The Bubble Effect on the Predictive Ability of Dividend Yield

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Abstract

This paper addresses a puzzle: why dividend yield has lost its predictive ability since the 1990s. Campbell and Shiller's (1988) dynamic Gordon model provides a theoretical foundation to explain DY's predictability of stock returns, however, when the transversality condition fails to hold (i.e., when a bubble is present), this implies that DY can not predict stock returns. Using a recursive test procedure, developed by Phillips et al. (2009), to detect periodically collapsing bubbles in the NYSE index, we find periodically collapsing bubbles indeed occurred from the end of 1991 on. Along with major real world events that influenced financial markets and the early-1990s sharp drop in DY, the empirical evidence coincides with our theoretical inference, showing that DY is indeed a useful variable in predicting future stock returns during a no-bubble period, but that it loses its predictive ability when bubbles are present.

JEL Classifications: G12
Keywords: Periodically collapsing bubbles; Predictive regressions; Dividend yield

1. Introduction

Whether or not dividend yield (DY) can predict aggregate stock returns has been at the center of much empirical and theoretical debate and research in finance for the last twenty years. Motivation for the articulation of the role of dividend yield as a regressor in the predictive regression comes from the dynamic Gordon model, where the log dividend yield can be written as a discounted value of future expected returns minus dividend growth rates (see Campbell and Shiller (1988)). To the extent researchers find DY to be a useful variable in predicting future returns (e.g., Fama and French (1988), and Lewellen (2004)), there is emerging literature arguing that the dividend yield "lost" its predictive ability in the 1990s (e.g., Goyal and Welch (2003), Lettau and Ludvigson (2005), and Ang and Bekaert (2007)).

There are a number of reasons why instability in the parameter that relates stock returns to state variable can occur. Changes in monetary and debt management policies, learning by investors, bursting or creation of speculative bubbles, and major changes in market sentiment are some examples of possible sources of instability in predictive regression models (see Pesaran and Timmermann (2002)). As for the 1990s, DY experienced sharp drops. Some academic researchers attribute this episode – by emphasizing that fundamentals had basically not changed – to the stock market being seriously overvalued (e.g., Campbell and Shiller (2001)), while others have attributed it to financial bubbles (e.g., Greenspan (1996), Lamont and Thaler (2003), Ofek and Richardson (2003), Phillips et al. (2009))[1].

If bubbles were indeed present in the 1990s, how did they affect the predictive ability of DY in stock returns? Theoretically, Campbell and Shiller's (1988)

[1] Greenspan (1996) coined the phrase "irrational exuberance" to characterize herd stock market behavior. This term can be interpreted as a cryptic warning that the stock market might be in risk of a financial bubble.

dynamic Gordon model provides a foundation to explain the predictability of stock returns based on DY, although when the transversality condition fails to hold (i.e., when a bubble is present), DY will lose its ability to predict stock returns. Recently, a good number of researchers have indicated that bubbles can emerge if investors hold heterogeneous beliefs, potentially due to psychological biases, and they agree to disagree about the fundamental value (e.g., Ofek and Richardson (2003), Dhar and Goetzmann (2006), Hong, Scheinkman and Xiong (2006), Boswijk, Hommes and Manzan (2007), and David (2008)).

Boswijk, Hommes and Manzan (2007) develop an asset pricing model using behavioral heterogeneity, assuming investors have different beliefs about the persistence of deviations of stock prices from the fundamental benchmark. They suggest that there are two different regimes: one is called “mean reversion,” where investors recognize a mispricing of the asset and expect the stock price to return toward its fundamental value; the other is “trend-following,” where investors expect the stock price deviations from the fundamental to become a trend. They also find that the trend-following regime was activated only occasionally before the 1990s, but after the ‘90s, the fraction of investors believing in a trend increased close to one and persisted for a number of years[2]. In a related study, Hommes, Sonnemans, Tuinstra and Velden (2008) conduct a laboratory experiment to investigate bubbles and find that bubbles seem to be driven by the trend-chasing behavior of participants who within a group tend to coordinate on a common prediction strategy.

In a sense, this implies that dividend yield can predict stock returns because investors believe in mean reversion of stock prices toward the benchmark fundamental value in the mean reversion regime (no bubble period)[3]. In the

[2] Boswijk et al. (2007) also denote that these two investor types co-exist, and their fractions show considerable fluctuations over time.

[3] That is, DY is low when stocks are overpriced, predicting low future returns as prices return to

trend-following regime, investors can use relative past profits to adjust their beliefs or forecasting strategies. This action causes extreme price deviations from fundamentals and causes bubbles to continue for a long time. In the latter situation, "rational" investors may ride bubbles to get more profits, and might not use fundamentals to predict stock returns, which in turn negates DY's predictive ability.[4]

To shed some light on this issue, we examine empirically whether bubbles play an important role to influence DY in predicting stock returns. We hypothesize that DY is a useful variable in predicting future stock returns during a no-bubble period, but loses its predictive ability when a bubble is present. In order to test our hypothesis, we adopt the following two procedures. Firstly, we use a recursive test procedure, developed by Phillips et al. (2009), to detect periodically collapsing bubbles in the NYSE index, dating the beginning and ending of the bubble period. Secondly, we apply Lewellen's bias-adjusted predictability test to solve the problem of DY being extremely persistent and compare predictive ability of DY between the bubble and no-bubble periods.

This empirical investigation yields two interesting results. First, we clearly identify that the periodically collapsing bubble period occurred from the end of 1991 on.[5] The successful identification of periodically collapsing bubbles means we confirm that stock prices deviated from fundamentals since the early-1990s, which also offers an explanation why the dividend yield "lost" its predictive ability.[6] Second, we find that DY drops sharply from the early-1990s and never returns to its

fundamentals.

[4] Abreu and Brunnermeier (2003) and Brunnermeier and Nagel (2004) show that rational investors may prefer to ride bubbles because of predictable investor sentiment and limits to arbitrage.

[5] Goyal and Welch (2003), Lettau and Ludvigson (2005), and Ang and Bekaert (2007) all argue that stock return predictability disappeared sometime in the 1990s decade, however, their 1990's sample periods are not consistent.

[6] Hirota and Sunder (2007), in a laboratory experiment, find that bubbles are more likely to occur in markets for securities with more uncertain dividends, consistent with the stylized facts of the susceptibility of high-growth and new technology stocks to bubble formation.

mean. This coincides with the timing of the periodically collapsing bubble. In the real world, first came the Internet stock bubble beginning in the 1990s, followed by the housing, credit and commodities bubbles from 2003. In other words, we conclude that the empirical findings correspond to major financial events that have occurred in the real world since the early 1990s.

The rest of the paper is organized as follows. Section 2 provides the theoretical motivation. Section 3 describes the econometric methodologies we use to test for periodically collapsing bubbles in the NYSE index, and the extremely persistent property of DY in predictive regression model. Section 4 describes the data and descriptive statistics. Section 5 gives the empirical results. Section 6 concludes our main findings.

2. Theoretical Motivation

This section discusses the theoretical motivation: to examine the connection between bubbles and DY's predictive ability.

The standard present value model that relates the real stock price to the discounted next period's expected stock price and real dividends can be written as:

$$P_t = \frac{1}{1+r} E_t(P_{t+1} + D_{t+1}) \tag{1}$$

where P_t refers to the real stock price, D_t to real dividends, and $(1+r)^{-1}$ is the constant discount factor, while $E_t(\cdot)$ is the expectations operator conditioned on information up to *t*.

Under transversality condition,

$$\lim_{i\to\infty} \frac{1}{(1+r)^i} E_t(P_{t+i}) = 0 \tag{2}$$

the stock price can be re-written as equation(3). That is, the stock price, P_t, is equal to fundamental value F_t, presented as the discounted expected future real dividends.

$$F_t = \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} E_t(D_{t+j}) \tag{3}$$

On the other hand, if the transversality condition fails to hold, then the real stock price can be thought of as the sum of fundamental value F_t and a rational bubble B_t.

$$P_t = F_t + B_t \tag{4}$$

where the bubble term satisfies equation (5)

$$B_t = \frac{1}{1+r} E_t(B_{t+1}) \tag{5}$$

Considering the present value model with a time-varying discount rate, which is more realistic and complicated, Campbell and Shiller (1988) derive a log-linear approximation of log return γ in terms of log stock price, p_t ,and log dividend, d_t,

$$\gamma = \tau + \rho E_t p_{t+1} + (1-\rho) E_t d_t - p_t \tag{6}$$

where ρ is close to but a little smaller than one, and τ is a constant term. In other words, equation (6) relates log return to the log levels of dividend and price, d_t and p_t. Campbell and Shiller rewrite it in terms of the log dividend yield $\delta_t = d_{t-1} - p_t$, and the log dividend growth rate Δd_t. Rewriting equation (6) and substituting h_t for γ results in

$$h_t = \tau + \delta_t - \rho\delta_{t+1} + \Delta d_t \tag{7}$$

Solving equation (7) forward recursively and imposing the terminal condition

$$\lim_{i\to\infty} \rho^i \delta_{t+i} = 0 \tag{8}$$

results in the following dynamic Gordon model:

$$\delta_t = E_t \sum_{j=0}^{\infty} \rho^j (h_{t+j} - \Delta d_{t+j}) + c \tag{9}$$

where h_{t+j} and Δd_{t+j} are the future stock return and dividend growth, and c is a constant.

This relationship states that dividend yield includes future expected returns in excess of dividend growth, and provides the basic rationale for predictability of stock returns. However, if the transversality condition (equation (2)) fails to hold, then the stock price should contain both the fundamental value and a bubble term. Once the stock market falls within the Boswijk, Hommes and Manzan's (2007) trend-following regime classification, where investors expect the stock price deviations from the fundamental to become a trend, the bubble component will dominate over fundamentals to govern the price.

Violating the transversality condition means that expected discounted value of a stock price will not converge to zero in the indefinite future (i.e., $\lim_{i\to\infty}\rho^i E_t(p_{t+i}) \neq 0$), and will lead to $\lim_{i\to\infty}\rho^i E_t(d_{t+i-1} - p_{t+i}) \neq 0$ because dividend cannot diverge, $\lim_{i\to\infty}\rho^i E_t(d_{t+i-1}) = 0$. This implies that the terminal condition of equation (8) also fails to hold. In other words, the expected discounted value of the log dividend yield δ_t $(= d_{t-1} - p_t)$ will not converge to zero in the indefinite future. The log dividend yield can, therefore, no longer be written as discounted value of all future returns and dividend growth. In conclusion, the presence of a bubble has an impact on the market so great in that it negates DY's ability to predict stock returns.

3. Research Methodology

In this section, we briefly discuss the definition of periodically collapsing bubbles and detecting method – forward recursive regression tests – developed by Phillips et al. (2009). Then, we introduce Lewellen's (2004) bias-adjusted stock return predictability test, which solves the problem of the predictor variable being extremely persistent.

3.1. Periodically Collapsing Bubbles

Generally speaking, if a bubble exists, then stock price will have explosive behavior, irrespective of whether the dividend process is I(1) or I(0). In this case, the first difference of price is also explosive (i.e., it cannot remain stationary). This is the motivation for unit root and co-integration tests for bubbles in Diba and Grossman (1988). Evans (1991), however, criticizes that the methodologies presented by Diba and Grossman (1988) will lead to the incorrect conclusion that speculative rational bubbles do not exist when periodically collapsing rational bubbles are present. He uses simulation to demonstrate that Diba and Grossman's test has low power due to the fact that a periodically collapsing bubble process is like an I(1) process or even like a stationary linear autoregressive process, rather than an explosive process, provided the probability of the bubble collapsing is not negligible.

Evans (1991) suggests the following model for a bubble process B_t that collapses periodically:

$$B_{t+1} = (1+r)B_t u_{t+1}, \qquad \text{if } B_t \le c \tag{10a}$$

$$B_{t+1} = [\zeta + \frac{(1+r)}{\pi}\theta_{t+1}(B_t - \frac{\zeta}{(1+r)})]u_{t+1}, \qquad \text{if } B_t > c \tag{10b}$$

Here, ζ and c are positive parameters with $0 < \zeta < (1+r)c$, and π denotes a probability. u_{t+1} is an exogenous i.i.d. positive random variable with $E_t u_{t+1}$ =1, and θ_{t+1} is an exogenous i.i.d. Bernoulli process that takes the value 1 with probability π and 0 with probability 1-π, where $0 < \pi \le 1$. As long as the bubble size (B_t) is smaller than the threshold value (c), the bubble grows at mean $1+r$. Once the bubble size (B_t) is bigger than the threshold value (c), the bubble grows at a faster rate $(1+r)\pi^{-1}$ as long as the eruption continues, with probability π, but the bubble may collapse with probability 1-π per period. When the bubble collapses, it falls to a positive mean value of ζ, and the process begins again.

3.2. Forward Recursive Regression Tests for Detecting Bubble Period

According to the aforementioned discussion, the result from using Diba and Grossman's test was confounded between explosive bubbles and periodically collapsing bubbles in the empirical evidence. In order for the unit root test procedure to be powerful in detecting periodically collapsing bubbles, Phillips et al. (2009) propose the use of forward recursive regression techniques to detect and date the time of periodically collapsing bubbles. For time series X_t, Phillips et al. (2009) apply the augmented Dickey-Fuller (ADF) test for a unit root against the alternative of an explosive root (the right-tailed). They estimate the following autoregressive specification by least squares for some given value of the lag parameter J.

$$X_t = \mu_X + \delta X_{t-1} + \sum_{j=1}^{J} \varphi_j \Delta X_{t-j} + \xi_{X,t} \tag{11}$$

$\xi_{X,t}$ denotes independent and normal distribution random variable with mean 0 and variance σ_X^2. The unit root null hypothesis is H_0: $\delta = 1$ and the right-tailed alternative hypothesis is H_1: $\delta > 1$.

The expanding window method, the statistic estimated recursively by adding one observation at each pass, is employed in forward recursive regression (equation (11)). That is, the first regression contains n_{S0} =[ns_0] observations where s_0 is the least proportion of the whole samples and [ ] is the integer part of its argument. Succeeding regressions use the original subsample along with the following observations giving a sample of size $n_s = [ns]$ for $s_0 \le s \le 1$. Indicate the corresponding t-statistic by ADF_s and therefore ADF_1 corresponds to the full sample. To find the time of origin and ending of bubbles, one can match the time series of ADF_s with $s \in [s_0, 1]$ against the right-tailed critical values from the asymptotic distribution of the standard Dickey-Fuller t-statistic.

3.3. *Lewellen's Bias-Adjusted Stock Return Predictability Test*

This study focuses on the regression

$$y_t = \alpha + \beta x_{t-1} + \varepsilon_t \tag{12}$$

where y_t is the return in month t and x_{t-1} is a predictive variable (DY) known at the beginning of the month and is assumed to follow a stationary AR(1) process:

$$x_t = \phi + \rho x_{t-1} + \mu_t \tag{13}$$

where ρ <1.

When the predictive variable is DY, the residuals in (12) and (13) will be negatively correlated since an increase in price leads to a decrease in DY. It follows that ε_t is correlated with x_t in the predictive regression, violating the OLS assumption of requiring independence at all leads and lags. As a consequence, estimation errors in the two equations are closely connected:

$$\hat{\beta} - \beta = \gamma(\hat{\rho} - \rho) + \eta \tag{14}$$

where η is a random error with mean zero and γ is a negative constant.

The bias in $\hat{\beta}$ is typically found by taking expectations of both sides of (14). However, this approach implicitly discards any information we have about $\hat{\rho} - \rho$. In particular, Lewellen (2004) shows that for stationary predictive variables such as DY, the bias in $\hat{\beta}$ is at most $\gamma(\hat{\rho} - 1)$. This upper bound will be less than the standard bias-adjustment if $\hat{\rho}$ is close to one, and empirical tests that ignore the information in $\hat{\rho}$ will understate DY's predictive power.

The tests in this article therefore use the Lewellen (2004) bias-adjusted estimator

$$\hat{\beta}_{adj} = \hat{\beta} - \gamma(\hat{\rho} - \rho) \tag{15}$$

where ρ is assumed to be approximately one (operationalized as ρ =0.9999). The variance of $\hat{\beta}_{adj}$ is $\sigma_v^2 (X'X)^{-1}_{(2,2)}$. To implement the test, we can estimate γ and σ_v from $\varepsilon_t = \gamma\mu_t + v_t$, where ε_t and μ_t are the residuals in (12) and (13). Operationally, Lewellen (2004) used the following equation to estimate $\hat{\beta}_{adj}$ and γ:

$$y_t = \alpha + \beta x_{t-1} + \gamma(x_t - 0.9999x_{t-1}) + v_t \tag{16}$$

4. Data and Descriptive Statistics

Prices and dividends come from the Center for Research in Security Prices (CRSP) database. Dividend yield (DY) is defined as dividends paid over the prior year divided by the current level of the index, and is calculated monthly on the value-weighted NYSE index. We use value-weighted DY to predict returns on both the value- and equal-weighted NYSE indices. Predictive regressions use the natural log of DY. The empirical tests with DY focus on the period January 1946 to December 2007 and focus exclusively on short-horizon tests—monthly returns regressed on lagged DY—to avoid the complications arising from overlapping returns.

Table 1 provides summary statistics for the data[7]. In Panel A (full sample period), Log(DY) averages 1.21% with a standard deviation of 0.38%; Panel B (no-bubble period) averages 1.38% Log(DY), while Panel C (bubble period) averages

[7] Dating of the bubble period is discussed in Empirical Results section.

0.72% Log(DY). This finding confirms the common concept that the Log(DY) during the bubble period is lower than that in the no-bubble period. The table also shows that our predictor variable is extremely persistent. The first order autocorrelation is 0.995, 0.984 and 0.974 for the full sample, no-bubble and bubble periods, respectively. The autocorrelations tend to diminish as the lag increases. That the log(DY) is found to be highly autocorrelated is important for empirical tests since the bias-adjustment depends on $\hat{\rho}-1$. The table also provides corresponding summary statistics for nominal returns on the value- and equal-weighted NYSE indices.

Fig. 1. shows the DY's progress for the full sample period . From January 1946 to February 1991, DY consistently crossed its mean value; however, DY drops sharply after February 1991and never returns to its average. Since the 1990s, U.S. stock markets have experienced an extraordinary rise. Therefore, the decline in DY seems attributable to an increase in stock prices, not a decrease in dividends (see Lewellen (2004)). Some researchers attribute the episode to a stock price bubble (e.g., Greenspan (1996), Ofek and Richardson (2003), Lamont and Thaler (2003), Phillips et al. (2009)). In order to examine whether bubbles indeed were present during the 1990s, in the next session we use the forward recursive methodology, which was developed by Phillips et al. (2009), to detect periodically collapsing bubbles for stock prices.

5. Empirical Results

The hypothesis, that stock bubbles affect predictive ability of DY in stock returns, is examined in this section. According to the forward recursive methodology, if there is a periodically-collapsing stock bubble, we will date the beginning and ending of the bubble period and then divide the full sample into sub-periods with bubble and without bubble. Secondly, we apply Lewellen's bias-adjusted predictability test to compare predictive ability of DY between these sub-periods.

5.1. Dating the Stock Bubble Period

In order to find the periods in which periodically collapsing bubbles occurred during January 1960 to December 2007, we applied Phillips et al.'s forward recursive methodology. Fig. 2 shows the time series of the ADF_s t-statistics for the logarithmic real stock prices. Real stock prices are monthly data from the NYSE value-weighted index, deflated by the consumer price index. From Fig. 2, this method successfully captures the short-term 1987 NYSE bubble period (July-September 1987) before the big crash in October 1987, indicating ADF_s t-statistics are very powerful in detecting periodically collapsing bubbles.

Fig. 2 also shows that ADF_s t-statistics erupted from December 1991 and never went down to the critical value. Hence we can identify that NYSE index's periodically collapsing bubbles started from December 1991 and continued to December 2007. Comparing Fig.1 with Fig.2, we find the link between the DY drop and periodically collapsing bubbles. Why these two events coincide offers an explanation regarding the sharp drop in DY after the early 1990s and its failure to never return to its average. The bubble is believed to be a related cause to the DY drop.

5.2. Predictive Ability of DY

According to the aforementioned finding, we divided the full sample period into two sub-periods. The first sub-period, from January 1946 to November 1991(551 months), is called the No-Bubble Period; the second sub-period, dated December 1991-December 2007 (193 months), is referred to as the Bubble Period. To solve the problem that DY is extremely persistent, we use Lewellen (2004)'s autocorrelation bias-adjusted estimator to test predictive ability of DY.

Table 2 explores the predictive ability of DY in the full sample, 1946-2007. We estimate regressions for NYSE value- and equal-weighted returns and for nominal and excess returns (measured net of the one-month T-bill rate). All of the regressions use DY for the value-weighted NYSE index. For the nominal return on the value-weighted index (VWNY), Lewellen's (2004) conditional test provides a bias-adjusted estimate of 0.4758 with a p -value of 0.0000. The bias-adjusted slope for equal-weighted index (EWNY), 0.4527, is similar to the estimate of VWNY but with a slightly higher p -value (0.0424). This table also shows that excess returns are similar to those in nominal returns

Table 3 reports the results of predictive regressions accounting for the bubble effect. Panel A shows the results for the no-bubble period and Panel B shows the results for the bubble period. During the no-bubble period, the slope coefficients are all significant. The bias-adjusted slopes for VWNY and EWNY are 0.9161and 1.0115, respectively. Regressions with excess returns are similar to those in nominal returns. During the bubble period, however, the slope coefficients are all very small and insignificant.

Taken as a whole, the above evidence supports our hypothesis that bubbles will affect predictive ability of DY in stock returns. The bias-adjusted predictability tests show that although DY shows strong predictive ability during the no-bubble period, however, DY does not show significant predictive ability during the bubble period, an approximately 16-year dry spell of unpredictability with respect to DY.

6. Conclusion

To answer the question why dividend yield has lost its predictive ability since the 1990s, we look to Campbell and Shiller's (1988) dynamic Gordon model. While it provides a sound theoretical foundation to explain DY's predictive ability of stock returns in no-bubble periods, when a bubble is present, DY's ability as a predictor of stock returns is negated due to terminal condition failure. To look deeper into this issue, we investigate empirically whether bubbles play an important role in influencing DY in predicting stock returns.

Firstly, we use a recursive test procedure to detect periodically collapsing bubbles in the NYSE index, and find a periodically collapsing bubble period indeed occurred from the end of 1991 on. This coincides with the timing of the early-1990's sharp drop in DY that never returns to its mean. In the real world, first came the Internet stock bubble beginning in the 1990s, followed by the housing, credit and commodities bubbles from 2003. In other words, our empirical findings coincide with major financial events that have occurred since the early 1990s.

Secondly, we divide the full sample period into two sub-periods according to the time of the bubble's origin, and apply Lewellen's bias-adjusted predictability test to compare predictive ability of DY between the bubble and no-bubble periods. The empirical evidence coincides with our theoretical inference and shows that DY is indeed a useful variable in predicting future stock returns during a no-bubble period, but loses its predictive ability when bubbles are present.

This can be understood by looking as well at investors' differing beliefs about persistence of deviations of stock prices from the fundamental benchmark as proposed by Boswijk et al. (2007). "Rational" investors use relative past profits to adjust their beliefs or forecasting strategies during a bubble period, ride bubbles to get more profits, and might not use fundamentals to predict stock returns, which in turn negates DY's predictive ability.

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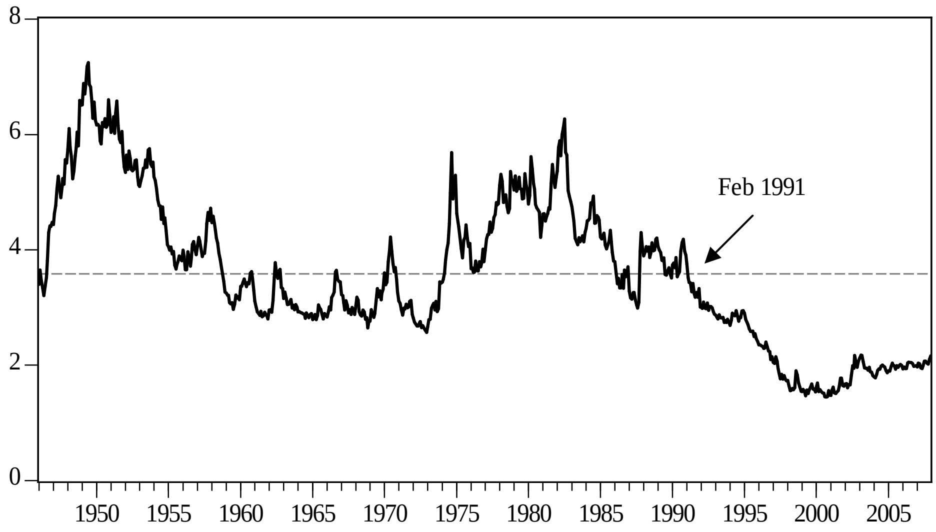

Figure1: Time series plots of DY, monthly data, January 1946 to December 2007. The dotted line is the mean of DY.

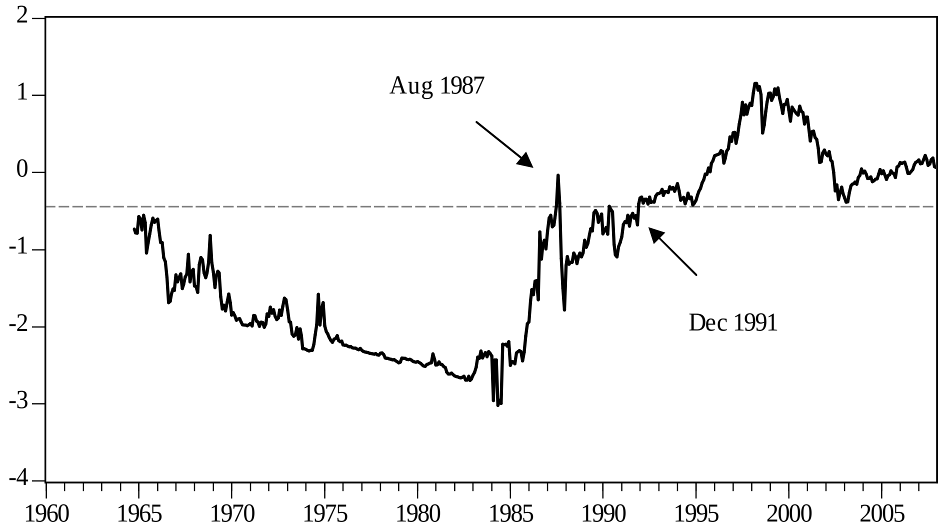

Figure2: Time series of the ADF_s t-statistics for the logarithmic real NYSE index.

Table1. Summary Statistics

This table reports summary statistics for stock returns and DY. Observations are monthly and the variables are expressed in percent: Log(DY) represents DY in logarithm; EWNY and VWNY are returns on equal- and value-weighted NYSE indices, respectively. DY is defined as dividends paid over the prior year dividend by the current level of index. The full sample period covers January 1946 to December 2007 (744 months); the no-bubble sub-period covers January 1946 to November 1991 (551 months); and the bubble sub-period covers December 1991 to December 2007 (193 months).

				Autocorrelation		
Variable	Mean	S.D.	Skew	ρ_1	ρ_{12}	ρ_{24}
Panel A: Full sample period						
VWNY	0.99	4.01	-0.38	0.041	0.038	0.028
EWNY	1.12	4.70	-0.19	0.142	0.059	0.034
DY	3.59	1.28	0.41	0.992	0.901	0.829
Log(DY)	1.21	0.38	-0.34	0.995	0.931	0.875
Panel B: No-bubble sub-period						
VWNY	0.99	4.17	-0.34	0.055	0.033	0.016
EWNY	1.12	5.03	-0.10	0.136	0.068	0.027
DY	4.10	1.04	0.69	0.983	0.791	0.661
Log(DY)	1.38	0.25	0.30	0.984	0.785	0.652
Panel C: Bubble sub-period						
VWNY	0.98	3.54	-0.58	-0.011	0.056	0.068
EWNY	1.11	3.63	-0.83	0.170	0.014	0.063
DY	2.10	0.47	0.62	0.972	0.759	0.580
Log(DY)	0.72	0.22	0.35	0.974	0.782	0.607

Table2. Dividend Yield and Expected Return, 1946-2007

This table reports AR(1) regressions for DY and predictive regressions for stock returns covering the sample period January 1946 to December 2007 (744 months). DY is the dividend yield on the value-weighted NYSE index and log(DY) represents DY in logarithm. VWNY and EWNY are returns on value- and equal-weighted NYSE indices, respectively. Excess returns are calculated as VWNY and EWNY minus the one-month T-bill rate; returns are expressed in percents.

$\log(DY_t) = \phi + \rho \log(DY_{t-1}) + \mu_t$

	ϕ	S.E. (ϕ)	p-value	ρ	S.E. (ρ)	p-value	Adj. R^2	S.E. (μ)
AR(1)	0.0059	0.0052	0.2596	0.9946	0.0041	0.0000	0.9875	0.0420

$y_t = \alpha + \beta \log(DY_{t-1}) + \gamma(\log(DY_t) - 0.9999 * \log(DY_{t-1})) + \varepsilon_t$

	β	S.E. (β)	p-value	γ	S.E. (γ)	p-value
VWNY	0.4758	0.1164	0.0000	-90.82	1.04	0.0000
EWNY	0.4527	0.2227	0.0424	-97.38	1.99	0.0000
Excess VWNY	0.4059	0.1189	0.0007	-91.11	1.06	0.0000
Excess EWNY	0.3828	0.2242	0.0881	-97.67	2.00	0.0000

Table3. Dividend Yield and Expected Return for Accounting Bubble Effect

This table reports AR(1) regressions for DY and predictive regressions for stock returns. Panel A reports the estimated results for the no-bubble sub-period from January 1946 to November 1991 (551 months); Panel B reports the estimated results for the bubble sub-period covering December 1991 to December 2007 (193 months). DY is the dividend yield on the value-weighted NYSE index and log(DY) represents DY in logarithm. VWNY and EWNY are returns on value- and equal-weighted NYSE indices, respectively. Excess returns are calculated as VWNY and EWNY minus the one-month T-bill rate; returns are expressed in percents.

Panel A: No-Bubble sub-period

$\log(DY_t) = \phi + \rho \log(DY_{t-1}) + \mu_t$

	ϕ	S.E.(ϕ)	p-value	ρ	S.E.(ρ)	p-value	Adj. R^2	S.E.(μ)
AR(1)	0.0218	0.0107	0.0411	0.9842	0.0076	0.0000	0.9683	0.0437

$y_t = \alpha + \beta \log(DY_{t-1}) + \gamma(\log(DY_t) - 0.9999 * \log(DY_{t-1})) + \varepsilon_t$

	β	S.E.(β)	p-value	γ	S.E.(γ)	p-value
VWNY	0.9161	0.2180	0.0000	-90.06	1.22	0.0000
EWNY	1.0115	0.4028	0.0123	-100.93	2.26	0.0000
Excess VWNY	0.9149	0.2229	0.0000	-90.43	1.25	0.0000
Excess EWNY	1.0102	0.4041	0.0127	-101.31	2.26	0.0000

Panel B: Bubble sub-period

$\log(DY_t) = \phi + \rho \log(DY_{t-1}) + \mu_t$

	ϕ	S.E.(ϕ)	p-value	ρ	S.E.(ρ)	p-value	Adj. R^2	S.E.(μ)
AR(1)	0.0164	0.0089	0.0667	0.9742	0.0118	0.0000	0.9726	0.0361

$y_t = \alpha + \beta \log(DY_{t-1}) + \gamma(\log(DY_t) - 0.9999 * \log(DY_{t-1})) + \varepsilon_t$

	β	S.E.(β)	p-value	γ	S.E.(γ)	p-value
VWNY	0.0846	0.3243	0.7945	-93.30	1.97	0.0000
EWNY	-0.4317	0.6883	0.5313	-82.22	4.17	0.0000
Excess VWNY	0.1276	0.3287	0.6983	-92.96	1.99	0.0000
Excess EWNY	-0.3887	0.6977	0.5781	-81.88	4.23	0.0000