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Structural Change in the Price-Dividend Ratio and Implications on Stock Return Prediction Regression

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<abstract>

The price-dividend ratio is one of the most frequently used financial variables to predict long-horizon stock return. However, the persistency of the price-dividend ratio is found to cause the spuriousness of the stock return prediction regression. The stable relationship between the stock price and the dividend, however, seems to weaken after World War II and to experience structural break. In this paper, we identify a structural change in the cointegrating relationship between the log of the stock price and the log of the dividend. Confirming a structural break in 1962, we subdivide the sample and apply the fully modified estimator to correct for the nonstationarity of the regressor. With the subdivided sample, we exercise the nonparametric bootstrap procedure to derive the empirical distribution of the test statistics and fail to find return predictability in each subsample period.

Keywords : Parameter Instability, Structural Change, Price-Dividend Ratio, Long-Horizon Regression Model, Bootstrapping

Ⅰ. Introduction

Issues of parameter instability against several alternatives of interest in the context of cointegrated regression models date back to Chow (1960) and Quandt (1960). The structural stability of predictive regression models of stock returns has received limited

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attention in extant literature. Instead of formal tests, structural change is typically addressed by estimating predictive regression models for various subsamples. Using CRSP data for the period 1927～1986, the Cowles data for 1872～1926, and additional CRSP data for 1987～2000, Schwert (2002) shows that the incremental data both before and after the 1927～1986 period shows a much weaker relation between aggregate dividend yields and stock returns. None of the t-statistics for the slope coefficient are larger than 2.0, even for the 1872～2000 sample.

Viceira (1997) focuses on tests for structural changes in a predictive regression model of stock returns based on the dividend-price ratio for the 1926～1995 period but fails to find one. Neely and Weller (2000) test the structural stability of trivariate VAR models used to predict international equity and foreign exchange market returns over the 1981～1996 period in a reexamination of Bekaert and Hodrick (1992), who detected evidence of in-sample predictability in international equity and foreign exchange markets using VAR methodology for a variety of countries from 1981～1989. For the extended sample period, however, Neely and Weller find that the VAR predictions are significantly biased in most out-of-sample forecasts and are conclusively outperformed by a simple benchmark model at horizons of up to six months. This conclusion is supported by an examination of structural break statistics. In a forecasting model based on the dividend-yield and earnings-yield, Lettau and Ludvigson (2001) find some evidence of instability in the second half of the 1990s. Likewise, Goyal and Welch (2002) uncover instability in the return prediction model based on the dividend yields when data from the 1990s is added to the sample. Ang and Bekaert (2006) find that “the predictability patterns formerly found in US data appear not to be robust to the addition of the last few years of the 1990s.” While these papers thus identify a shift that appears to have occurred some time during the 1990s or earlier, they do not determine the exact time of the break, nor do they consider the possibility of earlier breaks. These studies put focus on uncovering the fact that good in-sample performance is not a guarantee for out-of-sample performance in the stock return prediction context, and therefore argue that a structural break might be the cause of poor out-of-sample forecast performance.

A formal structural break test with an unknown breakdate is an obvious candidate for an investigation of parameter instability in the stock return prediction regression.

This test, proposed by Quandt (1960), bases its inferences on the *LR* statistic, which is the maximal Chow statistic (*F*-statistic) over a range of possible breakdates. Andrews (1990, 1993), Andrews and Ploberger (1994), and Hansen (1990) provide the null asymptotic distribution of the Quandt likelihood ratio statistic. Developing further on this line, Bai and Perron (1998, 2001) develop two statistics to test for multiple structural breaks. The double maximum statistics, for testing the null hypothesis of no structural breaks against the alternative of an unknown number of breaks with upper bound, are jointly used with the sequential *SupF* statistic to determine the number of structural breaks. The sequential $SupF(k+1|k)$ test procedure begins with the minimized sum of squared residuals for a model with k breaks. Each of the intervals defined by the k breaks is then analyzed for an additional structural break. From all of the intervals, the partition allowing for an additional break that results in the largest reduction in the sum of squared residuals is treated as the model with $k+1$ breaks. The $SupF(k+1|k)$ statistic is used to test whether the additional break leads to a significant reduction in the sum of squared residuals. Bai and Perron (1998, 2001) derive asymptotic distributions for the double maximum and $SupF(k+1|k)$ statistics and provide critical values for various values of π (the trimming parameter) and M (maximal allowed number of breaks). Rapach and Wohar (2004) adds to existing literature by formally testing the structural stability of a large number of predictive regression models of stock returns based on many of the financial variables appearing in extant literature. In an independent study, Paye and Timmermann (2002) use the Bai and Perron methodology to test for structural breaks in predictive regression models of stock returns for a number of size and industry-sorted US portfolios, as well as international portfolios. Their predictive regression models are based on four financial variables (dividend-price ratio, short-term interest rate, term spread, default spread) from extant literature. In general, their findings suggest that predictability is very much a time-varying phenomenon. Empirical evidence of predictability is not uniform over time and appears to be concentrated in certain periods. The predictability suggested by R^2-values based on long samples of returns should be viewed as an historical average for predictability. In particular, they find that ex post predictability was relatively high in the 1970s and 1980s and relatively low in the 1960s and 1990s. The methodological issues of the above two studies lie in the fact that they use Andrews *SupF* statistics and Bai-Perron procedures in order to test for formal structural breaks, even though we have a unit root or highly persistent regressor in the stock return prediction regression.

Hansen (2000) shows that the limiting distribution derived by Andrews (1993) for the *SupF* statistic does not apply in the presence of a variety of nonstationarities in the regressors, including mean and variance breaks and stochastic trends. Hansen (2000) develops a heteroskedastic fixed-regressor bootstrap that delivers the correct asymptotic distribution for the *SupF* statistic in the presence of general nonstationarities in the regressors. He finds that this bootstrap has good size properties in finite samples in Monte Carlo simulations.

In this paper, to address the stability of the link in the valuation ratio and its implications on the real stock return predictability in the US from 1871 to 2002, we attempt a different approach. We are going to investigate whether the valuation ratio is determined by a linearly stable cointegration relationship between the log of the stock price and the log of the dividend or by a nonlinearly stable relationship with structural breaks. Which of these views is upheld statistically is a topic of ongoing debate, and the series of tests mentioned play a central role.

The remainder of the paper is organized as follows. Section 2 addresses the question of variation in predictive results by observing the structural change in cointegration relationship in the regressor. Section 3 investigates the stock return predictability before and after the structural break, which is identified in section 2. Section 4 summarizes our findings.

Ⅱ. The Structural Change in Cointegration Relationship in the Regressor

1. Residual-Based Cointegration Tests

As the simplest approach, consider testing for cointegration between the log of the stock price and the log of the dividend, assuming the cointegrating vector is not known.

Let $Y_t = (p_t, d_t)'$ and normalize the cointegrating vector on p_t so that $\beta = (1, -\beta_2)'$. The normalized cointegrating coefficient β_2 is estimated by least squares from the regression

$$p_t = c + \beta_2 d_t + u_t,$$

giving the estimated cointegrating residual $\hat{u}_t = p_t - \hat{c} - \hat{\beta}_2 d_t$.

We use the annual S&P500 nominal stock price($p_t = \ln(P_t)$) and the dividend index ($d_t = \ln(D_t)$) from Campbell and Shiller (2002), which begin in 1871 and extend to 2001. We deflate the nominal indexes using the consumer price index in order to obtain the series for real stock prices and real dividends. Here, the dividend is defined as real dividends over the previous calendar year and the stock price as the January real stock price. Summing dividends over a full year removes any seasonal patterns in dividend payments, but the current stock index is used to incorporate the most recent information in stock prices.

The OLS is used to estimate the above regression :

$$\begin{array}{ll} & p_t = 2.09 + 1.49\,\mathrm{d_t} \\ s.d. & \quad (0.14)\ (0.06) \\ \mathrm{p-value} & \quad (0.00)\ (0.00) \end{array}$$

$$R^2 = 0.81$$

$$Adjusted\ \mathrm{R}^2 = 0.80$$

$$Jarque - Bera\,\mathrm{Stat} = 7.26\ (\mathrm{p-value}\ 0.03)$$

$$LB\ Q- Stat = 146.40\ (\mathrm{p-value}\ 0.00)$$

The estimated value of β_2 is 1.49 and is very different from the $\beta_2 = 1$, implied by the present value model of stock prices. We exercised the residual-based tests for cointegration using the ADF and PP tests. Because the mean of $\hat{u}_t$ is zero, the unit root test regressions are estimated without a constant or trend. The ADF t-statistic is computed using 2 lags, and the PP t-statistic is computed using an automatic lag truncation parameter. The ADF t-statistic is -4.26, and the PP t-statistic is -4.33 (p-value = 0.014).

Since p_t and d_t are both I(1) with drift, the 10%, 5%, and 1% quantiles from the appropriate Phillips-Ouliaris distribution for the ADF t-statistics are -3.55, -3.85, and -4.45, respectively. The no-cointegration null hypothesis is rejected at the 5% level using the ADF and PP t-statistic.

2. Cointegration Tests with Regime Shifts

Gregory and Hansen (1996) develop a procedure which tests the null hypothesis of no cointegration against the alternative hypothesis of cointegration, which allows for the possibility of regime shift in the cointegrating vector at one unknown breakdate in the sample. Since the standard tests for cointegration hypothesize the time-invariant cointegrating vector under the alternative hypothesis, a class of residual-based test for cointegration by Gregory and Hansen is appropriate.[1] As a pre-test, however, a rejection of the null hypothesis of no cointegration may not guarantee the existence of a regime shift in the cointegration vector, since this test has also power against the alternative of stable cointegration and the existence of a time-invariant cointegrating relationship can be the cause of such a rejection. By exercising the two categories of cointegration tests, we could have more evidence than the next step specification tests would offer. If the Engel and Granger test does not reject the null of no cointegration but the Gregory and Hansen test does, that could mean that we fail to reject the null of no cointegration due to the low power of the former test caused by a regime shift in DGP. If both types of tests reject the null of no cointegration, we take this as strong evidence in favor of a long-run stable relationship which may suffer a break at one unknown breakdate. After we confirm the existence of a cointegrating relationship, we can employ Hansen (1992) tests for parameter instability as a structural break specification test.

Gregory and Hansen (1996) allow for cointegration with structural change of three cases under the alternative hypothesis. Model 1 is the standard model of cointegration with no structural change. A simple case of structural change in a cointegrating relation-

1) These tests can be viewed as multivariate extensions of the univariate tests of Perron (1989), Banerjee, Lumsdaine, and Stock (1992), Perron and Vogelsang (1992), Christiano (1992), and Zivot and Andrews (1992). They tested the null of a unit root against the alternative of stationarity in a univariate time series, while allowing for a structural break in the deterministic component of the series.

ship is that there is a level shift in the cointegrating relationship, which can be modeled as a change in the intercept c, while the slope coefficient β_2 is held constant. Gregory and Hansen call this a *level shift* model denoted by *C*. In this parameterization, c_1 represents the intercept before the shift, and c_2 represents the change in the intercept at the time of the shift. In model 3 below, they introduce a time trend into the level shift model. The most general structural break in the cointegrating relationship is to allow for the slope vector to shift as well. They call this the *regime shift* model. In this case c_1 and c_2 are as in the level shift model, β_2 denotes the cointegrating slope coefficients before the regime shift, and β_3 denotes the change in the slope coefficients.

Model 1 : Standard cointegration

$$p_t = c + \beta_2 d_t + u_t, \quad t = 1, \cdots, n,$$

where p_t and d_t are *I(1)* and u_t is *I(0)*.

Model 2 : Level Shift Cointegration (C)

$$p_t = c_1 + c_2 D_{t\tau} + \beta_2 d_t + u_t$$

Model 3 : Level Shift with Trend Cointegration (C / T)

$$p_t = c_1 + c_2 D_{t\tau} + \delta t + \beta_2 d_t + u_t$$

Model 4 : Regime Shift Cointegration (C/S)

$$p_t = c_1 + c_2 D_{t\tau} + \beta_2 d_t + \beta_3 d_t D_{t\tau} + u_t$$

where D_t is a dummy variable and is defined as follows :

$$D_{t\tau} = \begin{matrix} 0 & \text{if} & t \leq [n\tau] \\ 1 & \text{if} & t > [n\tau] \end{matrix}$$

where the unknown parameter $\tau \in (0, 1)$ denotes the relative timing of the change point, and [ ] denotes integer part.

<Table 1> Testing for Regime Shifts in the Cointegration between the Log Stock Price and the Log Dividend

Alternative Model	ADF Test		Phillips Z_t Test		Phillips Z_α Test	
	Test Stat.	Breakpoint	Test Stat.	Breakpoint	Test Stat.	Breakpoint
			AIC chosen AR Lag			
C	-5.09^{**}	0.27	-5.36^{**}	0.26	-52.38^{**}	0.26
Breakdate		(1908)		(1906)		(1906)
C/T	-4.74^{*}	0.25	-4.95^{*}	0.28	-44.42^{*}	0.28
Breakdate		(1905)		(1909)		(1906)
C/S	-4.91^{*}	0.72	-5.70^{**}	0.79	-55.45^{**}	0.79
Breakdate		(1967)		(1976)		(1976)
			BIC chosen AR Lag			
C	-5.11^{**}	0.28	-5.36^{**}	0.26	-52.38^{**}	0.26
Breakdate		(1909)		(1906)		(1906)
C/T	-4.85^{*}	0.28	-4.95^{*}	0.28	-44.42^{*}	0.28
Breakdate		(1909)		(1909)		(1909)
C/S	-5.50^{**}	0.79	-5.70^{**}	0.79	-55.45^{**}	0.79
Breakdate		(1976)		(1976)		(1976)
			Downward *t* chosen AR Lag			
C	-5.11^{**}	0.28	-5.36^{**}	0.26	-52.38^{**}	0.26
Breakdate		(1909)		(1906)		(1906)
C/T	-4.74^{*}	0.25	-4.95^{*}	0.28	-44.42^{*}	0.28
Breakdate		(1905)		(1909)		(1909)
C/S	-5.47^{**}	0.80	-5.70^{**}	0.79	-55.45^{**}	0.79
Breakdate		(1977)		(1976)		(1976)

Note) Alternative models, C, C/T, and C/S, represent model 2 : level shift cointegration, model 3 : level shift with trend cointegration, and model 4 : regime shift cointegration, respectively. The lags selected for ADF tests for the C, C/T, and C/S are (0, 0, 3) for the AIC, (0, 0, 0) for the BIC, and (0, 0, 0) for the downward t chosen AR lags, respectively. The null hypothesis of no cointegration is rejected by our new tests using the C, C/T and C/S type formulations where * and ** indicates significance at the 10% and 5% levels.

According to the results in <Table 1>, it is possible to reject the null of no cointegration in the three models. However, there are some structural changes : models 2 and 3 place them at the beginning of the sample, in 1905~1909, whereas model 4 finds a regime change later in the sample, in 1967~1977. Following the strategy described in

Gregory and Hansen (1996) and taking into account that the third test has higher power when the change occurs at the end of the sample, there is an evidence of a long-run relationship, although there also seem to be signs of instability. Gregory and Hansen recommend complementing this analysis with Hansen's (1992), to which we now turn.

3. Parameter Constancy and Cointegration Tests with *I*(*1*) Regressor

Along with the development of the asymptotic distribution of the Quandt likelihood ratio statistic by Andrews (1993) and Andrews and Ploberger (1994), Nyblom (1989) derived the statistic with likelihood function for generally nonlinar, nonnormal models, where he specifies the alternative hypothesis as random walks. However, the asymptotics of the Nyblom statistic suffers from overrejection if regressions have large autoregressive parameters.

The limitation of the previous studies with reference to structural instability or parameter nonconstancy tests is that they did not consider models with integrated regressors. As pointed out by Hansen (1992), however, the asymptotic distributions of the test statistics for structural breaks are found to depend on the stochastic process describing the regressors.

We exercise the unit root test on the log of the price-dividend ratio process. The appropriate trend specification is to include a constant in the test regression. Regarding the maximum lag length for the test regression, we follow a useful rule of thumb for determining $p_{\max}$, which is

$$p_{\max} = [12 \cdot (T/100)^{1/4}].$$

Considering remaining autocorrelation in Δ (log price-dividend ratio), we choose $p_{\max} = 12$. Following the Ng and Perron backward selection procedure, we select $p = 2$. After the lag length selection, we exercise the ADF test again to get the results as follows. With 2 lags the ADF t-statistic is -1.11, so we have strong evidence for a unit root in the log of the price-dividend ratio. It is also found that there is a unit root in the log price-dividend ratio with the ADF normalized bias test statistic. We fail to reject the null of unit root hypothesis with the Phillips-Perron Z_t-statistic of -2.16 and the 10% significance level critical value of -2.58.

With the results above, we test the parameter instability in the coefficient of co-integrating regression between the log of the stock price and the log of the dividend processes using the procedure by Hansen (1992). In estimating the coefficient of the cointegrating regression, the fully modified estimator of Phillips and Hansen (1990) is employed. Since the cointegrating residuals have a significant degree of serial correlation, a kernel estimate with a large bandwidth parameter is used to estimate the covariance matrices. Phillips and Hansen apply a kernel estimator to the prewhitened residuals with *VAR(1)* to get covariance matrices.[2] After transforming the dependent variables using covariance estimates, the fully modified estimator of the cointegrating vector can be estimated. In the second step, three tests, *SupF*, *MeanF*, and L_C , which test the same null hypotheses of parameter constancy but differ in their choice of alternative hypothesis are employed. The *SupF* test is appropriate when the instantaneous structural break in the parameter is assumed. On the other hand, *MeanF* and L_C tests are used when the notion of martingale parameters under the alternative hypothesis is more appropriate, and it captures the notion of an unstable model that gradually shifts over time.

We apply Hansen's procedure to the log of the stock price and the log of the dividend processes from 1871~2002. The covariance parameters are estimated using a Bartlett kernel on prewhitened residuals with the plug-in bandwidth recommended by Andrews and Monahan (1992). For comparison, we also estimate the covariance parameter by applying the Parzen kernel and the Quadratic spectral (QS) kernel on prewhitened residuals. The choice of bandwidth parameter is made by Andrews' (1991) guideline, where he provided the method based on the minimization of an asymptotic truncated mean squared error. As pointed out by Andrews' (1990), the trimming region must not include the endpoints 0 and 1 because the test statistic will diverge to infinity almost

2) A kernel estimator requires a choice of kernel and bandwidth parameter. Generally, Bartlett, Parzen, and quadratic spectral (QS) kernels are used. Also, Andrews (1991) provides guidelines based on the minimization of asymptotic truncated mean squared error to plug-in bandwidth estimator. Refer to Phillips and Hansen (1990) and Hansen (1992) for a detailed discussion.

surely if we include the end points. All of the *SupF* and *MeanF* statistics are calculated using the trimming region [.15, .85], which corresponds to [1892 ; 1983] for this reason. When we apply a fully modified estimator on the log of the stock price and the log of the dividend, we can reject the null of parameter stability, since the p-values from the test statistics are 0.01 for all three cases.

$$p_t = 1.51 + 1.76\mathrm{d}_t$$
$$(0.26)\ (0.12)$$

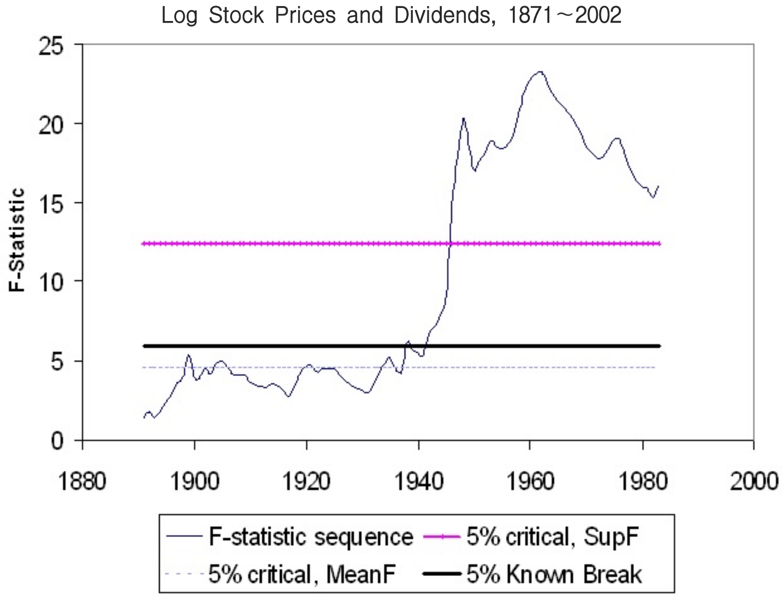
$$\widehat{\mathrm{M}} = 1.46$$

$$F = 82.7\ (0.01)$$

$$Mean\ F = 33.2\ (0.01)$$

$$L_c = 1.34\ (0.01)$$

[Figure 1] F-statistic sequence for the log stock price and dividend



Note) The plot of the sequence of F statistics is displayed. The sequence for the regression crosses the 5% *SupF* critical value in 1934 with the value of F-statistic at 13.3, achieving its maximal value in 1962 with the value of F-statistic at 82.7. This supports the conjecture that the relationship between the log of the stock price and the log of the dividend has significantly changed in 1962.

The *SupF* and *MeanF* test statistics are highly significant and suggest that the relationship is not stable. Note that the estimated bandwidth parameter is 1.46, indicating that not all of the serial correlation in the residuals was captured by the prewhitening procedure.

The plot of the sequence of F statistics is displayed in [Figure 1].

The sequence for the regression crosses the 5% *SupF* critical value in 1934 with the value of F-statistic at 13.3, achieving its maximal value in 1962 with the value of F-statistic at 82.7. This supports the conjecture that the relationship between the log of the stock price and the log of the dividend has changed.

Ⅲ. Long-Horizon Predictability Tests using a Linear Valuation Model

1. Without Correcting for the Nonstationarity of the regressor : The Price-Dividend Ratio with a Cointegrating Vector (1, -1)

In this section, we adopt Mark's (1995) nonparametric bootstrap procedure to derive an empirical distribution of the test statistic by resampling the fitted residuals with replacement. By doing so, we take into account the various facts, such as a persistent regressor, a small sample, and correlation between the disturbances of the prediction regression and the autoregressive representation of the regressor. Given the null hypothesis of no stock return predictability, a bootstrap DGP can be specified as follows.

$$r_{t+k} = a_k + \epsilon_{1,t+k}$$
$$z_t = b_0 + \sum_{i=1}^{I} b_j z_{t-i} + \epsilon_{2,t}.$$

where r_t is the continuously compounded real stock return, that is, $r^k_{t+k} = p_{t+k} - p_t$, with p_t representing the log of the real stock price of January of each year, and $z_t = p_t - d_t$, with d_t representing the log of real dividends over the previous calender year. The above DGP specification is for cointegration between p_t and d_t. Thus, it assumes a priori the existence of a long-run relationship between p_t and d_t.

We estimate each equation in DGP using OLS. In estimating a valuation ratio equation, we allow up to 5 lags and minimum AIC is achieved when we set lags as 3. After correcting for bias using Shaman and Stine (1988), the equation for the valuation ratio and the equation for stock return under the null of no predictability are estimated as,

$$r_t = 0.0221 + \widehat{\epsilon_{1,t}}$$

$$z_t = 0.2062 + 0.8625 z_{t-1} - 0.1962 z_{t-2} + 0.2734 z_{t-3} + \widehat{\epsilon_{2,t}}, \quad \hat{s}^2 = 0.0381.$$

This serves as the data generating process to calculate bootstrap distribution. However, when $k > 1$, the dependent variables overlap, and this induces $(k-1)^{th}$*-order* serial correlation into the disturbance term, ϵ^k_{t+k} under the null. When estimating the spectral density matrix of $(\epsilon^k_{t+k}, \epsilon^k_{t+k} z_t)$ at frequency zero in order to construct a heteroskedasticity autocorrelation consistent covariance matrix, we take the version of Andrews (1991) in order to determine the truncation lag for the Bartlett window. Also, as an approximation to a parametric model of Andrews procedure, we employ a univariate *AR(1)* model. Let ρ_1 and ρ_2 be the estimated autocorrelation coefficients of ϵ^k_{t+k} and $\epsilon^k_{t+k} z_t$ respectively. Also, let s_1^2 and s_2^2 be the estimated disturbance variance from the *AR(1)* processes. The truncation lag, *a*, for the Bartlett window in Newey and West's estimator given by Andrews' rule is $a = 1.1447[a_1 T]^{1/3}$, where

$$a_1 = \frac{\sum_{j=1}^{2} \frac{4\rho^2 s_j^4}{(1-\rho_j)^6 (1+\rho_j)^2}}{\sum_{j=1}^{2} \frac{s_j^4}{(1-\rho)^4}}.$$

<Table 2>~<Table 4> report predictive regression estimation results for various horizons of the form,

$$r_{t+k}^{k} = a_k + b_k z_t + \epsilon_{t+k}^{k} \ .$$

When p_t is above its fundamental value, it is expected to fall over time, which means that the coefficient of the forecasting variable z_t should be negative and increase with the forecasting horizon *k*. We consider $k = 1, 2, \cdots, 10$ years as forecasting horizons. Data used in long-horizon predictability tests are from Campbell and Shiller (1998 ; 2002). This data covers the period from 1871 to 2002. We deflate the price and dividend series using the consumer price index in order to get real valued series. We employ the valuation ratio of the price-dividend ratio (January real stock prices divided by real dividends over the previous calendar year) as a forecasting variable for the continuously compounded real stock returns.

As we can see in <Table 2>, the *p*-values from the stock return prediction regression are significant for most of the forecasting horizons.

<Table 2> Predictability Test Results without Correcting for the Nonstationarity of the Regressor : 1871～1962

Horizon(*k*)	$z_t = p_t - d_t$		
	β_K	t_A	*p*-value
1 year	-0.056	-0.837	0.273
2 years	-0.227	-2.212	0.063
3 years	-0.294	-1.935	0.110
4 years	-0.501	-2.703	0.060
5 years	-0.624	-3.555	0.028
6 years	-0.606	-3.357	0.045
7 years	-0.655	-3.743	0.038
8 years	-0.793	-4.750	0.018
9 years	-0.755	-4.105	0.037
10 years	-0.692	-3.338	0.083

Note) We do not correct for the nonstationarity of the regressor. The *p*-values are significant under the 10% level except for the forecasting horizons of 1 year and 3 years. t_A is the heteroskedasticity autocorrelation consistent *t*-statistics for the coefficient in the long horizon regression with a truncation lag by Andrew's (1991) procedure.

<Table 3> Predictability Test Results without Correcting for the Nonstationarity of the Regressor : 1963~2002

Horizon(k)	$z_t = p_t - dt$		
	β_K	t_A	p-value
1 year	−0.023	−0.376	0.351
2 years	−0.027	−0.201	0.430
3 years	0.057	0.328	0.578
4 years	0.120	0.432	0.598
5 years	0.018	0.042	0.494
6 years	−0.198	−0.342	0.432
7 years	−0.433	−0.706	0.378
8 years	−0.739	−1.288	0.318
9 years	−1.163	−1.870	0.254
10 years	−1.486	−2.357	0.230

Note) We do not correct for the nonstationarity of the regressor. The p-values are insignificant under the 10% level for all forecasting horizons. t_A is the heteroskedasticity autocorrelation consistent t-statistics for the coefficient in the long horizon regression with a truncation lag by Andrew's(1991) procedure.

<Table 4> Predictability Test Results without Correcting for the Nonstationarity of the Regressor : 1871~2002

Horizon(k)	$z_t = p_t - dt$		
	β_K	t_A	p-value
1 year	−0.022	−0.571	0.522
2 years	−0.072	−0.857	0.428
3 years	−0.065	−0.514	0.560
4 years	−0.130	−0.684	0.514
5 years	−0.209	−0.879	0.462
6 years	−0.242	−0.897	0.466
7 years	−0.304	−1.087	0.408
8 years	−0.426	−1.555	0.321
9 years	−0.482	−1.715	0.289
10 years	−0.512	−1.773	0.307

Note) We do not correct for the nonstationarity of the regressor. The p-values are insignificant under the 10% level for all forecasting horizons. t_A is the heteroskedasticity autocorrelation consistent t-statistics for the coefficient in the long horizon regression with a truncation lag by Andrew's (1991) procedure.

However, we fail to find the return predictability in the sample from 1963 to 2002 reported in <Table 3>, as the p-values exceed the 10% significance level. The price-dividend ratio's predictive ability shifts toward an ability to predict its own future value (higher autoregressive root of the price-dividend ratio) rather than the stock return. This explains why the predictability of stock returns is weak after the break of 1962. <Table 4> shows the results of the predictability of stock returns with the sample from 1871 to 2002 with cointegrating vector of (1, -1), that is, without correcting for the nonstationarity of the regressor. The p-values are insignificant under the 10% significance level for all forecasting horizons.

2. With Correcting for the Nonstationarity of the regressor : The Price-Dividend Ratio with an Estimated Cointegrating Vector

The cointegrating vector estimates differ by estimator. For example, the OLS estimate is (1, -1.49), and the DOLS estimate by Stock and Watson (1993) is (1, -1.51), whereas the FM estimate is (1, -1.76), and all of theses are significantly different from the hypothesized value of (1, -1). When we test the null hypothesis of a unit root for the price-dividend ratio with a cointegrating vector, (1, -1), we fail to reject the null of unit root. When we use the price-dividend ratio with a cointegrating vector, (1, -1), as a forecasting variable, we have a nonstationary regressor in the stock return prediction regression.

In order to investigate the role of a nonstationary regressor in the stock return prediction regression, we use the transformed price-dividend ratio as a regressor in the nonparametric bootstrap procedure. Based on the FM estimate, for the sample period 1872~1962 (pre-break sample), we use the price-dividend ratio of $z_t = p_t - 1.41d_t$. We also construct the price-dividend ratio of $z_t = p_t - 5.00d_t$ for the sample period 1963~2002, whereas we use $z_t = p_t - 1.76d_t$ for the entire sample. <Table 5>~<Table 7> report predictive regression estimation results for various horizons from 1 year to 15 years.

Compared to the previous return predictability using a nonstationary price-dividend ratio, $z_t = p_t - d_t$, reported in <Table 2>~<Table 4>, the stock return predictability

<Table 5> Predictability Test Results with Correcting for the Nonstationarity of the Regressor : 1871～1962

	$z_t = p_t - 1.41dt$		
Horizon(k)	β_K	t_A	p-value
1 year	0.001	0.011	0.595
2 years	−0.111	−1.221	0.215
3 years	−0.128	−1.045	0.286
4 years	−0.275	−1.799	0.143
5 years	−0.361	−2.176	0.124
6 years	−0.305	−1.657	0.214
7 years	−0.297	−1.649	0.231
8 years	−0.381	−2.337	0.140
9 years	−0.321	−2.085	0.177
10 years	−0.248	−1.493	0.305
11 years	−0.287	−1.758	0.271
12 years	−0.334	−2.381	0.194
13 years	−0.359	−2.788	0.156
14 years	−0.346	−2.904	0.161
15 years	−0.401	−4.295	0.067

Note) We correct for the nonstationarity of the regressor by using the fully modified(FM) estimate of the cointegrating vector. The p-values are insignificant under the 10% level except for the forecasting horizon of 15 years. t_A is the heteroskedasticity autocorrelation consistent t-statistics for the co-efficient in the long horizon regression with a truncation lag by Andrew's (1991) procedure.

<Table 6> Predictability Test Results with Correcting for the Nonstationarity of the Regressor : 1963～2002

	$z_t = p_t - 5.00dt$		
Horizon(k)	β_K	t_A	p-value
1 year	−0.141	−1.600	0.066
2 years	−0.271	−1.563	0.119
3 years	−0.303	−1.364	0.194
4 years	−0.326	−1.346	0.217
5 years	−0.406	−1.364	0.244
6 years	−0.522	−1.604	0.229
7 years	−0.562	−1.582	0.255
8 years	−0.507	−1.157	0.330
9 years	−0.456	−1.026	0.355
10 years	−0.248	−1.493	0.390
11 years	−0.316	−0.775	0.441
12 years	0.157	0.514	0.560
13 years	0.531	1.860	0.676

Note) We correct for the nonstationarity of the regressor by using the fully modified(FM) estimate of the cointegrating vector. The p-values are insignificant under the 10% level except for the forecasting horizon of 1 year. t_A is the heteroskedasticity autocorrelation consistent t-statistics for the co-efficient in the long horizon regression with a truncation lag by Andrew's (1991) procedure.

<Table 7> Predictability Test Results with Correcting for the Nonstationarity of the Regressor : 1871～2002

Horizon(k)	$z_t = p_t - 1.76d_t$		
	β_K	t_A	p-value
1 year	0.005	0.100	0.752
2 years	-0.048	-0.728	0.484
3 years	-0.029	-0.350	0.618
4 years	-0.103	-0.988	0.426
5 years	-0.181	-1.541	0.289
6 years	-0.166	-1.252	0.378
7 years	-0.171	-1.177	0.404
8 years	-0.242	-1.590	0.306
9 years	-0.244	-1.505	0.325
10 years	-0.229	-1.255	0.409
11 years	-0.287	-1.458	0.380
12 years	-0.349	-1.749	0.329
13 years	-0.410	-1.981	0.288
14 years	-0.458	-1.945	0.307
15 years	-0.540	-2.186	0.274

Note) We correct for the nonstationarity of the regressor by using the fully modified(FM) estimate of the cointegrating vector. The p-values are insignificant under the 10% level for all forecasting horizons. t_A is the heteroskedasticity autocorrelation consistent t-statistics for the coefficient in the long horizon regression with a truncation lag by Andrew's (1991) procedure.

by the transformed price-dividend ratio decreased significantly. The stock return predictability measured by the mean-reverting behavior of the price-dividend ratio is weak. Most of the p-values from the bootstrap procedure are insignificant regardless of the sample period and the forecasting horizon. We can conclude that stock return predictability, if any, is not as strong as we might expect from a long-run stable relationship between stock prices and dividends.

Ⅳ. Conclusion

The present value model implies that the log of the stock price and the log of the dividend are cointegrated and hence, the log of the price-dividend ratio is linear in the optimal forecast of the one-period change in the stock price and the present value of all future dividend growth. However, the price-dividend ratio may not be an appropriate variable to be used in the stock return prediction regression unless the log of stock price and the log of dividend are cointegrated with a cointegrating vector (1, -1).

The concept of cointegration by Engle and Granger (1987) is that over the long run a time-invariant linear combination of nonstationary variables may be stationary. As we are dealing with the long spans of data characterized by institutional change, we are interested in allowing cointegrating relationships to change over time. In this paper we extend the cointegration test by setting the alternative hypothesis to be cointegration while allowing for a one-time regime shift of unknown timing. The standard ADF statistic and the new ADF statistic both test the null of no cointegration, so rejection by either statistic implies that there is some long-run relationship in the data. Both the ADF and the new ADF tests reject the null of no cointegration. Although no inference that structural change has occurred can be made from the various cointegration tests, the tests of Hansen (1992) are useful to determine whether the cointegrating relationship has been subject to a regime shift. And we confirm that there is a structural break in the cointegrating relationship between the log of the stock price and the log of the dividend in 1962.

From the various tests applied in this paper, some conclusions can be drawn. First, there is general evidence of cointegration between the log of the stock price and the log of the dividend. Second, there is evidence of the existence of structural change. Third, some of the tests place the break point at the beginning of the sample, whereas others place it at the end. Taking into account the fact that the majority of the tests suffer from the trimming problem, this may explain the lack of complete agreement between the different tests. Fourth, the vector linking the log of the stock price and the log of the dividend is different from (1, -1), as predicted by the theory. Finally, nonparametric bootstrap procedure to derive an empirical distribution of the test statistic to test stock return predictability confirms the following results.

When we assume the log of the stock price and the log of the dividend to be cointegrated with the cointegrating vector of (1, -1), we find quite a strong return predictability before the structural break in 1962. However, the return predictability disappears with the sample period from 1963 to 2002. The predictability patterns formerly found in the U.S. data appear not to be robust to the addition of the latter part of the sample.

Further, when we apply the FM estimate of the cointegrating vector in order to correct for the nonstationarity of the regressor, the return predictability previously found in the sample completely disappears. Considering the fact that the only difference between the two nonparametric bootstrap procedure is the correction for nonstationarity of the regressor, we can conclude that the nonstationarity of the log of the price-dividend ratio contributes to the stock return predictability.

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