Economics Bulletin

Volume 32, Issue 1

Stock return predictability and stationarity of dividend yield

Kuang-Liang Chang
Department of Applied Economics, National Chiayi University, Taiwan

Abstract

This paper first investigates the stationarity of dividend yield and then analyzes the predictive ability of the adjusted dividend yield which removes structural changes and high persistence characteristics. Empirical results have found that the dividend yield follows a mean-reverting process in each regime, and the convergence speed depends on the mean and variance. Moreover, the dividend yield is also global stationary. Finally, the adjusted dividend yield can predict future stock returns, and its predictive ability is time-invariant.

The author would like to thank an anonymous referee for useful suggestions. Part of this paper was written while I was at Feng Chia University.
Citation: Kuang-Liang Chang, (2012) "Stock return predictability and stationarity of dividend yield", *Economics Bulletin*, Vol. 32 No. 1 pp. 715-729.
Contact: Kuang-Liang Chang - klchang@mail.ncyu.edu.tw.
Submitted: September 05, 2011. **Published:** February 24, 2012.

1. Introduction

Many financial variables (such as dividend yield, dividend-price ratio, price-earnings ratio, term spread, default spread, etc) have been used to predict stock returns. However, empirical studies have demonstrated that the evidence for the predictive ability of financial variables is ambiguous. Specifically, empirical results have been highly related to the persistence of financial variables and the non-constant impact of financial variables on stock returns. This paper focuses on the dividend yield of the Dow Jones Industrials Average (DJIA) index and investigates whether the adjusted dividend yield, which removes the persistence and structural change simultaneously, acts as a predictor of future stock returns for the DJIA index.

Researchers face two important difficulties when investigating stock return predictability. The first difficulty is that the stationarity of the dividend yield or dividend-price ratio will affect the explanatory power of dividend yield on the corresponding stock return. Although previous studies support the evidence that an increase in dividend yield is conducive to raising stock prices (Fama and French, 1988; Schwert, 1990), some recent studies have shown that whether or not the dividend yield is stationary plays a vital role in determining the intensity of predictability. For example, Lewellen (2004) points out that the predictive ability of dividend-price will decrease when there is no difference in dynamics between the dividend yield of the NSYE index and the unit root series. Park (2010) proves that the effect of dividend-price on stock returns becomes insignificant if the dividend yield experiences non-stationary dynamics. Campbell and Yogo (2006) find that the dividend yield of the S&P500 index does not have a significant positive impact on stock returns as the dividend yield follows a non-stationary process.

The second difficulty is in regard to the stability of parameter estimates representing the predictive ability of dividend yield. When the selected sample period is longer, the relationship between dividend yield and stock return may be dramatically changed. For example, Pesaran and Timmermann (2002) show that the process of parameter estimate for dividend yield shows dramatic changes when the rolling window method is utilized. Pay and Timmermann (2006) provide evidence as to the unstable predictability of dividend yield; that is, the impact of dividend yield on stock return differs among subsamples. Similarly, Rapach and Wohar (2006) demonstrate that the magnitude of the predictive ability of dividend yield is different among sub-periods, divided according to break dates identified by statistical procedure.

Previous literature concerning the stationarity of dividend yield focuses on the unit root tests. The traditional unit root tests, such as the Augment Dickey Fuller test (ADF), the Phillips Perron test (PP) and the Kwiatkowski, Phillips, Schmidt and Shin test (KPSS), are not suitable when data undergo structural breaks (Perron, 1989). To overcome this drawback, this paper adopts the Markov regime switching technique, which allows structural changes in intercept, autoregressive terms and variance when investigating the local and global stationarity of dividend yield. Specifically, the regime-switching mean-reversion specification is used to detect the existence of stationarity or explosiveness in each regime. Whether or not the dividend yield is locally stationary is determined by the speed of reversion to the regime-dependent mean. The second-order stationarity condition derived by Francq and Zakoian (2001) is used to verify the existence of global stationarity.

In order to alleviate the possibility that the predictive ability of the dividend-price ratio may be misestimated, Lettau and Nieuwerburgh (2008) use the demeaned dividend-price ratio, which removes the regime switches in mean to explore the predictive ability of the demeaned variable. They find evidence in favor of the existence of the predictive ability of the demeaned variable. However, Park (2010) uses the method of Lettau and Nieuwerburgh (2008) to investigate whether the demeaned dividend yield can predict stock returns for many stock markets. Park (2010) finds that predictive ability can not be preserved for some markets even if a high persistence arising from regime switches in mean has been extracted. Park (2010) further demonstrates that the persistence of dividend-price ratio is more important than the regime switches. To take into consideration the insignificance of predictive ability due to high persistent process and structural breaks, this paper adopts a filtered approach extended from the method of Lettau and Nieuwerburgh (2008) to simultaneously remove the possible high persistence and structural changes. To the best of my knowledge, this is the first paper to investigate the local and global stationarity of dividend yield before analyzing stock return predictability.

This paper also investigates the predictive ability of filtered dividend yield and performs a test to determine whether the effect of filtered dividend yield on stock return is fixed; the structural break test of Bai and Perron (2003) is used.

The remainder of this paper is constructed as follows. Section 2 presents the regime-switching mean-reversion model and discusses the global stationary condition. Section 3 reports the estimation results. The impacts of dividend yield and filtered dividend yield on stock returns are examined in Section 4. The conclusions are presented in the final section.

2. Empirical Specification and Stationarity

To investigate whether the dividend yield is stationary and to describe its dynamics at every time period, this paper examines the stationarity from two different angles: local stationarity and global stationarity. The regime-switching mean-reversion model derived from the traditional ADF test model is used to explore the local stationarity. Following Hall et al. (1999), Raybaudi et al. (2004), Kanas and Genius (2005) and Kanas (2008), the empirical specification can be expressed as follows:

$$\Delta DY_t = \alpha_{s_t} + \beta_{s_t} DY_{t-1} + \sum_{i=1}^{P} \phi_{i,s_t} \Delta DY_{t-i} + \delta_{s_t} \sqrt{\sigma^2} u_t \ , \tag{1}$$

where DY_t is the dividend yield at time t, Δ is the difference operator, s_t is an unobservable state variable with k different regimes and u_t is the normally distributed random error with mean 0 and variance 1. Note that all parameters are related to the state variable, except for σ^2. The parameter α_i refers to the intercept term in regime i. The scale parameter δ_1 is normalized to 1. Consequently, σ^2 is the volatility in regime 1. The coefficient ϕ_{i,s_t} denotes the autoregressive coefficient of order i under the regime s_t.

The regime switching mean-reversion effect is captured by the parameter β_{s_t}. If mean reversion parameter $\beta_{s_t} < 0$, the dividend yield shows a mean-reversion pattern. The smaller the value of β_{s_t}, the higher the speed of convergence towards the corresponding regime-mean.

The transition probabilities of the state variable can be represented as:

$$P\left(s_t = j \middle| s_{t-1} = n\right) = P_{nj}, \quad n, j = 1, 2, ..., k \tag{2}$$

Here, the restrictions that $P_{nj} \geq 0$ and $\sum_{j=1}^{k} P_{nj} = 1$ are imposed. Accordingly, the transition probability matrix has the following form:

$$P = \begin{bmatrix} P_{11} & P_{21} & P_{31} \\ P_{12} & P_{22} & P_{32} \\ P_{13} & P_{23} & P_{33} \end{bmatrix} \tag{3}$$

Even though parameter β_{s_t} shows the evidence of local stationarity, the global stationarity of the series itself is still unknown. The criterion derived by Francq and Zakoian (2001) is utilized to examine whether or not the dividend yield is globally stationary. Equation (1) is rewritten as a regime-switching autoregressive model of order p+1:

$$\mathrm{DY}_t = \alpha_{s_t} + \sum_{j=1}^{p+1} \theta_{j,s_t} \mathrm{DY}_{t-j} + \delta_{s_t} \sqrt{\sigma^2} u_t \tag{4}$$

where

$$\theta_{j,S_t} = \begin{cases} 1+\beta_{s_t}+\phi_{1,s_t}, & j = 1 \\ \phi_{j,s_t}-\phi_{j-1,s_t}, & j = 2,\cdots,p \\ -\phi_{p,s_t}, & j = p+1 \end{cases}$$

Define $\mathrm{M} = \Theta \times (\mathrm{P} \otimes \mathrm{I}_{(p+1)^2})$. Here, $\otimes$ represents the Kronecker product operator, $\mathrm{I}_{(p+1)^2}$ is defined as a identity matrix of dimension $(p+1)^2$ and

$$\Theta = \begin{bmatrix} \Theta_1 \otimes \Theta_1 & 0 & \cdots & 0 \\ 0 & \Theta_2 \otimes \Theta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Theta_k \otimes \Theta_k \end{bmatrix}$$

is a square matrix of dimension $k(p+1)^2$. The element Θ_i is a $(p+1)\times(p+1)$ matrix defined as follows:

$$\Theta_i = \begin{bmatrix} \theta_{1,i} & \theta_{2,i} & \cdots & \theta_{p,i} & \theta_{p+1,i} \\ 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}$$

Francq and Zakoian (2001) show that the series is a second-order stationary process if the largest eigenvalue of matrix M is smaller than 1.

3. Empirical Results

3.1 Data

The monthly stock price and dividend yield for the DJIA index are discussed in this paper. They are collected from the Datastream database. The time series data for dividend yield is available from March 1978. The sample period selected here is from March 1978 to July 2007.[1]

In the empirical literature, some studies, including Campbell and Yogo (2006), Rapach and Wohar (2006) and Lettau and Nieuwerburgh (2008), use the logarithm of financial

[1]Many studies use longer sample periods to explore the effect of dividend yield on stock returns. Based on the Datastream database, the available data for the dividend yield of the DJIA index begins at March 1978. Hence, the sample period is shorter. Similarly, Park (2010) uses the Datastream database and has a shorter sample period.

variable, while other studies, such as Fama and French (1988), Paye and Timmermann (2006), Park (2010), Becker et al. (2010), use the level of financial variable. The time series plots for stock returns, dividend yield and logarithm of dividend yield are illustrated in Figure 1. Table 1 reports the summary statistics for the variables used in this paper. The autocorrelation coefficients for dividend yield and its logarithm are similar, and their correlation is 0.981. As shown in Figure 1, the time series paths for the two variables show similar patterns. Due to the similar patterns between dividend yield and the logarithm of dividend yield, this paper only focuses on the behavior of dividend yield. The autocorrelation in stock returns is not evident, but the dividend yield shows very strong autocorrelation. In terms of unit root tests (ADF, PP and KPSS), the stock return is stationary, but the corresponding dividend yield is non-stationary.

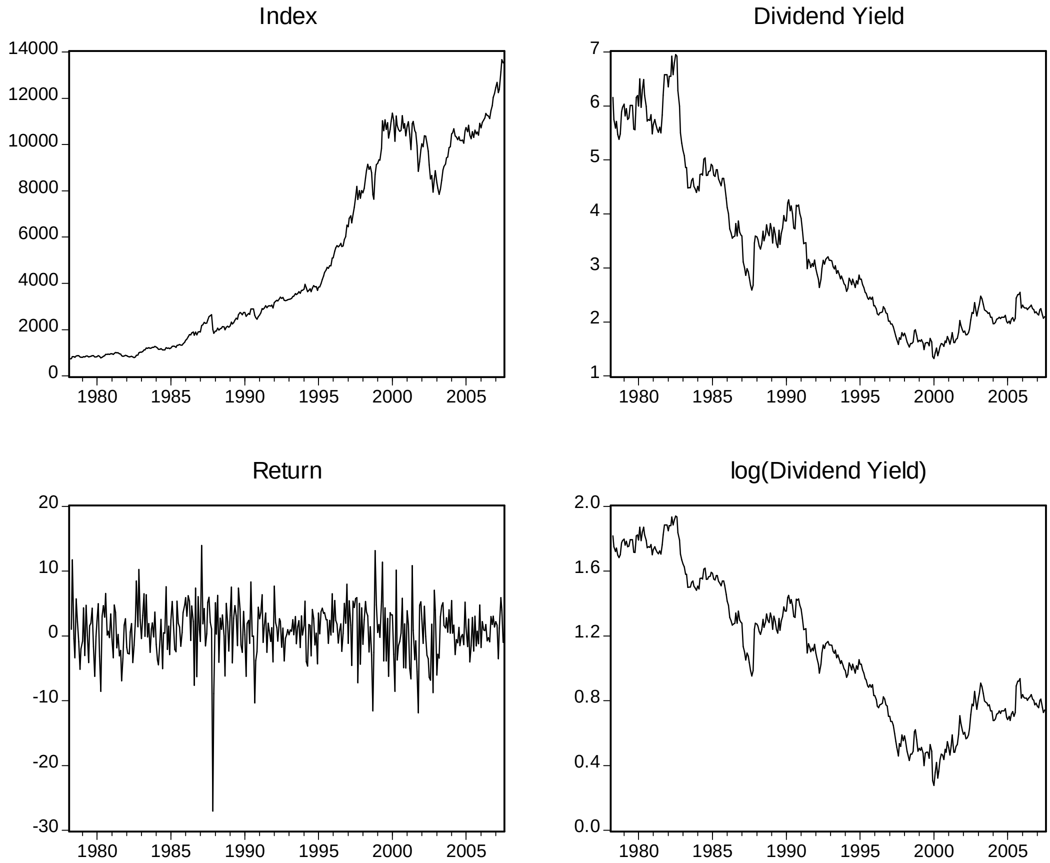

Figure 1 Index, Return and Dividend Yield

Determining how to choose the number of states and the lags of autoregressive parameters simultaneously is a troublesome problem. Psaradakis and Spagnolo (2006) confirm that the Akaike information criterion (AIC) is an easy and useful method to use to solve this problem. They also demonstrated that the AIC has a better identification performance than either the Bayesian information criterion (BIC) or the Hannan-Quinn criterion (HQC). In this paper, the maximum numbers for state and lag term are 3 and 5, respectively.[2] Table 2 shows the criteria. When $k = 3$ and $p = 0$, the regime-switching mean-reversion specification has the smallest AIC. The BIC and HQC determine that the regime switching model with $k = 2$ and $p = 0$ is the best specification. There is no consistent result.

Table 1 Summary statistics

	Stock Return	Dividend Yield	Log(Dividend Yield)	Adjusted Dividend Yield
Panel A: autocorrelation				
ρ_1	0.006	0.988	0.990	0.840
ρ_4	-0.055	0.958	0.963	0.650
Panel B: unit root tests				
ADF	-18.547***	-2.028	-1.934	-4.986***
PP	-18.549***	-2.055	-1.879	-6.457***
KPSS	0.059	0.361***	0.268***	0.089

Notes: *** indicates significance at 1%.

Table 2 Values for AIC, BIC and HQ

	p=0	p=1	p=2	p=3	p=4	p=5
Panel A: AIC						
k=2	-1.107	-1.096	-1.086	-1.076	-1.070	-1.063
k=3	-1.116	-1.099	-1.086	-1.073	-1.057	-1.050
Panel B: BIC						
k=2	-1.019	-0.986	-0.955	-0.922	-0.895	-0.865
k=3	-0.973	-0.924	-0.877	-0.831	-0.782	-0.742
Panel C: HQC						
k=2	-1.072	-1.052	-1.034	-1.015	-1.001	-0.984
k=3	-1.059	-1.029	-1.003	-0.977	-0.948	-0.928

This paper further adopts the regime classification measure (RCM) of Ang and Bakaert (2002) to compare the fitting performance for different specifications. The measure can be shown as:

[2]The reason that the maximum state number is 3 will be provided in subsection 3.2.

$$RCM = \frac{100 \times k^2}{M} \sum_{t=1}^{M} \left(\prod_{j=1}^{k} P(s_t = j \mid \Omega_T) \right) \tag{5}$$

where $P(s_t = j \mid \Omega_T)$ are the smoothed probabilities, and M is the number of sample observations. The RCM is 0.006 for the specification where $k = 3$ and $p = 0$ and is 5.641 for the specification where $k = 2$ and $p = 0$. This result indicates that three-state specification is better than two-state specification; hence, this paper only focuses on the three-state model.

Table 3 Estimation results

Parameter	Regime 1	Regime 2	Regime 3
α	1.142***	0.171**	0.060**
	(0.308)	(0.076)	(0.026)
β	-0.188***	-0.051***	-0.032***
	(0.050)	(0.019)	(0.012)
σ^2	0.061***	0.061***	0.061***
	(0.014)	(0.014)	(0.014)
δ	1.000	0.687***	0.330***
	$(-)$	(0.096)	(0.044)
Transition probability matrix			
Regime 1	0.962***	0.016	0.000
	(0.029)	(0.013)	(---)
Regime 2	0.038	0.969***	0.011
	(---)	(0.019)	(---)
Regime 3	0.000	0.015	0.989***
	(---)	(---)	(0.008)
Unconditional mean	6.074	3.353	1.882
Unconditional standard deviation	0.247	0.169	0.081
Expected duration	26.233	32.584	95.147
Unconditional probability	0.155	0.359	0.486
Log-likelihood function		209.371	
AIC		-1.116	

Notes: Values reported in parentheses are standard errors. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

3.2 Estimation Results

Table 3 shows the quasi-maximum likelihood results for the regime-switching mean-reversion model. Three different types of dynamics in dividend yield are shown. The unconditional mean is 6.074 for regime 1, 3.353 for regime 2 and 1.882 for regime 3. The standard error is 0.247 for regime 1, 0.169 for regime 2 and 0.081 for regime 3. Accordingly, regime 1 can be classified as a high dividend yield and high volatility regime. Regime 2 fits a medium dividend yield and moderate volatility regime. Regime 3 has the properties of low dividend yield and low volatility.

The transition probabilities for the same regime occurring are very close to 1. It is 0.962 for regime 1, 0.969 for regime 2 and 0.989 for regime 3, showing that the regime persistence for regime 3 is strongest. The average durations for regimes 1, 2 and 3 are about 27, 33 and 96 months, respectively. The transition probability for p_{13} and p_{31} is zero, indicating that the dynamics cannot shift between regimes 1 and 3.

Figure 2 displays the smoothed probabilities. The periods for the different regimes are listed in Table 4. The two periods 1978:m6-1982:m9 and 1987:m11 belong to regime 1. The four periods 1978:m4-1978:m5, 1982:m10-1987:m10, 1987:m12-1992:m8 and 2005:m7-2005:m7 are classified as regime 2. The remaining dates are identified as regime 3. Furthermore, the proportions of regimes 1, 2 and 3 are 15.05%, 35.80% and 49.15%, respectively, and they are close to the unconditional probabilities (15.5% for regime 1, 35.9% for regime 2 and 48.6% for regime 3).

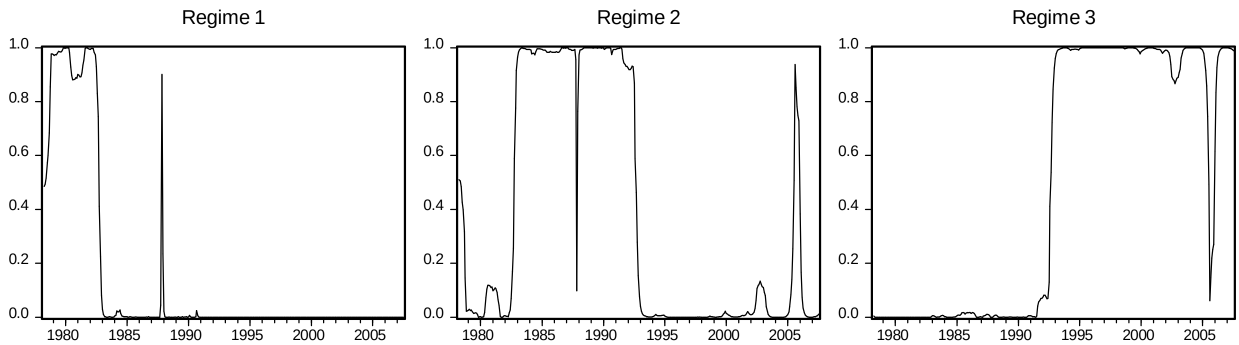

Figure 2 Smoothed Probabilities

This paper does not allow four or more states because three states do not mean that there are only two structural change points. In the 3-state regime switching model, there are 8 sub-periods, implying that 7 break points are observed. As discussed above, two transition probabilities are zeros in the 3-state model. When a 4-state structure is allowed, many transition probabilities will be zero. Consequently, archiving convergence is an unfeasible task.

Table 4 The Periods for Each Regime

Regime	Periods
Regime 1	1978M06-1982M09 1987M11
Regime 2	1978M04-1978M05 1982M10-1987M10 1987M12-1992M08 2005M07-2005M12
Regime 3	1992M09-2005M06 2006M01-2007M07

An interesting problem worth investigating is why the structural change points found in this paper differ from those identified by the Rapach and Wohar (2006).[3] Rapach and Wohar (2006) investigate the dividend yield of the S&P500 for the period spanning from March 1965 to April 2000 and find a structural change point in March 1990. The first possible reason for the difference is that a different sample and sample period are selected. This paper uses the DJIA index, while Rapach and Wohar (2006) use the S&P500. Moreover, the sample size is smaller in this paper. The second reason is that the mechanism to determine structural changes is different. In the study of Rapach and Wohar (2006), structural changes are determined by the sequential examination of the sum of the squared errors of different partitions. Structural changes are determined by the transition probabilities in this paper. When the number of states is restricted to 2, one structural point is observed. The break data occurs in January 1992 and is close to that identified by Rapach and Wohar (2006).[4]

This paper turns to the issue of regime-switching mean reversion. The estimate of the mean-reversion parameter is negative and significant at the 1% significance level for each regime, showing an indication of regime-switching mean reverting behavior. Furthermore, the adjustment speed of mean reversion is asymmetric and hinges greatly on the level and volatility of dividend yield. The magnitude of mean-reversion is largest in regime 1 and smallest in regime 3.

Although mean-reversion behavior of dividend yield has been established, until now the global behavior of dividend yield has been unknown. The global stationarity condition will be examined now. This paper finds that the dividend yield follows a globally stationary process as the largest eigenvalue of matrix M is 0.068 and is less than 1, which is contrary to the result obtained using traditional unit root tests. In summary, if the series has structural changes in mean, autoregressive coefficients and variance as well as being global stationary,

[3]The author thanks an anonymous referee for providing this suggestion.
[4] The period 1978:m3-1991:m12 is classified as the high-mean and high-variance state. The period 1992:m1-2007:m7 is classified as the low-mean and low-variance state. Empirical results are available upon request.

the traditional unit root tests for stationarity may draw incorrect conclusions.

3.3 Time-varying transition probabilities

In Equation (3), each transition probability is constant. This paper allows the transition probabilities to change with the business variables by extending the specification of Diebold et al. (1994), Filardo (1994) and Kanas (2008).[5] The transition probability matrix is as follows:

$$P_t = \begin{bmatrix} P_{11,t} & P_{21,t} & P_{31,t} \\ P_{12,t} & P_{22,t} & P_{32,t} \\ P_{13,t} & P_{23,t} & P_{33,t} \end{bmatrix} = \begin{bmatrix} \Phi_{11,t} & \Phi_{21,t} & \Phi_{31,t} \\ 1\text{-}\Phi_{11,t}\text{-}\Phi_{13,t} & 1\text{-}\Phi_{21,t}\text{-}\Phi_{23,t} & 1\text{-}\Phi_{31,t}\text{-}\Phi_{33,t} \\ \Phi_{13,t} & \Phi_{23,t} & \Phi_{33,t} \end{bmatrix} \quad (6)$$

where $\Phi_{ij,t} = \mathrm{F}(\mathrm{a}_{ij} + \mathrm{b}_{ij}\mathrm{z}_{t-1})$. Here, F represents the cumulative distribution of the standard normal distribution and z_{t-1} is the explanatory variable. The explanatory variable will be the difference of the federal fund rate and the Chicago Fed National Activity Index (CFNAI) of Federal Reserve Bank of Chicago. This first variable can be treated as the monetary policy instrument while the latter one represents the business condition.[6]

Table 5 reports the effects of macroeconomic variables on the transition probabilities. It is clear that neither the difference of federal fund rate nor the CFNAI can explain the process of transition probabilities.

4. Stock Return Predictability

Although the dividend yield is a stationary series, there exists very strong persistence in each regime. The autoregressive coefficient is 0.812 in regime 1, 0.949 in regime 2 and 0.968 in regime 3. As emphasized in the introduction, the inconsistent conclusions regarding stock return predictability can be attributed to a high degree of persistence. This paper employs the concept derived by Lettau and Nieuwerburgh (2008) to alleviate the problem of high persistence. The adjusted approach is given by

$$\mathrm{DY}_t^* = \begin{cases} \mathrm{DY}_t - \mathrm{E}(\mathrm{DY}_t|\mathrm{s}_t = 1) & \textit{if} \quad \mathrm{s}_t = 1 \\ \mathrm{DY}_t - \mathrm{E}(\mathrm{DY}_t|\mathrm{s}_t = 2) & \textit{if} \quad \mathrm{s}_t = 2 \\ \mathrm{DY}_t - \mathrm{E}(\mathrm{DY}_t|\mathrm{s}_t = 3) & \textit{if} \quad \mathrm{s}_t = 3 \end{cases} \quad (7)$$

Similar to the model of Lettau and Nieuwerburgh (2008), the specification used in this paper is a generalized version of the regime switching model. Specifically, when $\theta_{j,s_t} = 0$ and

[5]The author thanks an anonymous referee for providing this suggestion.

[6]Many different variables can be used to represent monetary policy and business conditions. For simplicity, only two common variables are adopted here.

$\delta_{s_t}=1$, Equation (4) is collapsed to the specification of Lettau and Nieuwerburgh (2008).

Table 5 Estimation results for the time-varying transition probabilities

Parameter	Difference of Federal Fund Rate	CFNAI
a_{11}	1.510**	1.796***
	(0.694)	(0.412)
a_{13}	-5.226	-5.736
	(51299.930)	(312046.909)
a_{21}	-2.528**	-2.804
	(0.994)	(2.196)
a_{23}	-2.237***	-2.082***
	(0.426)	(0.334)
a_{31}	-5.050	-5.738
	(11252.485)	(415908.134)
a_{33}	2.431***	2.532***
	(0.621)	(0.684)
b_{11}	0.720	0.055
	(0.685)	(0.307)
b_{13}	-0.070	0.012
	(29678.080)	(21588.915)
b_{21}	2.257	0.815
	(2.625)	(1.614)
b_{23}	-0.020	0.059
	(2.118)	(0.508)
b_{31}	-0.010	-0.006
	(45709.572)	(169574.112)
b_{33}	-2.153	-0.630
	(2.955)	(0.980)

Notes: Values reported in parentheses are standard errors. ** and *** indicate significance at 5% and 1%, respectively.

The summary statistics and unit root tests for the adjusted dividend yield are shown in the last column of Table 1. Compared to the original dividend yield, the autocorrelation greatly declines for the adjusted series. The 4th-order autocorrelation coefficient is 0.958 for the original series, and it is simply 0.650 for the adjusted series. Moreover, all of the unit root tests find that the adjusted dividend yield is stationary.

Next, this paper examines whether the adjusted dividend yield can predict stock returns by incorporating the possible instability of parameters.[7] The multiple structural change model of Bai and Perron (2003) is:

$$R_t = d_{0\theta} + d_{1\theta} X_{t-1} + \varepsilon_t, \quad \theta = 1, 2, \ldots, m \tag{8}$$

where R_t is the stock return, $X_{t\text{-}1}$ refers to the adjusted dividend yield and m refers to the number of structural changes. The sup $F_T(\theta+1|\theta)$ statistic is proposed to test the null hypothesis $H_0: \theta$ breaks against the alternative hypothesis $H_1: \theta+1$ breaks. Moreover, Bayesian information criterion (BIC) and the modified Schwarz criterion (LWZ) are also criteria to determine the number of breaks.

It is obvious from Table 6 that the all statistics support the hypothesis of no structural change. Moreover, the adjusted dividend yield has a significant positive effect on stock returns. Table 7 reports the results for the original dividend yield. The original dividend yield cannot forecast stock returns. This is consistent with the findings of previous studies, such as Goyal and Welch (2003), Lewellen (2004) and Ang and Bekaert (2007).

Table 6 Results for the adjusted dividend yield

Panel A: information criterion						
	m=0	m=1	m=2	m=3	m=4	m=5
BIC	2.830	2.871	2.887	2.928	2.954	2.988
LWZ	2.836	2.940	3.020	3.124	3.213	3.311
Panel B: sup F test						
	$F_T(2\|1)$	$F_T(3\|2)$	$F_T(4\|3)$	$F_T(5\|4)$		
statistics	7.376	2.677	10.291	0.000		
Panel C: result for stock return predictability						
	d_1	$S.E.(d_1)$	R^2			
parameter	1.308***	0.367	4.132%			

Notes: *** indicate significance at 1% level.

5. Conclusions

This study provides evidence that the dividend yield of the DJIA index is not only a regime switching mean reversion, but is also global stationary. The regime switching mean reversion signifies that the convergence speed is different in each regime. The convergence speed is highest in the regime with the highest mean and highest variance. In addition to the existence of local stationarity, the dividend yield is also globally stationary in terms of the covariance stationary test. Compared to the insignificance of the original dividend yield, the adjusted dividend yield, which removes structural change and persistence characteristics, can predict

[7]The author thanks an anonymous referee for providing this suggestion.

future stock returns.

Table 7 Results for the original dividend yield

Panel A: information criterion						
	m=0	m=1	m=2	m=3	m=4	m=5
BIC	2.871	2.896	2.909	2.942	2.973	3.007
LWZ	2.877	2.965	3.042	3.138	3.232	3.330
Panel B: sup F test						
	$F_T(2\|1)$	$F_T(3\|2)$	$F_T(4\|3)$	$F_T(5\|4)$		
statistics	0.166	0.021	0.002	0.019		
Panel C: result for stock return predictability						
	d_1	$S.E.(d_1)$	R^2			
parameter	0.098	0.149	0.123%			

References

Ang, A. and Bakaert, G. (2002) “Regime switching in interest rate” *Journal of Business and Economic Statistics* **20**, 163-182.

Ang, A. and Bekaert, G. (2007) “Stock return predictability: is it there?” *Review of Financial Studies* **20**, 651-707.

Bai, J. and Perron, P. (2003) “Computation and analysis of multiple structural change models” *Journal of Applied Econometrics* **18**, 1-22.

Becker, R., Lee, J. and Gup, B. E. (2010) “An empirical analysis of mean reversion of the S&P500’s P/E ratios” *Journal of Economic and Finance* doi 10.1007/212197-010-9145-8.

Campbell, J. Y. and Yogo, M. (2006) “Efficient tests of stock return predictability” *Journal of Financial Economics* **81**, 27-60.

Diebold, F. X., Lee, J. H. and Weinbach, G. C. (1994) “Regime switching with time-varying transition probabilities” Non-stationary Time Series Analysis and Cointegration, ed. C. Hargreaves, Oxford University Press, Oxford, U.K.

Fama, E. and French, K. (1988) “Dividend yields and expected stock returns” *Journal of Financial Economics* **22**, 3-25.

Filardo, A. J. (1994) “Business-cycle phases and their transitional dynamics” *Journal of Business and Economic Statistics* **12**, 299-308.

Francq, C. and Zakoian, J. M. (2001) “Stationarity of multivariate Markov-switching ARMA models” *Journal of Econometrics* **102**, 339-364.

Goyal, A. and Welch, I. (2003) “Predicting the equity premium with dividend ratios” *Management Science* **49**, 639-654.

Hall, S. G., Psaradakis, Z. and Sola, M. (1999) “Detecting periodically collapsing bubbles: a

Markov-switching unit root test" *Journal of Applied Econometrics* **14**, 143-154.

Kanas, A. (2008) "On real interest rate dynamics and regime switching" *Journal of Banking and Finance* **32**, 2089-2098.

Kanas, A. and Genius, M. (2005) "Regime (non)stationarity in the US/UK real exchange rate" *Economics Letters* **87**, 407-413.

Lettau, M. and Nieuwerburgh, S. V. (2008) "Reconciling the return predictability evidence" *Review of Financial Studies* **21**, 1607-1652.

Lewellen, J. (2004) "Predicting returns with financial ratios" *Journal of Financial Economics* **74**, 209-235.

Paye, B. S. and Timmermann, A. (2006) "Instability of return prediction models" *Journal of Empirical Finance* **13**, 274-315.

Park, C. (2010). "When does the dividend-price ratio predict stock return?" *Journal of Empirical Finance* **17**, 81-101.

Pesaran, M. H. and Timmermann, A. (2002) "Market timing and return prediction under model instability" *Journal of Empirical Finance* ***9***, 495-510.

Perron, P. (1989) "The great crash, the oil price shock, and the unit root hypothesis" *Econometrica* **57**, 1361-1401.

Psaradakis, Z. and Spagnolo, N. (2006) "Joint determination of the state dimension and autoregressive order for models with Markov regime switching" *Journal of Time Series Analysis* **27**, 753-766.

Rapach, D. E. and Wohar, M. E. (2006) "Structural breaks and predictive regression models of aggregate U.S. stock returns" *Journal of Financial Econometrics* **4**, 238-274.

Raybaudi, M., Sola, M. and Spagnolo, F. (2004) "Red signals: current account deficits and sustainability" *Economics Letters* **84**, 217-223.

Schwert, G. W. (1990) "Stock returns and real activity: a century of evidence" *Journal of Finance* **45**, 1237-1257.