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Departamento de Fundamentos del Análisis Económico II

Department of Foundations of Economic Analysis II
University of the Basque Country
Avda. Lehendakari Aguirre 83
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Juan M. Londoño, Marta Regúlez
& Jesús Vázquez

Another Look to the Price-Dividend Ratio: A Markov-Switching Approach

Another Look to the Price-Dividend Ratio: A Markov-Switching Approach*

Juan-Miguel Londoño, Marta Regúlez, Jesús Vázquez†

Universidad del País Vasco

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Abstract

A necessary condition for the validity of the present value model is that the price-dividend ratio must be stationary. However, significant market episodes in the late 20th century seem to provide evidence of nonstationarity. This paper analyzes the stationarity of this ratio in the context of a Markov-switching model à la Hamilton (1989) where an asymmetric speed of adjustment is introduced. This particular specification robustly supports a nonlinear reversion process and identifies two relevant episodes: the post-war period from the mid-50's to the mid-70's and the so called "90's boom" period. A three-regime Markov-switching model displays the best regime identification and reveals that only the first part of the 90's boom (1985-1995) and the post-war period are near-nonstationary states. Interestingly, the last part of the 90's boom (1996-2000), characterized by a growing price-dividend ratio, is entirely attributed to a regime featuring a highly reverting process.

JEL Classification: C32, G12

Keywords: Markov regime-switching, price-dividend ratio stationarity

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†Correspondence to: Marta Regúlez, Departamento de Economía Aplicada III, Universidad del País Vasco, Av. Lehendakari Aguirre 83, 48015 Bilbao, Spain. Phone: (34) 94-601-3738, e-mail: marta.regulez@ehu.es

1 Introduction

Around 1985 the U.S. stock market started its last remarkable episode of apparent divergence between prices and dividends. The stock market has undergone major changes in recent years that could partially explain the sustained increase in the price-dividend (PD) ratio. Dividends seem to have become less important, at least in the U.S. Fama and French (2001) show that, regardless of their characteristics, firms have become less likely to pay dividends. Some changes in the law have also had an important effect on the market, especially the enactment of the U.S. Securities and Exchange Commission (SEC) rule 10b-18 in 1982.[1] The so-called run-up in stock prices or "90's boom" has reopened the debate about whether dividends can no longer explain stock prices.

Since the seminal paper by Shiller (1981), many authors have tried to explain the dynamic features of the relationship between stock prices and dividends. The related papers belong to two strands of literature: the first considers that the reversion process of the PD ratio exhibits linear dynamics. However, these studies have found nonconclusive empirical evidence for the cointegration relation linking stock prices and dividends as shown in Cochrane (1992, 2001) and Lettau and Ludvigson (2005), among others. In particular, the evidence on cointegration is highly sensitive to the sample considered. The second strand allows for the possibility of an asymmetric reverting process. Even though in the long-run the stable relationship implied by the present value (PV) model holds, the existence of transaction costs, noise traders and changing features such as swings in market sentiment may play an important role in the reversion process of the PD ratio. Moreover, the different characteristics exhibited by alternative stock market episodes suggest the presence of asymmetric behavior, which implies that the reversion process may not be linear. Then, any inference based on a linear framework might be at least misleading.

The main contribution of this paper is to identify different episodes in the reversion process of the PD ratio and analyze whether they present different characteristics in the reversion process to a possible long-run equilibrium or attractor. We estimate a Markov-switching (MS) model à la Hamilton (1989). By following this econometric approach we do not impose any given characteristics on the regimes that may have been present during the sample period. In contrast, previous studies that consider non-linear dynamics in the PD ratio reversion process (such as Bohl and Siklos, 2004; Coakley and Fuertes, 2006; and McMillan, 2006, 2007) assume

[1] SEC rule 10b-18 provided a legal safe harbor for firms repurchasing their shares. The repurchase of stocks then became a very important form of payout, as mentioned by Boudoukh, Michaely, Richardson and Roberts (2004), among others.

that the asymmetric speed of adjustment to an attractor depends on a threshold variable driving regime-switches. These papers propose different versions of threshold autorregresive (TAR) family models. We argue that the MS approach is more flexible since estimation results from TAR models may depend on the definition of the threshold variable chosen by the researcher and that imposes *a priori* features identifying the alternative regimes implied by the threshold. In contrast, the switching process characterized by an MS approach is governed by a latent variable that is not predefined by the researcher (as the threshold variable is). In this sense, we believe that the MS approach allows the data to speak more freely than a TAR approach because the variable governing regime-switches is not defined a priori under the MS approach.

Empirical evidence is presented for the U.S. stock market using annual data from 1871 to 2006. We analyze the particular characteristics of some relevant historical episodes, specially, the post-war period (up to 1975) and the 90's boom. In particular, we want to test whether the last boom episode exhibits reversion features similar to those associated with previous episodes showing an upward drift of the PD ratio. We find that the post-war period is characterized by near-nonstationary behavior, and two sub-periods can be identified in the 90's boom. The post-war period and first sub-period in the 90's boom share similar features whereas the second sub-period, characterized by a fast growing PD ratio, features a strong reversion regime. Interestingly, this last result suggests that the period 1996-2000 is characterized by a stationary regime, in sharp contrast to the conclusions reached by previous papers which relied on a TAR approach.

Another important estimation result found is that the estimated values of the attractor are larger than those found in previous related literature. The empirical evidence on a high estimated attractor suggests that the apparent divergence between prices and dividends featured in the late 90's reflects the transition process to a long-run equilibrium that has never been reached in the past.

The rest of the paper is organized as follows. Section 2 summarizes the related literature on the analysis of PD ratio stationarity within the PV framework. Section 3 presents the MS framework considered in this paper. Section 4 describes the data and presents a preliminary analysis of the stability of the reversion process to a possible attractor. Section 5 discusses the empirical results found using a three-state MS model and the robustness analysis for different samples and different MS model specifications. Section 6 concludes.

2 Related literature

Campbell and Shiller (1988a, 1988b) develop a log-linear approximation to the PV framework that can be used to study stock price behavior under any model of expected returns. Their approach leads to the following PV equation:

$$p_t = \frac{k_d}{(1-\rho_d)} + E_t \left\{ \sum_{j=0}^{\infty} \rho_d^j [(1-\rho_d) d_{t+j+1} - r_{t+1+j}] \right\} + \lim_{j\to\infty} E_t(\rho_d^j p_{t+j}), \qquad (1)$$

where p_t is the logged value of the stock price at the beginning of period t, d_t is the logged value of the dividend accruing to the stock paid out throughout period t and r_t is the log return associated with stocks at time t (i.e. $r_t = \ln(1+R_{t+1})$). Finally, k_d and ρ_d are constants obtained from the log-linear approximation. Equation (1) can be written in terms of the PD ratio as follows:

$$p_t - d_{t-1} = \frac{k_d}{(1-\rho_d)} + E_t \left\{ \sum_{j=0}^{\infty} \rho_d^j [\Delta d_{t+j} - r_{t+1+j}] \right\} + \lim_{j\to\infty} E_t[\rho_d^j (p_{t+j} - d_{t-1+j})]. \quad (2)$$

The last term on the RHS of equation (2) drops out under the transversality condition.[2] In addition, if the dividends are assumed to be I(1) and the returns are stationary, equation (2) can be written as

$$p_t - d_{t-1} = \frac{k_d}{(1-\rho_d)} + E_t \left\{ \sum_{j=0}^{\infty} \rho_d^j [\Delta d_{t+j} - r_{t+1+j}] \right\}. \qquad (3)$$

Equation (3) then implies that the stationarity of the PD ratio can be viewed as a necessary condition for the validity of the PV model, and the logged values of prices and dividends are then cointegrated, with a cointegration vector given by $(1, -1)$. To understand this cointegration relation, one may intuitively think that if current stock prices are high in relation to current dividends (i.e. investors are willing to pay more or the stock is overpriced), dividends are expected to grow. If agents are fully rational under this model, prices and dividends cannot drift apart forever and the ratio will show a reverting behavior towards an attractor. From the point of view of rational agents assigning unique prices to stocks in relation to dividend payments, the stationarity of the PD ratio is a necessary condition for the PV model.

Previous studies (Cochrane, 1992, 2001; and Lettau and Ludvigson, 2005, among others) that consider linear dynamics for the analysis of the PD ratio reversion

[2] Imposing the transversality condition ensures the uniqueness solution for stock prices obtained from the PV model.

process have considered different samples and alternative model specifications. These studies have found nonconclusive evidence for the cointegration relationship. The evidence on cointegration reported in these studies depends highly on the sample period considered.

The different characteristics of the stock market episodes suggest that the reversion process may not be linear, so inference based on a linear framework might be at least misleading. The main difference between papers following a nonlinear approach comes from the alternative driving forces assumed for the asymmetric reversion process. There is a branch of literature in which the PV model is analyzed as a whole and non-linearity features come from stock price fundamentals (for instance, dividends). In Shiller (1989) for example, there are different types of agent who react differently to historical events, macroeconomic news or just fads. Long-run investors show more stable behavior, whereas noise traders tend to react to fads or overreact to news. Alternatively, Froot and Obstfeld (1991) introduce the possibility of an "intrinsic bubble" which depends exclusively on dividends. Drifill and Sola (1998) further extended the intrinsic bubble specification by including a regime-switching dividend process. The possibility of having structural breaks in the dividends series is motivated by the empirical evidence on unstable dividend processes, which made way for other regime-switching specifications as in Evans (1998) and Gutiérrez and Vázquez (2004).[3]

Another branch of literature focuses entirely on the stationarity of the PD ratio implied by the PV model and considers that stock prices are driven by non-fundamental components. In particular, Bohl and Siklos (2004), Coakley and Fuertes (2006), Kapetanios et al.(2006) and McMillan (2006, 2007), introduce a non-fundamental term u_t in equation (3)

$$p_t - d_{t-1} = \frac{k_d}{(1-\rho_d)} + E_t \left\{ \sum_{j=0}^{\infty} \rho_d^j [\Delta d_{t+j} - r_{t+1+j}] \right\} + u_t.$$

As mentioned above, there are different interpretations of this error term u_t. For example, Bohl and Siklos (2004) argue that u_t is a bubble term that captures run-ups in stock prices before a crash, suggesting the presence of asymmetries in the PD ratio reverting process. Kapetanios et al.(2006) interpret this term as capturing the presence of transaction costs such that small uncorrected deviations may arise, but larger deviations would be arbitraged away. McMillan (2006, 2007) and Coakley and Fuertes (2006) link this misspricing term to market sentiment as in behavioral

[3]Related literature considering alternative specifications including regime changes not directly linked with the dividend process can be found in Cecchetti, Lang and Mark (1990), Veronessi (1999), Timmermann (2001), and Bonomo and Garcia (1994), among others.

finance models. The existence of noise traders in the market who react differently to the arrival of good or bad fundamental news explains the possible source of asymmetries. Thus, the trend-chasing behavior of such traders after the arrival of positive news will lead to a market over-reaction such that the change in price will be greater than required by the news. On the other hand, noise traders would be more conservative in bear markets, thus anchoring prices to dividends. Therefore, the reversion process of the PD ratio could be more persistent in bull markets and more rapidly reverting in bear markets.

The evidence found by Bohl and Siklos (2004), Coakley and Fuertes (2006) and McMillan (2007) is based on a two-regime framework. In general, these articles consider alternative TAR specifications for the dynamics of the PD ratio that build on the model of Enders and Granger (1998), i.e. using a model similar to the augmented Dickey-Fuller (ADF) regression specification:

$$\Delta pd_t = I_t \rho_1 (pd_{t-1} - \mu) + (1 - I_t)\rho_2 (pd_{t-1} - \mu) + \sum_{j=1}^{l} \beta_j (\Delta pd_{t-j}) + \varepsilon_t, \qquad (4)$$

where pd_t denotes the price-dividend ratio at time t; ρ_j $(j = 1, 2)$ is the speed of adjustment in each regime to the long-run equilibrium or attractor, μ; ε_t is an i.i.d. shock; and I_t is an indicator function that takes the value of one if $q_t \geq 0$, and zero otherwise, where q_t is the threshold variable that predetermines the regimes.

The identification of different episodes, their individual characteristics and their relationship with reversion analysis are particularly interesting in Coakley and Fuertes (2006). They propose a priori a two-regime framework (called bull and bear regimes) that may show an asymmetric speed of adjustment around the same long-run equilibrium. The threshold variable is highly persistent with respect to dividend growth and is defined as $q_t(w, d) = w_1 \Delta pd_{t-1} + ...w_d \Delta pd_{t-d}$, where $w' = (w_1, ...w_d) > 0$ is a vector of predefined weights and d is the number of lags to be selected from the data. If $q_t > 0$, the stock market is in a bull episode with speed of adjustment ρ_1, and if $q_t < 0$ the market is in a bear episode with ρ_2. In contrast, Bohl and Siklos (2004) assume a threshold variable showing lower persistence simply defined as $q_t = \Delta pd_{t-1} - \tau$, where τ is a threshold parameter to be estimated.

McMillan (2006, 2007) considers an exponential smooth transition model specification for the dividend-price ratio. His model implies that the dynamics of the middle ground differ from the dynamics associated with large deviations. He also introduces asymmetries between regimes of rising and falling prices. This model falls into the STAR family of models, where a continuous transition function $G(q_t)$ between 0 and 1 is used instead of the indicator function I_t.[4]

In general, the empirical evidence found in the latter branch of literature suggests that there is an asymmetric reversion process when considering two different regimes. Nevertheless, the evidence found is sometimes mixed depending on the periods considered. Bohl and Siklos (2004) analyze the (demeaned and detrended) U.S. log dividend-price ratio from 1871:1 to 2001:9. They find evidence of a stationary ratio and bubble-like asymmetric short-run adjustments such that stock prices increase relative to fundamentals followed by a crash. The exception is the period 1947-1982. They suggest that the different pattern observed for this period is due to the absence of bull market periods followed by crashes, so it is an atypical period relative to all the other sample periods considered. They also find a strong difference between two non-overlapping periods: 1871-1936 and 1937-2001. In the first period they find no evidence of a unit root in the log dividend-price ratio or of asymmetric effects, whereas the opposite is true of the second period.

The analysis by Coakley and Fuertes (2006) is based on monthly data from 1871:1 to 2001:9 for the Standard and Poors PD ratio. Based on their two-regime TAR framework, they find support for the hypothesis that the PD ratio regularly behaves as a random walk with an upward drift where stock prices drift away from fundamentals during bull market episodes. In particular, they find that the 90's fall into this category. In bear markets, however, the adjustment of the ratio towards the equilibrium level is reinstated. Their conclusion remains the same if observations from 1993:01 onwards are excluded. This result could be interpreted either as quite robust or as driven by the small weight of the observations corresponding to the last eight years relative to the whole sample. Moreover, Coakley and Fuertes (2006) report an estimate of the attractor smaller than the historical mean, but they do not show any measure of precision associated with their estimated value, so its significance cannot be assessed.

Finally, McMillan (2006) finds that for the period 1980-1995 the strength of the cointegrating relationship between stock prices and dividends gets stronger. From the beginning of 1995 there is an increase in real dividends that is followed by an increase in real prices. The strength of the stationary relation falls quite significantly for the period 1995-1999, entering a slow transition from a reverting regime to a random walk regime. For 2000 to 2004, however, McMillan (2006) finds that the adjustment becomes stronger again, even though the transition from the random

[4]For a generalization of TAR models and their reversion analysis see, for instance, Tong (1993) and Enders and Granger (1998).

walk regime to a reverting one is not so significant. McMillan (2007) analyzes data from the U.S. and other countries. The results support the presence of a stationary PD ratio for U.S. data in the period 1965:2-2004:5 as a whole, when an asymmetric adjustment is allowed for in the reversion process. The speed of transition is lower when stock prices rise relative to dividends than when prices are below the level supported by dividends. He also finds that the recent dynamics of the PD ratio fall into a random walk regime where stock prices seem to diverge from fundamentals. McMillan (2006, 2007) considers demeaned time series, so the historical mean is taken as the long-run attractor.

3 An MS model for adjusting the PD ratio

In the family of TAR models reviewed in the previous section, the characterization of the alternative regimes is driven by the choice of a particular threshold variable and the transition function between regimes. Thus, the characterization of each regime in Coakley and Fuertes (2006) is directly linked with particular market episodes, such as persistent growth of the PD ratio (bull market) or persistent reduction of the PD ratio (bear market). However, on one hand, the definition of the threshold variable chosen by the researcher clearly determines the features and the asymmetric behavior of the PD ratio associated with each regime. On the other hand, the number of regimes considered is limited by the features assumed by the researcher *a priori*, such as growing and decreasing markets, run-ups in prices and crashes, or bubble episodes, etc.

In this paper we propose a more flexible nonlinear framework for the dynamics of the PD ratio based on the MS approach proposed by Hamilton (1989). This framework can be seen as a generalization of equation (4) given by the following model:

$$\Delta pd_t = \alpha + \rho_{s_t}(pd_{t-1} - \mu) + \sum_{j=1}^{l} \beta_j (\Delta pd_{t-j}) + \varepsilon_t. \tag{5}$$

In this framework, the variable characterizing the transition between regimes is not defined by the researcher. Instead, it is driven by an unobserved variable s_t that describes the state or regime of the process at time t. The latent variable s_t

is the outcome of a k-regime Markov chain with s_t being independent of ε_t. The MS methodology is briefly described in Appendix 1. The basic difference between imposing a threshold variable as in TAR models and the k-state MS model is that the latter does not impose any particular characteristic on each regime. In this paper, we only impose the possibility of having three states and estimate the parameters in equation (5) by allowing for a different speed of adjustment to the long-run equilibrium or attractor μ in each regime. Moreover, the MS approach allows us (i) to identify which episodes belong to each regime; (ii) to assess which episodes exhibit a reverting behavior; and (iii) to link those regimes to particular stock market episodes previously discussed in the relevant literature.

By no means are we arguing that an MS approach is always better than a TAR approach under all circumstances. The MS approach followed in this paper should be viewed rather as a way of assessing, and perhaps challenging, some of the results and interpretations obtained in the related literature by following alternative TAR approaches.

4 Data and preliminary stability analysis

This paper considers annual data for the Standard and Poor's index price (January data) and annual data for the dividends accruing to this index in each year, available at Robert Shiller's web site. The (log of the) PD ratio is calculated as $pd_t = p_t - d_{t-1}$. We use data for the period 1871-2006.[5]

Table 1 shows a summary of descriptive statistics for the PD ratio for the two samples considered. It includes the two most commonly used tests for cointegration in a nonstate-dependant context: the ADF test and the Phillips-Perron (PP) test. Figure 1 shows the annual demeaned PD ratio for the full sample. From this figure at least three different periods can be preliminarily identified. From 1871 to 1950 the PD ratio shows a sequence of run-ups (or bull market episodes) followed by crashes. The second period is the post-war period (up to the mid 1970's) characterized by

[5] Even though data for dividends are related to payouts during each year considered, some papers in the related literature use monthly frequency data, as in Coakley and Fuertes (2006) and McMillan (2007), although monthly data from Shiller's web page are actually a linear interpolation of annual data. Moreover, we are interested in relating switching regimes to business cycles of length between 2 and 8 years and this relationship is in principle well captured by using annual data that ignores the noise associated with higher frequency data.

a moderate but sustained increase in the PD ratio value starting around 1950 and lasting until around 1975. Finally, the third period coincides with the 90's boom, which is clearly characterized by a considerable increase in the ratio starting around 1985 and lasting until the end of the millennium. Indeed, the PD ratio reaches a maximum value of 4.44 in the year 2000, almost twice its minimum value. This maximum value is also much larger than the sample mean (3.17). There is a sudden swing in the PD ratio dynamics from 2000 on, where it seems to revert to an attractor higher than the historical mean.

The unit-root tests values shown in Table 1 suggests that only for the whole sample can the null hypothesis of overall nonstationarity of the PD ratio not be rejected. If one does not consider the possibility of nonlinear reversion, the previous result implies that the hypothesis of the PD ratio being stationary is rejected only when the last part of the sample (1993-2006) is included in the analysis. Put differently, the stationarity of the PD ratio implied by the PV model is not supported by the data if the whole sample is considered.

The information in Table 1 and Figure 1 basically summarizes the evidence already found in the relevant literature considering a linear framework for the analysis of PD ratio stationarity. In sum, the previous evidence has been nonconclusive when trying to test the stationarity implications of the PV model. It basically suggests how difficult it may prove to reach a conclusion about the stationarity of the PD ratio in a non state-dependant context, especially after the significant increase in the PD ratio that took place by the end of the millennium.

Figure 2 provides a highly intuitive, but preliminary analysis, for considering the possibility of an asymmetric speed of adjustment around a constant attractor. More precisely, this figure shows the rolling estimates for the parameters α and the speed of adjustment ρ in a non state-dependant framework based on a Dickey-Fuller-type equation for the PD ratio such as

$$\Delta x_t = \alpha + \rho x_{(dmd)t-1} + u_t, \tag{6}$$

where $x_{(dmd)t} = (x_t - \overline{x})$ is the demeaned value of the PD ratio using the sample mean for the whole sample.[6] To interpret Figure 2, it is useful to consider first the following equation

$$x_t = \eta_t + \gamma_t x_{t-1} + u_t. \tag{7}$$

[6] In the rolling-regression analysis carried out, we use a constant data size of 57 observations for each window. The choice of this number is determined by the number of observations available until the 1929 crash. The first window corresponds to an episode where the PD ratio seems to follow a stationary process fluctuating around the sample mean associated with this pre-crash period.

If we subtract x_{t-1} from both sides of the equation, we can write (7) as follows,

$$\Delta x_t = \rho_t(x_{t-1} - \mu_t) + u_t. \tag{8}$$

where $\rho_t = (\gamma_t - 1)$ and $\mu_t = \eta_t/(1 - \gamma_t)$ is the attractor whenever $|\gamma_t| < 1$. If we assume that the attractor μ is constant, we can write that

$$\mu = \overline{x} + a,$$

substituting this expression into (8) we obtain a time-varying parameter version of (6):

$$\Delta x_t = \alpha_t + \rho_t(x_{t-1} - \overline{x}) + u_t, \tag{9}$$

where $\alpha_t = -\rho_t a$. A non-zero parameter α_t, as Coakley and Fuertes (2006) point out, implies that the long-run equilibrium level μ_t is not necessarily well proxied by the historical mean of x_t. More importantly, α_t goes to zero whenever ρ_t goes to zero no matter what the sign of a is. Figure 2 reveals at least two remarkable episodes of sustained decrease, in absolute terms, in the estimated speed of adjustment. One episode starts around 1955 and lasts until around 1975. The other starts around 1990 and lasts until the end of the sample. In both periods, the rolling-estimate of ρ_t is getting closer to zero so, as a result, the parameter α_t also tends to zero. But this result is still consistent with a positive value of a, which implies that the attractor could be still above the historical sample mean and that the PD ratio is moving very slowly towards it.

5 Evidence from a three-regime MS model

The MS methodology provides an interesting framework for analyzing the dynamics of the PD ratio in two ways. First, the smoothed probabilities are estimated, and the relevant episodes are identified. Second, the characteristics of each state can be analyzed. In particular, we analyze the possibility of an asymmetric speed of adjustment around a constant attractor.

Table 2 shows the estimation results of the three-regime MS model (5) for the full and pre-1993 samples. Before discussing the estimation results, we focus our attention on Figure 3 that shows the estimated smoothed probabilities of being in each regime for the MS model. We find that the regimes are clearly identified by the three-state MS model (that is, at least one of the smoothed probabilities in each period is close to 1). Regime 1 is a state that occurs occasionally in very short episodes which never last more than 3 years, most of them before 1950. This regime is associated with a few relevant market episodes, such as the 1929 crash and the subsequence crises (1929-1932) and the first oil crisis (1974-1975). These are short episodes involving large drops in the PD ratio that took place just after a strong run-up in stock prices relative to dividends.

Regime 2 clearly identifies two key historical episodes, the post-war period up to the mid 70's and the first part of the 90's boom from 1980 to 1995, including the so-called second oil crisis and the enactment of SEC rule 10b-18 in 1982. Finally, regime 3 occurs only in the second part of the 90's boom from 1996 to 2000, so it can only be detected when the whole sample is considered. As in Coakley and Fuertes (2006), we also consider the pre-1993 sample. The fact that the regime classification during the pre-1993 period is robust to the inclusion of the last part of the sample (1993-2006) gives further support for the regime classification provided by the three-regime MS model and, more importantly, the presence of a third regime that only shows up when the whole sample is studied.[7]

The estimation results reported in Table 2 show that the reversion process of the PD ratio exhibits a nonlinear behavior, as found in Bohl and Siklos (2004), Coakley and Fuertes (2006) and McMillan(2006, 2007). More precisely, the hypothesis of a symmetric speed of adjustment in the dynamics of the PD ratio can clearly be rejected. That is, ρ_i $(i = 1, 2, 3)$ is significantly different across regimes. However, our estimation results differ from those reported in previous papers on the reversion features displayed by the alternative regimes. Thus, state 1 is clearly nonstationary state. The estimated speed of adjustment for this state is statistically non-significant no matter what specification and sample are used. At this point, it is worth remarking that a nonstationary episode in the dynamics of the PD ratio provides evidence that the PV model is not supported by the data. State 2 is a near-nonstationary state. The speed of adjustment corresponding to state 2 is close to 0 and depending on the model specification and the confidence level chosen, one might conclude that it is statistically non-significant.

Finally, state 3 is a very particular state. Before 1993, it only occurs occasionally in very short episodes that never last more than 2 years. Interestingly, it is clearly the most likely regime in the second part of the 90's boom, from 1996 to 2000. This state almost exclusively identifies the episode with the highest slope of the PD ratio during the 90's boom. Intuitively, we would think that if the estimated attractor

[7] We have also estimated a two-regime MS model considering the sample 1950-2006. The estimation results show that the second regime is associated with the period 1996-2000 and the regime features captured by the two-state model are similar to those displayed by the additional (third) regime under the three-regime MS specification.

is higher than the maximum value, as the upward drift of the PD ratio suggests, episodes of large and persistent growth of the PD ratio are related to a large speed of adjustment consistent with a highly reverting process to a high attractor.

Table 2 also shows the estimated value of the attractor. For every case considered, a large estimated value for this parameter is obtained, but the estimate always suffers from a lack of precision. More precisely, we obtain a very poor estimation of the attractor (i.e. a point estimate of 6.28 with a standard deviation of 1.13 for the full sample) and an even less efficient estimate for the pre-1993 sample (6.17 with a standard deviation of 2.61). To interpret these estimation results, it is useful to note that the estimated value is larger than the maximum value for the PD ratio (4.44) and its sample mean (3.17) for the whole sample period. As we illustrate above, the attractor might not be directly linked to the historical mean when the PD ratio starts from a low level and the transition to the long-run equilibrium or attractor is not symmetric. As shown in Figure 1, the long-run upward drift followed by the PD ratio seems to support this hypothesis. This upward drift in the PD ratio may be the outcome of several forces such as the fact that the firms have become less likely to pay dividends, as reported by Fama and French (2001), the legal changes introduced, such as the enactment of new SEC rules, and more favorable treatment for corporate taxes than for personal income tax. Under the view that the PD ratio is reverting to a high level of the attractor, it is reasonable to obtain an imprecise estimation of an attractor that has not yet been reached.

Once the attractor is allowed to be different from the sample mean, parameter α_t is somehow redundant as discussed above. Indeed, parameters μ and α are highly correlated (the correlation coefficient is -0.89 for the full sample). Then we can gain some efficiency by analyzing the speed of adjustment in a restricted three-regime MS model with $\alpha = 0$. The estimation results are reported in columns 3 and 5 of Table 2. In this case, the estimated values of the attractor for both samples are much closer to the maximum value of the PD ratio. This robustness test and others carried out are discussed in the following sub-section.

5.1 Robustness analysis

This sub-section starts with a study of the robustness of the estimated features associated with each state by considering a two-regime MS model and compares the estimation results with those obtained with the three-regime model analyzed above. Previous related literature has only considered two alternative regimes for the asymmetric analysis of the PD ratio reversion process due to the link established by the researcher between regime identification and the specific characteristics attributed to each regime (for instance, the market episodes defined as bull and bear markets in Coakley and Fuertes, 2006; and the outer -reverting- and inner -random walk- regimes defined by McMillan, 2006). In contrast, by following an MS approach we are not assigning a priori features either to the states identified or to the transition mechanism from one state to another. In other words, our approach does not impose, prior to estimating, any of the alternative definitions of states and market episodes proposed in the related literature.

Table 3 shows the estimation results for the two-state MS model. Those results are clearly not so robust as the ones obtained in the three-state MS model. As in the three-regime specification, we obtain again a high, poorly estimated attractor, especially if the full sample is considered. The estimated attractor is systematically lower if the pre-1993 sample is considered. The restricted model ($\alpha = 0$) provides again a more efficient estimation of the parameter. In this case, state 1 is a clearly nonstationary state for the two samples and the alternative specifications studied. State 2 characterizes a stationary PD ratio if we consider the unrestricted form of the model. By contrast, it is nonstationary if the restricted model is considered. Figure 6 shows that state 2 is more likely during the post-war period up to 1975 and the entire 90's boom period (1983-2006). This figure also shows important episodes of poor state identification, especially before 1950 and in the period between the post-war (up to mid 70's) and 90's boom episodes. Tables 2 and 3 also show regime classification measures (RCM) that build on the RCM suggested by Ang and Bekaert (2002).[8] The two RCMs considered are systematically higher for the two-regime model than for the three-state model. The nonrobust regime classification across samples and the high values of the RCM statistics associated with the two-state MS model clearly support the three-state model specification. Moreover, we clearly obtain a less satisfactory regime classification with the three-state MS model for the pre-1993 sample than for the whole sample because the third state is mainly identified with the 90's boom. In sum, the comparison of the estimation results from the two- and three-regime MS models clearly favours the three-regime specification where the additional third regime considered mainly captures the dynamics of the PD ratio during the last boom episode (1996-2000).

The highest log-likelihood function value obtained under the unrestricted specification of the three-regime MS model for the whole sample provides extra support for this model. Moreover, the RCM values are very similar if we consider a restricted ($\alpha = 0$) or an unrestricted model for the full sample. This result holds when considering the restricted form for the pre-1993 sample.

[8] Appendix 2 provides a brief description of these alternative RCMs.

By comparing Figures 3-5, we can conclude that the state identification remains robust if we compare the full sample and the pre-1993 sample as well as different model specifications as we can see in Figures 4 and 5. These two figures show the smoothed probabilities comparing the restricted ($\alpha = 0$) and unrestricted specifications of the model for the full sample and the restricted specification of the model for both samples, respectively.

As a final robustness and diagnostic test, we carried out Hansen's (1982) procedure to jointly test the orthogonality conditions for the mean, variance, skewness and kurtosis of the model residuals. For every model specification and sample studied, the residual test statistics reported in Tables 2 and 3 support the hypothesis that the residuals are properly distributed.[9]

6 Conclusions

Previous research related to the present value model and its implications for the stationarity of the price-dividend (PD) ratio has been nonconclusive to say the least when analyzing the reversion process of the PD ratio in a linear framework. We find strong empirical evidence that the speed of adjustment of the PD ratio has not been constant over time. Moreover, our empirical results show major changing episodes closely related to historical events in the U.S. stock market. The nonlinear analysis of the reversion process of the PD ratio based on a three-regime Markov-switching (MS) model à la Hamilton (1989) carried out in this paper shows robust evidence of switching regimes in the parameters characterizing the speed of adjustment of the PD ratio around a constant long-run equilibrium.

For a two-regime MS model, a poor and nonrobust state identification is obtained. For this model we also observe a lack of robustness in the estimated characteristics of each state when we consider different samples and model specifications. We find evidence of an asymmetric speed of adjustment identifying at least two relevant market episodes: the post-war period (up to 1975) and the so called "90's boom". A three-regime MS model shows a sharp regime classification.

[9] We also estimated a two-state MS model where the standard deviation of the innovations, σ, is state-dependant. The empirical evidence in this case suggests that the hypothesis that $\sigma_1 = \sigma_2$ cannot be rejected. Moreover, we have estimated MS models where μ is also state-dependant, but the regime classification was really poor in those cases. Estimation results for these alternative model specifications (where ρ and/or σ and/or μ are state-dependant) are available upon request from the authors.

Moreover, the three-regime model suggests that the post-war period (up to 1975) and the 90's boom episodes do not share the same characteristics and that the additional third state is needed to properly model the PD ratio dynamics. In this context, the post-war period is characterized by a near-nonstationary regime, and the 90's boom is divided in two parts. The first part exhibits features similar to the post-war period, whereas the second part, when the PD ratio grows faster and the apparent divergence between prices and dividends becomes higher, is characterized by a new regime with a stronger reversion to the attractor. This implies that the period 1996-2000 is most likely characterized by a stationary regime with respect to the high estimated attractor. Even when the attractor is poorly identified, by using alternative samples and MS specifications we robustly find higher estimated values for this parameter than those estimated in the previous related literature. The empirical evidence of a high estimated attractor then suggests that the apparent divergence between prices and dividends reflects the transition to a long-run equilibrium (attractor) that has not yet been reached. The evidence then suggests that the high increase of the PD ratio during the 90's boom is consistent with a higher speed of adjustment to the long-run equilibrium. This interpretation stands in sharp contrast to alternative interpretations of this episode suggested in the previous literature. For instance, Coakley and Fuertes (2006) view it as a bull market episode.

The evidence found for the three-state MS model supports the stationarity hypothesis implied by the present value model. While there are occasional episodes of nonstationary behavior of the PD ratio (as in state 1), these episodes are followed with higher probability by stationary regimes (state 2 in almost the entire sample and state 3 in the last part of it). Nonstationarity episodes can therefore be understood as only temporary episodes.

APPENDIX 1

State-dependant models: the Markov-switching approach

This appendix briefly describes the MS framework for estimating nonlinear models. Following Hamilton (1989, 1990), in a 2-state MS model, for estimating an equation such as (5), a transition matrix for s_t (the latent variable governing the switching-regime process) has to be defined as:

$$\mathbf{P} = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix},$$

where $p_{ij} = P(s_t = i \mid s_{t-1} = j, x_{t-1})$, and x_{t-1} is a vector containing all observations for the PD ratio obtained through date $t-1$. If at time t, $s_t = j$, the conditional density of Δx_t will be given by:

$$f(\Delta x_t \mid x_{t-1}, s_t = j, s_{t-1} = i, s_{t-2} = k, ...; \Theta),$$

where Θ is a vector containing the estimated parameters (depending on each case considered). It is assumed that the conditional density depends only on the current regime s_t, so the conditional density is given by:

$$f(\Delta x_t \mid x_{t-1}, s_t = j; \Theta).$$

For instance, in the 2-state model, the conditional densities will be gathered together on a vector denoted by $\boldsymbol{\eta}_t$

$$\boldsymbol{\eta}_t = \begin{bmatrix} f(\Delta x_t \mid x_{t-1}, s_t = 1; \Theta) \\ f(\Delta x_t \mid x_{t-1}, s_t = 2; \Theta) \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ \frac{-(\Delta x_t - \alpha - \rho_1(x_{t-1} - \mu) - \beta_1(\Delta x_{t-1}))^2}{2\sigma^2} \right\} \\ \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ \frac{-(\Delta x_t - \alpha - \rho_2(x_{t-1} - \mu) - \beta_1(\Delta x_{t-1}))^2}{2\sigma^2} \right\} \end{bmatrix}.$$

The maximum-likelihood algorithm seeks to find a vector Θ^* that maximizes the log-likelihood function $\mathcal{L}(\Theta)$ for the observed data x_t. $\mathcal{L}(\Theta)$ is given by

$$\mathcal{L}(\Theta) = \sum_{t=1}^{T} \log f(\Delta x_t \mid x_{t-1}; \Theta), \tag{10}$$

where

$$f(\Delta x_t \mid x_{t-1}; \Theta) = \mathbf{1}'(\widehat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t),$$

$\mathbf{1}$ is a (2x1) vector of ones, and $\widehat{\xi}_{t|t-1}$ are the filtered probabilities defined as

$$\widehat{\xi}_{t|t-1} = \mathbf{P} \cdot \widehat{\xi}_{t-1|t-1}, \tag{11}$$

where

$$\widehat{\xi}_{t-1|t-1} = \frac{(\widehat{\xi}_{t-1|t-2} \odot \boldsymbol{\eta}_{t-1})}{\mathbf{1}'(\widehat{\xi}_{t-1|t-2} \odot \boldsymbol{\eta}_{t-1})}. \tag{12}$$

The optimization algorithm works as follows. Given an initial value $\widehat{\xi}_{1|0}$, equations (12) and (11) can be used to calculate $\widehat{\xi}_{t|t-1}$ and $\widehat{\xi}_{t|t}$ for any t. Following Hamilton (1989), we choose set $\xi_{1|0}$ equal to the vector of unconditional probabilities, $\boldsymbol{\pi}$, determined by $\pi = (A'A)^{-1}A'e_3$, where $A = [I_3 - P,\ 1']'$ and e_3 denotes the third column of I_3 (i.e. the 3x3 identity matrix). The value of $\widehat{\xi}_{t|t-1}$ is introduced in (10) and the procedure iterates until Θ^* is found according to a predefined convergence criterion.

In addition to the filtered probabilities previously obtained for each t, as a by product the procedure also finds the probability of being in each state given the information from the whole sample considered. These probabilities are called smoothed probabilities

$$p_{i,t} = P(s_t = i \mid x_T; \Theta).$$

Kim and Nelson (1999) suggest the following algorithm to compute the smoothed probabilities:

$$\widehat{\xi}_{t|T} = \widehat{\xi}_{t|t} \odot \left\{ \mathbf{P'} \cdot [\widehat{\xi}_{t+1|T} (\div) \widehat{\xi}_{t+1|t}] \right\},$$

where (÷) denotes element-by-element division and from the filtered probabilities, one can obtain the vector $\widehat{\xi}_{T|T}$ and iterate backward to obtain the smoothed probabilities for each t.

APPENDIX 2

Model diagnostics

Two tests are commonly used in the literature for evaluating performance when estimating MS models. The first evaluates the correct specification of each model in each sample considered. The specification tests evaluate whether the standardized residuals are actually standard normally distributed. The second evaluates the ability of the model to correctly identify states. An RCM evaluates whether the model can clearly attribute a regime to each period of time.

- **Standardized residual tests**

  For each specification considered we are interested in testing whether the model adequately captures the data generating process. This can be done by testing whether the standardized residuals, $\widehat{z}_t$, follow a standard normal distribution. We follow a commonly accepted method for jointly testing the orthogonality conditions for the mean, the variance, the skewness and the kurtosis of the residuals. These moment restrictions can be estimated using the generalized method of moments (GMM) as proposed by Hansen (1982). The statistic for this test is asymptotically distributed as a $\chi^2(n)$, where n is the number of restrictions to be tested.[10]

- **Regime classification measures**

  Ang and Bekaert (2002) suggest a summary statistic that evaluates the regime classification quality provided by a k-state MS model. The RCM is defined as

$$RCM = 100k^2 \frac{1}{T} (\sum_{t=1}^{T} \prod_{i=1}^{k} p_{i,t}),$$

[10] Bekaert and Harvey (1997) have shown that the small-sample distribution of this test statistic is fairly close to a χ^2 distribution.

where $p_{i,t}$ is the smoothed probability of being in state i in period t as defined in Appendix 1. This measure captures the fact that if at least one of the smoothed probabilities in t is close to 0 for every t, the RCM will also be close to 0. In this case, the states are properly identified and the model provides a good regime classification. If the states are not well identified, the probabilities of being in a particular state will be far from 1, and will be close to $1/k$ in the worst possible scenario. Thus, the RCM will be close to 100 in this case. The RCM measure is not always useful. For instance, it is not useful for comparing MS models with different numbers of states. Moreover, for $k > 2$, the RCM does not punish the fact that as more states are included, the probability of at least one of the states being close to zero is always higher, but this does not necessarily mean that the model correctly identifies at least one state. Baele (2002) proposes an RCM for k-state models that is equivalent to Ang and Bekaert's' (2002) measure when $k = 2$. His measure allows for a comparison between models with different numbers of states and correctly captures the case where the model is clearly identifying at least one state in each period. The RCM2 proposed by Baele (2002) is defined as:

$$RCM2 = 100(1 - \frac{k}{k-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{k}(p_{i,t} - \frac{1}{k})^2).$$

We propose a new classification measure also equivalent to RCM and RCM2 when $k = 2$. This new measure also shares with RCM2 two desired characteristics for an RCM. First, it is useful for comparing models with different numbers of regimes. Second, it provides a measure closer to 0 only when the model correctly identifies at least one state in each period and a measure closer to 100 when no information about the states identification is obtained. The adjusted RCM is defined as:

$$Adj\ RCM = 100(\frac{k}{k-1})^k \frac{1}{T}(\sum_{t=1}^{T}\prod_{i=1}^{k}(1 - p_{i,t})).$$

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Table 1. Summary Statistics and Unit-root tests.

Full Sample

								Unit-root tests	
Variable	Mean	Median	Min.	Max.	St. Dev	SK	Exc. Ku	ADF Test	PP Test
PD	3.1717	3.1263	2.3147	4.4475	0.4070	0.1283	1.2332	-2.4118	-2.5558

Pre-1993 sample

								Unit-root tests	
Variable	Mean	Median	Min.	Max.	St. Dev	SK	Exc. Ku	ADF Test	PP Test
PD	3.0721	3.0772	2.3147	3.6268	0.2806	-0.2587	-0.4407	-4.0340	-4.2498

NOTE: ADF and PP tests values are obtained for an equation with intercept and one lag for the PD ratio. For the full sample, the 1, 5 and 10% critical values for the ADF and PP tests are -3.49, -2.89 and -2.58 respectively. For the pre 1993 sample, the 1, 5 and 10% critical values for the ADF and PP tests are -3.48, -2.88 and -2.58 respectively.

Table 2. Estimated parameters and stationarity analysis results for the three-state model.

	Full sample		Pre 1993	
		α=0		α=0
Log-likelihood	**117.76227**	**114.30072**	**100.14991**	**99.595314**
RCM2	10.8625	10.8560	12.6461	10.8187
Adj RCM	12.2190	12.1213	14.2205	12.1708
Hansen stat. test joint dist.	5.6527	2.0706	4.2483	3.0242
p-value	*0.2266*	*0.7228*	*0.3734*	*0.5538*
LR 3 or 1 state	182.06	175.14	148.35	147.24
LR 3 or 2 states	81.43	84.61	55.78	74.61
Param.				
α	-0.2464		-0.3342	
st. dev	*0.1708*		*0.2747*	
ρ1	0.0005	0.1240	-0.0263	0.1043
	0.0506	*0.0411*	*0.0749*	*0.0644*
ρ2	-0.0897	-0.0203	-0.1200	-0.0250
	0.0260	*0.0219*	*0.0709*	*0.0095*
ρ3	-0.1742	-0.1526	-0.2052	-0.1423
	0.0283	*0.0292*	*0.1112*	*0.0600*
μ	6.2833	5.1658	6.1769	5.3792
	1.1314	*0.3405*	*2.6140*	*1.1482*
β1	0.1289	0.1538	0.1476	0.1372
	0.0419	*0.1515*	*0.0511*	*0.0701*
σ1	0.0759	0.0763	0.0793	0.0783
	0.0059	*0.0065*	*0.0060*	*0.0079*
P11	0.9760	0.9825	0.9723	0.9808
	0.0136	*0.0101*	*0.0154*	*0.0119*
P12	0.0206	0.0104	0.0222	0.0177
	0.0123	*0.0282*	*0.0142*	*0.0112*
P21	0.0415	0.0590	0.0333	0.0637
	0.0249	*0.0237*	*0.0201*	*0.0178*
P22	0.9289	0.9108	0.9355	0.9050
	0.0291	*0.0362*	*0.0262*	*0.0230*
P31	0.0086	0.0210	0.0187	0.0032
	0.0162	*0.0192*	*0.0362*	*0.0040*
P33	0.9557	0.9484	0.9493	0.9712
	0.0188	*0.0236*	*0.0420*	*0.0239*

Table 3. Estimated parameters and stationarity analysis results for the two-state model.

	Full sample		Pre 1993	
		α=0		α=0
Log-likelihood	**77.047591**	**71.994383**	**72.260971**	**62.289404**
RCM2	14.6083	23.2636	16.3206	23.4285
Adj RCM	14.6083	23.2636	16.3206	23.4285
Hansen stat. test joint dist.	3.3061	3.0633	4.2005	3.2895
p-value	0.5080	0.5473	0.3796	0.5106
LR 2 or 1 state	100.63	90.52	92.57	72.63
Param.				
α	-0.4306		-0.4991	
st. dev	*0.3430*		*0.3210*	
ρ1	-0.0667	0.0944	-0.1491	0.1417
	0.0550	*0.0542*	*0.0883*	*0.0748*
ρ2	-0.1563	-0.0755	-0.3078	-0.1128
	0.0345	*0.0483*	*0.0580*	*0.0874*
μ	6.8840	5.1301	5.1512	4.4281
	2.3844	*0.7496*	*1.0242*	*0.5109*
β1	-0.0043	-0.0505	0.0230	-0.0633
	0.0682	*0.0816*	*0.0792*	*0.0822*
σ1	0.1085	0.1145	0.1055	0.1155
	0.0090	*0.0096*	*0.0101*	*0.0111*
P1	0.9627	0.9629	0.9613	0.9661
	0.0130	*0.0425*	*0.0167*	*0.0486*
P2	0.9323	0.9301	0.9310	0.9250
	0.0150	*0.0302*	*0.0182*	*0.0381*

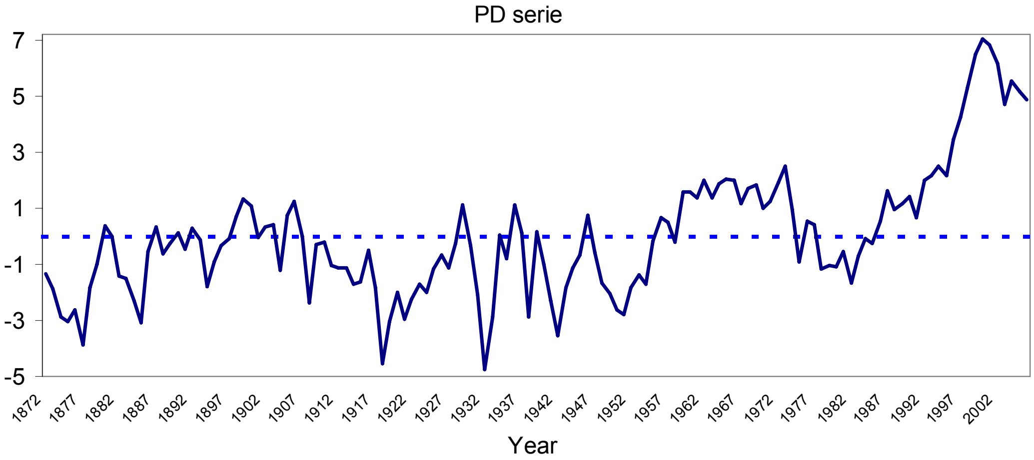
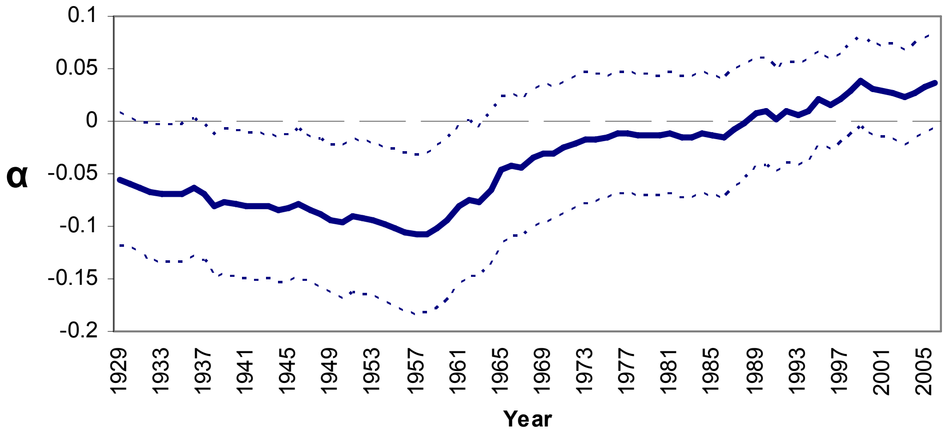


Figure 1. S&P Composite PD ratio. Full sample.

Note: Time series are demeaned and the value of 1970 normalized to one for illustrative purposes.



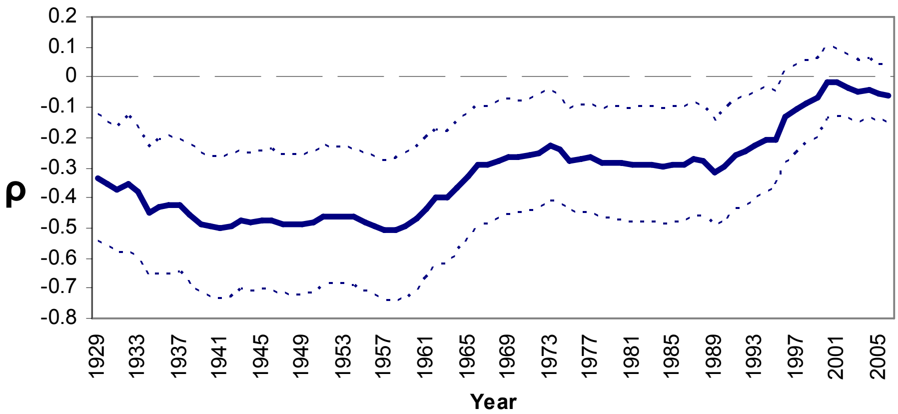


Figure 2. Rolling regression stability analysis for parameters α and ρ in equation $\Delta x_t = \alpha + \rho x_{(dmd)t-1} + u_t$, for the PD ratio and 95% confidence intervals.

Note: $x_{(dmd)t}$ is the demeaned value of the ratio in each t when the average PD ratio is considered as the attractor (constant attractor in the whole sample).

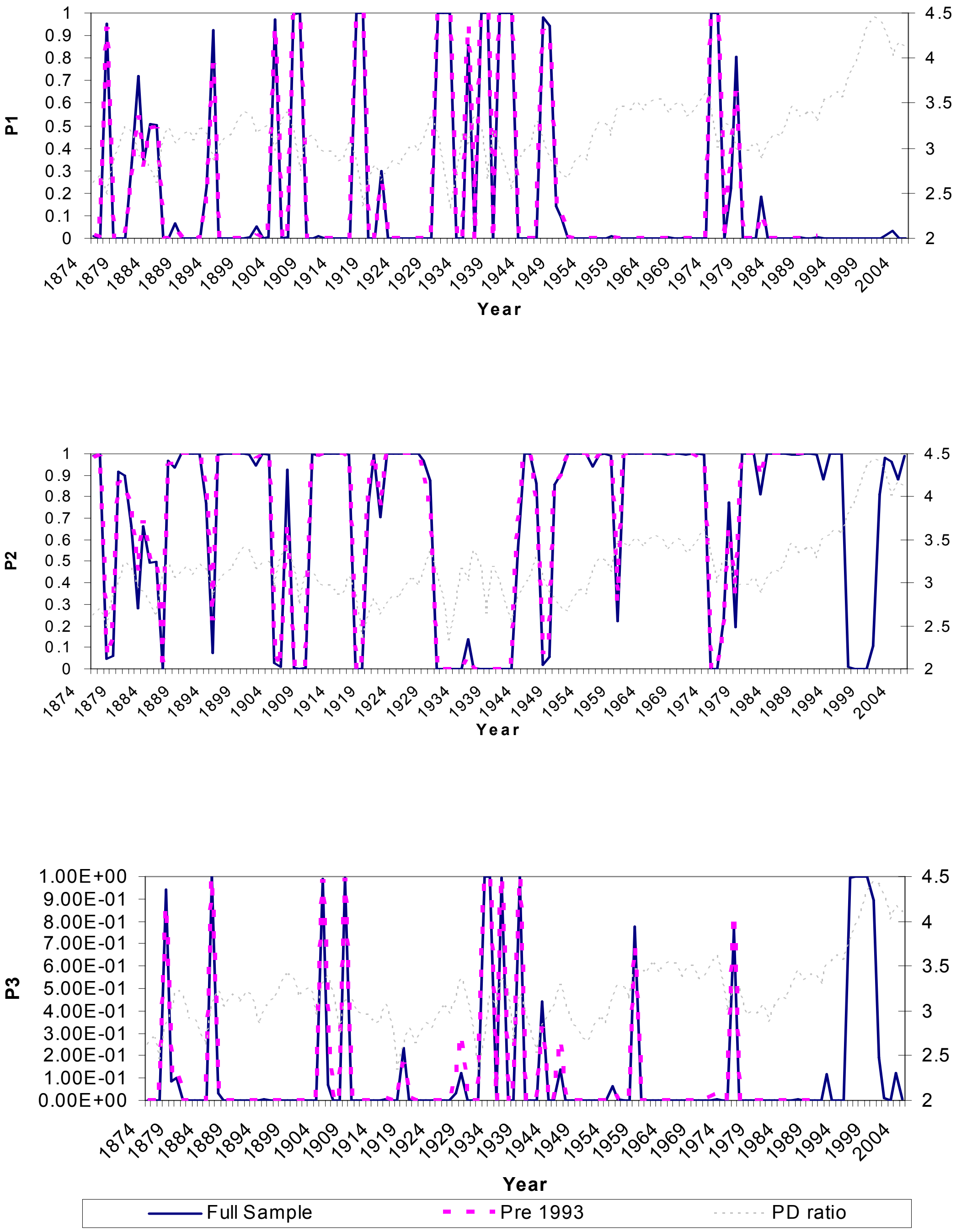


Figure 3. 3-state model. Smoothed probability of state 1, 2 and 3 for PD ratio. Full and Pre-1993 sample. Unrestricted model.

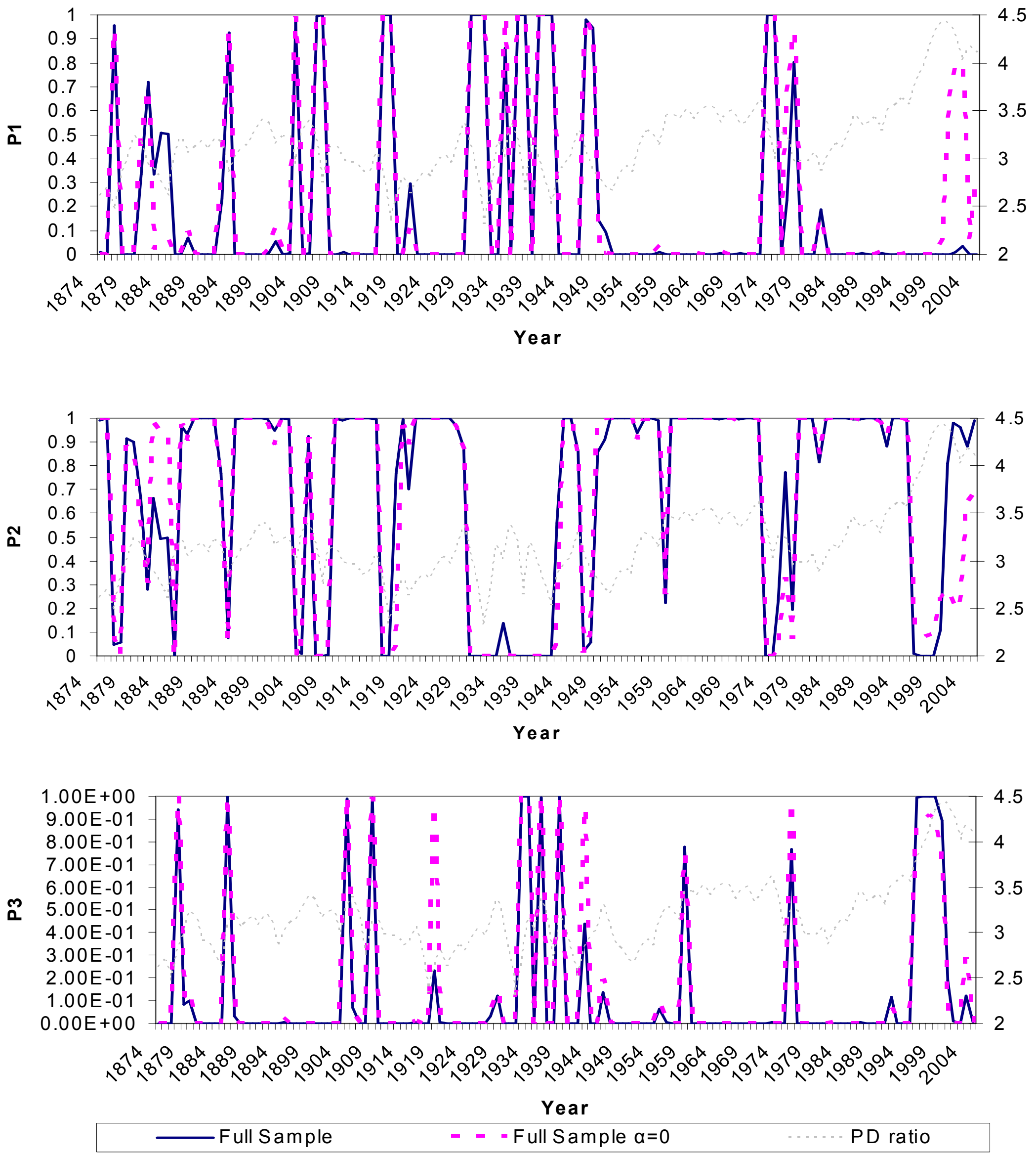


Figure 4. 3-state model. Smoothed probability of state 1, 2 and 3 for PD ratio. Full sample for the unrestricted model and the restricted model with no constant term.

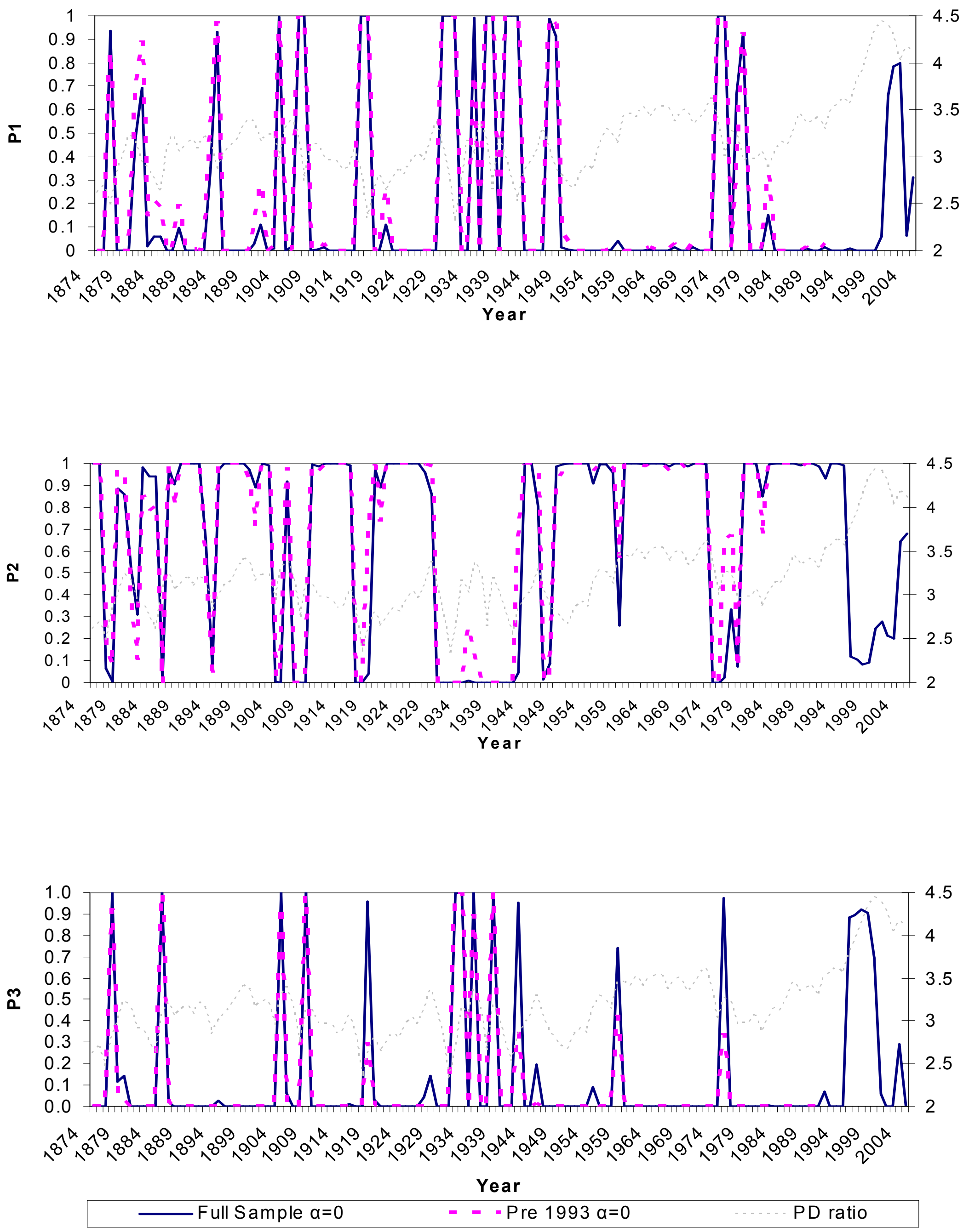


Figure 5. 3-state model. Smoothed probability of state 1, 2 and 3 for PD ratio. Full and pre 1993 sample for the restricted model with no constant term.

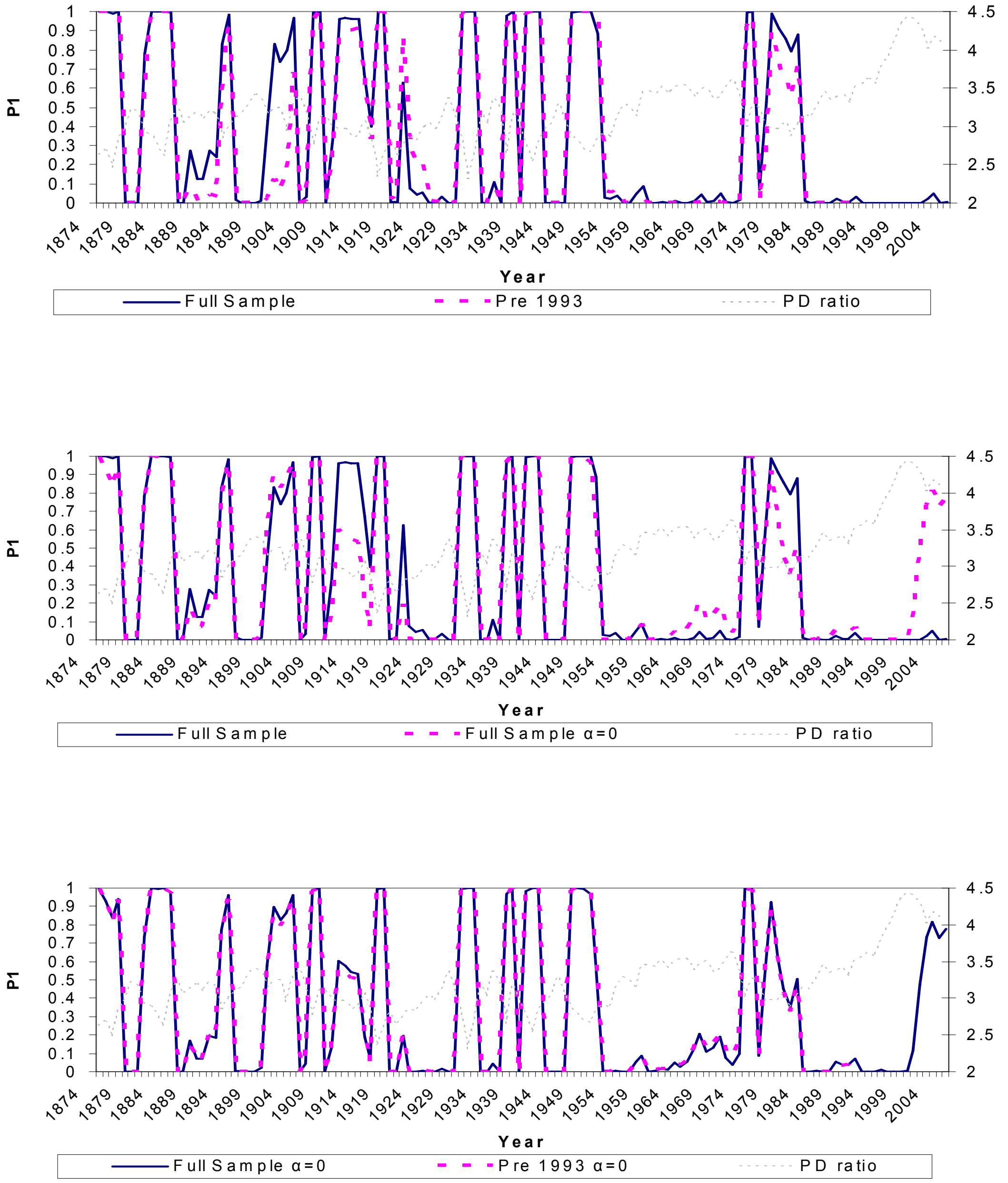


Figure 6. 2-state model. Smoothed probability of state 1 for PD ratio. (a) Full and Pre-1993 sample, (b) Full sample for the unrestricted model and the restricted model with no constant term, and (c) Full and pre 1993 sample for the restricted model with no constant term.