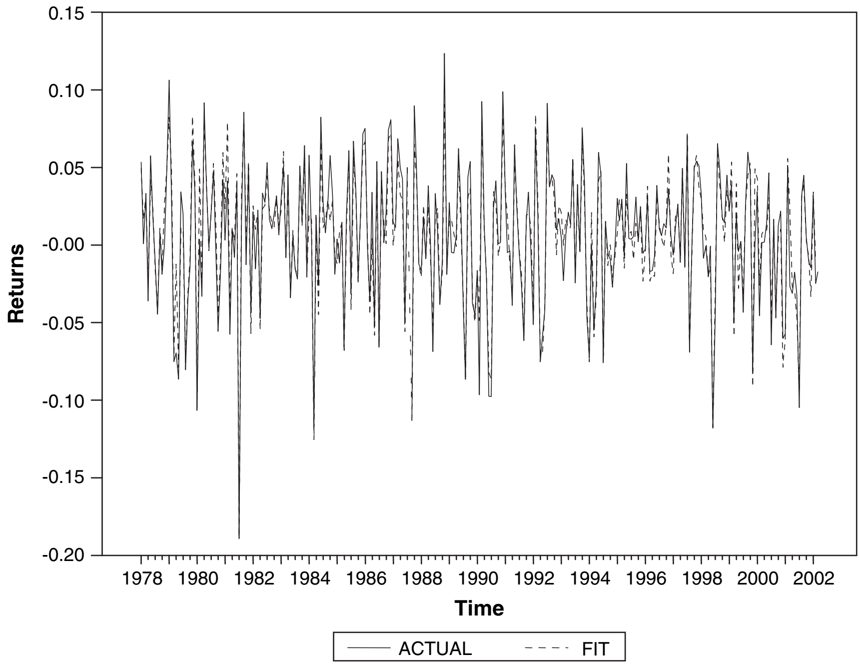

Fig. 4. UK-local regression surfaces estimation.

cointegration and locally-weighted regression techniques are consistent in suggesting that nonlinearity does exist in the contemporaneous stock price–dividend relation.

4.2. Nonlinearity in the dynamic stock price–dividend relation

Baek and Brock (1992) proposed a nonparametric method for detecting nonlinear dynamic causal relations between two time series. This method was modified by Hiemstra and Jones (1994) to allow for weak temporal dependence. The test has good power properties against a variety of nonlinear Granger causal and noncausal relations, and its asymptotic distribution is the same if the test is applied to the residuals from a vector autoregressive (VAR) model. To test for nonlinear Granger causality from dividend changes to stock returns, we estimate the VAR:

$$\begin{aligned} R_t &= A(L)R_t + B(L)D_t + U_{R,t} \\ D_t &= C(L)R_t + D(L)D_t + U_{D,t} \end{aligned} \tag{9}$$

where R_t and D_t are real stock returns and real dividend changes, respectively, and (L) is the lag operator. The regression errors $\{U_{R,t}\}$ and $\{U_{D,t}\}$ are assumed to be mutually exclusive and individually iid with mean zero and constant variance. The optimal lag length for the VAR is determined using the Akaike Information

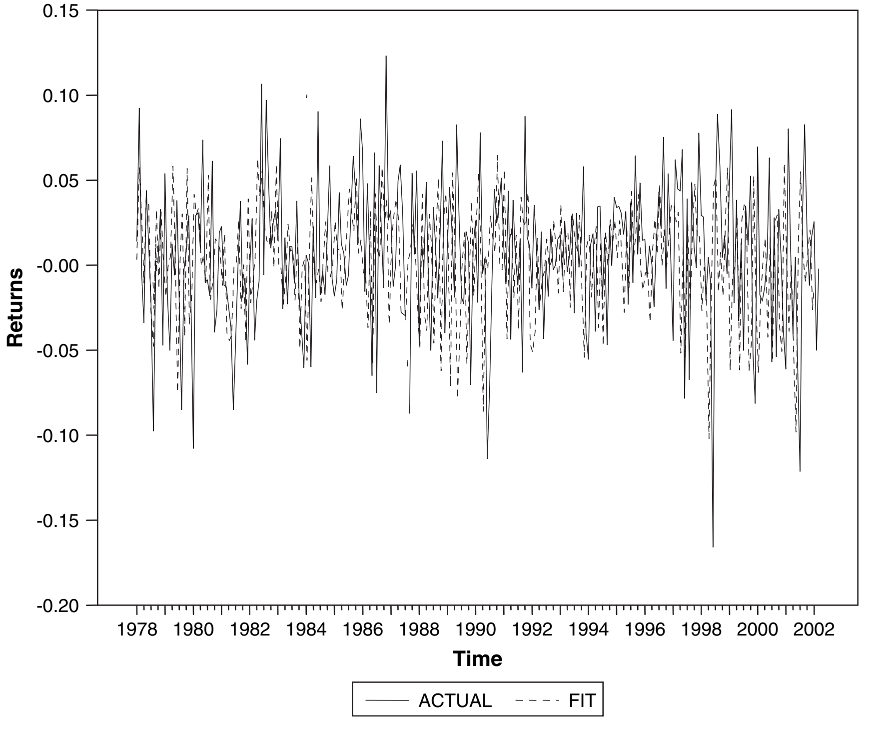

Fig. 5. US-local regression surfaces estimation.

Criterion (AIC).[10] On the basis of the chosen lag length, we estimate Eq. (9) using OLS, and obtain the estimated residuals, $\{\hat{U}_{R,t}\}$ and $\{\hat{U}_{D,t}\}$.

Prior to testing for nonlinear Granger causality from dividend changes to stock returns, we test for linear Granger causality. Testing for linear Granger causality involves estimating the VAR model given by Eq. (9), and carrying out a standard F-test of exclusion restrictions as to whether lagged dividend changes have significant linear predictive power for current stock returns. The null hypothesis is that dividend changes do not linearly Granger cause stock returns, and is rejected if the coefficients on the elements in $B(L)$ and $D(L)$ are jointly statistically significant. The results are reported in Table 9. This table shows that the p-value of the F-statistic is higher than 0.05 in all cases, thereby indicating that the null hypothesis cannot be rejected for any country at the 5% level. This result holds for the two sub-periods as well. Thus, lagged real dividend changes do not (linearly) Granger cause current real stock returns for any of the four countries.

We next turn to testing for nonlinear Granger causality. Table 10, Panels A (for the full sample period) and B (for the two sub-periods), presents the results of the

[10] The chosen lag length is 3 lags for the UK, 5 lags for the US, 2 lags for Germany and 4 lags for Japan.

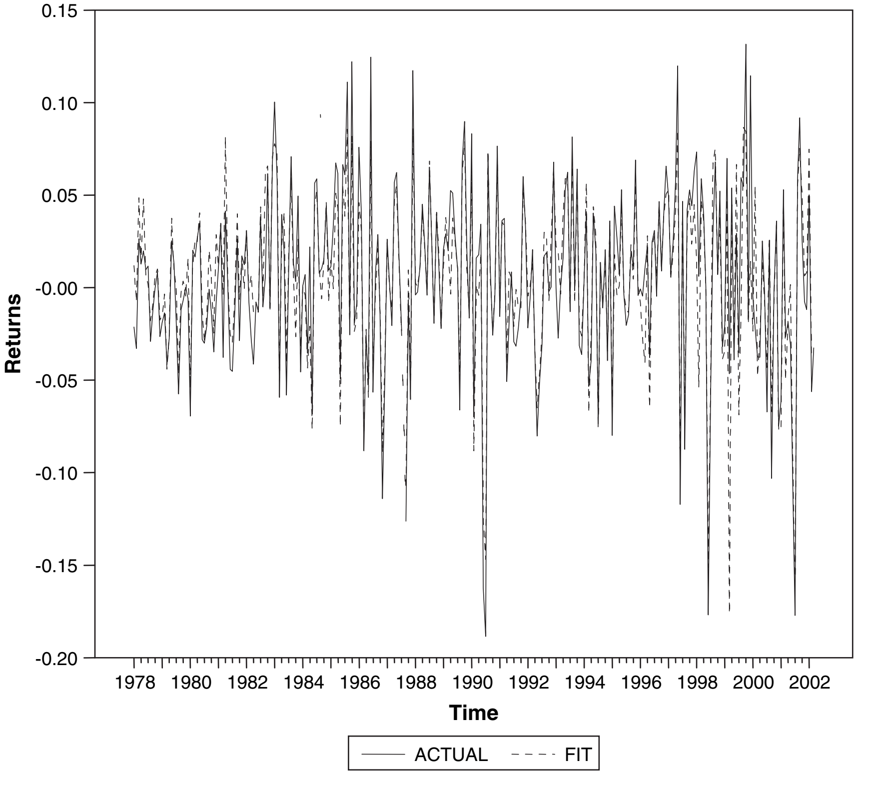

Fig. 6. Germany-local regression surfaces estimation.

modified Baek and Brock (1992) test applied to the estimated VAR residuals $\{\hat{U}_{R,t}\}$ and $\{\hat{U}_{D,t}\}$. The null hypothesis is that of no nonlinear Granger causality from lagged dividend changes to current stock returns. Panel A shows that, the test statistic is statistically significant at the 5% level for $L_w = L_z = 1$, 2 for the UK, $L_w = L_z = 2$, 3, and 4 for the US, $L_w = L_z = 4$, 5 for Germany, and $L_w = L_z = 3$, 4 for Japan. Similar results are obtained at various values of $L_w = L_z$ from the sub-period analysis (Panel B). Thus, the null of no nonlinear Granger causality is rejected at the 5% level in all four cases, indicating that lagged dividend changes do have a nonlinear predictive power for current stock returns.

The results from the linear and nonlinear Granger causality tests contrast sharply. Whilst lagged dividends have no linear predictive power for stock returns, they appear to have a nonlinear predictive power. Thus, nonlinearities do exist both in the contemporaneous and in the dynamic stock price–dividend relation. This result is in line with our empirical findings of long-horizon stock return predictability, which suggests that the assumption of constant expected stock returns is violated rendering the correct PV model to be nonlinear.

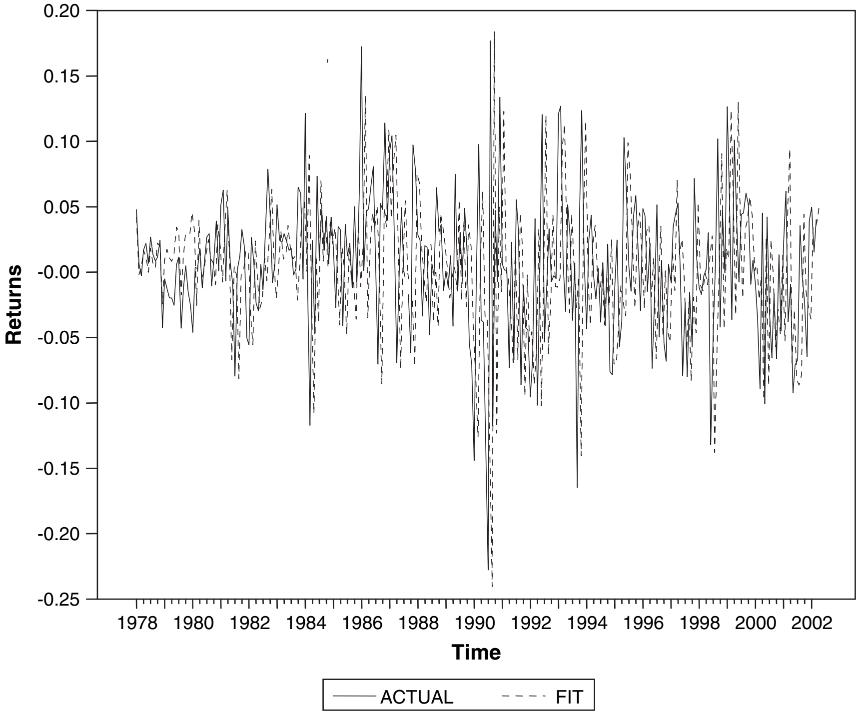

Fig. 7. Japan-local regression surfaces estimation.

5. Conclusion

We have addressed the issue of whether nonlinearity improves the ability of the PV model to explain the behaviour of stock prices of the UK, the US, Japan, and Germany. Our results are supportive of the existence of nonlinearity in the stock

Table 8
Forecast accuracy: locally-weighted regression (LWR) vs OLS (Full sample: 1978:1–2002:5)

	UK	US	Germany	Japan
RMSE using LWR	0.011	0.020	0.021	0.023
RMSE using OLS	0.017	0.029	0.028	0.030
Wilcoxon signed-rank test				
H_0: the two RMSEs are equal				
H_1: the RMSE of LWR is lower than the RMSE of OLS				
Z-test	−1.97* [0.02]	−1.98* [0.02]	−0.81 [0.20]	−1.70* [0.04]

Notes: In-sample period: 1978:1–1998:5; out-of-sample: 1998:6–2002:5. RMSE stands for Root Mean Square Error of the forecast. * Denotes that H_0 is rejected at the 5% level. *p*-values of the *Z*-test are given in square brackets.

Table 9
Linear Granger causality testing

H_0: Dividend changes do not Granger cause stock returns	*F*-statistic [*p*-value]		
	Full sample: 1978:1–2002:5	Sub-sample: 1978:1–1989:12	Sub-sample: 1990:1–2002:5
UK	0.25 [0.86]	2.55 [0.09]	0.42 [0.74]
US	0.53 [0.75]	0.26 [0.94]	0.39 [0.85]
Germany	2.37 [0.10]	2.02 [0.14]	1.10 [0.33]
Japan	0.27 [0.89]	1.01 [0.40]	1.07 [0.37]

price–dividend relation. We find that, whilst the original stock price and dividend series are not cointegrated, nonlinear ACE-transformations of stock prices and dividends are indeed cointegrated for all four countries. In addition, the out-of-sample forecasting accuracy of LWR-based forecasts is higher than the forecasting accuracy of OLS-based forecasts for the UK, the US, and Japan. Furthermore, there is evidence of nonlinear predictive power of lagged dividend changes for stock returns, whilst there is no evidence of linear predictive power. Our results are robust to sub-period analysis. These results are consistent with empirical evidence for all four countries that stock returns are predictable, which suggests that expected stock returns are time-varying and thus the correct PV model is nonlinear. These findings

Table 10
Nonlinear Granger causality testing

H_0: Dividend changes do not nonlinearly Granger cause stock index returns

$L_w = L_z$	UK	US	Germany	Japan
Panel A: Full sample: 1978:1–2002:5				
1	1.70*	0.38	1.13	0.66
2	2.24*	1.65*	1.08	1.47
3	0.65	2.38*	0.66	1.79*
4	0.41	2.69*	2.19*	2.05*
5	1.10	1.25	1.98*	1.31

$L_w = L_z$	UK		US		Germany		Japan	
	1978:1–1989:12	1990:1–2002:5	1978:1–1989:12	1990:1–2002:5	1978:1–1989:12	1990:1–2002:5	1978:1–1989:12	1990:1–2002:5
Panel B: Sub-samples 1978:1–1989:12 and 1990:1–2002:5								
1	1.37	1.71*	1.66*	2.20*	1.99*	1.33	0.60	2.11*
2	1.88*	1.95*	1.69*	1.89*	1.73*	1.74*	0.38	1.06
3	0.78	1.30	1.44	1.16	1.55	1.37	1.92*	2.32*
4	0.03	0.65	1.88*	1.25	1.60	0.35	1.70*	0.38
5	0.37	0.42	2.06*	1.10	1.63	0.86	1.13	0.40

Notes: The table entries are the test statistics of the modified Baek and Brock nonlinear Granger causality test applied to the VAR residuals corresponding to the stock returns and dividend changes series of the US, UK, Germany, and Japan. $L_w = L_z$ denotes the number of lags on the residuals series used in the test. In all tests, the lead length, m, is set to unity, and the length scale, e, is set to 1.0 (Hiemstra and Jones, 1994). Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed $N(0,1)$. * Denotes rejection of the null at the 5% level for the one-sided test.

may be useful in future research, as they suggest that researchers should consider nonlinear empirical regularities when evaluating and developing models of the joint dynamics of stock prices and dividends.

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