E C O N O M I C S   B U L L E T I N

Non-stationarity and Non-linearity in Stock Prices: Evidence from the OECD Countries

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Abstract

Using 11 OECD countries data, this study employs a Markov Switching unit root regression to investigate the issue of the non-stationarity and non-linearity of stock prices. The results convincingly support the view that the stock prices in the OECD countries are characterized by a two-regime Markov Switching unit root process. For Australia, Austria, Belgium, Finland, Iceland, Ireland, Netherlands and New Zealand, stock prices are characterized by a unit root process, consistent with the efficient market hypothesis that the stock price is either in the high-volatility regime or in the low-volatility regime. For Czech Republic, Denmark and Greece, the shocks to stock prices are highly persistent in one regime, but have finite lives in the other regime. The high-volatility regime arises in most of the countries considered and it tends to prevail over a relatively long period.

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1 Introduction

Testing for a unit root in stock prices has been attracted substantial interest ever since the studies conducted by Fama and French (1988a, 1988b), Lo and MacKinlay (1988) and Poterba and Summers (1988). This is because if there is a unit root in stock prices, then this implies that stock market returns cannot be predicted from previous prices changes and in line with the view of the efficient market hypothesis. It also implies that shocks have permanent effects and volatility in stock markets will increase in the long run without bound. On the other hand, if stock prices follow a mean reverting process, then there exists a tendency for the price level to return to its trend path over time and investors may be able to forecast future returns by using information on past returns.

A wealth of researches has been devoted their efforts to this issue. For example, to name a few, Kim et al. (1991), McQueen (1992), Urrutia (1995), Zhu (1998), Grieb and Reyes (1999), Chaudhuri and Wu (2003), Narayan (2005, 2006, 2007), Narayan and Smyth (2004, 2005, 2006, 2007). Three important features characterize these studies. First, the findings are mixed, if not contradictory, which means there is no corroborative conclusion vis-à-vis the stationarity property for stock prices. Second, the majority apply the traditional method in testing for the null hypothesis of a unit root of stock prices. It is well-known that the traditional unit root test is powerless if the true data generating process of a series exhibits structural breaks (Perron, 1989). Therefore, the bulk of these studies adopt new developed unit root test with structural breaks (Zivot and Andrew, 1992; Lumsdaine and Papell, 1997; Lee and Strazicich, 2003) to investigate the stationary property of stock prices. Third, despite the abundance of studies on the behavior of stock prices, the specification of volatility is commonly time-invariant. Recent studies, however, find that stock prices are tend to be specified as non-linear data generating processes, implying that the volatility may not be constant over time and indicating that the reliability of the findings from existing studies is questionable (Abhyankar et al. (1995, 1997), Atchison and White (1996), Kohers et al. (1997), Schaller and van Norden (1997), Qi (1999), Kanas (2001), Sarantis (2001), Shively (2003) and Narayan (2005, 2006)).

This paper attempts to overcome the above three problems by using the Markov Switching augmented Dickey-Fuller (hereafter MS-ADF) regression, pioneered by Hall et al. (1999), via 11

OECD countries. The merit of this approach is that there is no need to split the sample period into different sub-periods or to pre-impose regime dates. Thus, no prior knowledge of the dates of structural breaks or the number of breaks is needed. In addition, this approach endogenously identifies each volatility regime, which may not be constant. The unit root test is then conducted for each regime separately. Finally, the model does not need to assume the stationarity or non-stationarity of either regime. It is possible for both regimes to be (non)stationary or one to be stationary and the other non-stationary.

The remainder of this paper is organized as follows. Section 2 introduces the econometric methodology that we employ, and Section 3 describes the data and the empirical test results. Section 4 presents the conclusions that we draw from this research.

2 Testing Methodology

Let q_t denote the logarithm of the stock price index. The Markov Switching ADF regression is obtained by running the following regression:

$$\Delta q_t = a(S_t) + b(S_t)\Delta q_{t-1} + \sum_{k=1}^{p} \gamma_k(S_t)\Delta q_{t-k} + u_t, \quad u_t \sim NID(0, \sigma^2(S_t)), \tag{1}$$

where Δq_t denotes the first difference of the stock price q_t, $a(S_t)$, $b(S_t)$ and $\gamma_1(S_t), ..., \ \gamma_p(S_t)$ are regime-varying parameters, and u_t is the innovation process with a regime-dependent variance-covariance matrix $\sigma^2(S_t)$. The unobservable state variable S_t follows a first-order, two-state Markov Chain with the transition probability as follows:

$$p(S_t = j | S_{t-1} = i) = p_{ij}, \tag{2}$$

where $i, j = 1$ or 2. The unconditional probabilities for state 1 and state 2 are $p = \frac{1-p_{11}}{2-p_{11}-p_{22}}$ and $q = \frac{1-p_{22}}{2-p_{11}-p_{22}}$, respectively. The MS-ADF regression has two features. Firstly, it allows the volatility of the stock price to switch across regimes following a first order-Markov chain. Secondly, the autoregressive parameters in the ADF regression are also allowed to change as the volatility regimes shift, and hence they are regime-varying. In short, model (1) endogenously permits the volatility to switch as the date and regime changes. An interesting feature of this model is that no assumption is needed to impose the (non)stationarity of either regime. That is, this model allows both regimes to be (non)stationary or one to be stationary and the other non-stationary. Because the estimation procedure for the Markov Switching model is well documented in the literature, we omit any discussion of the estimation and refer readers to Hamilton (1989) and Kim and Nelson (1999).

3 Data and Results

We use the stock price data for 11 OECD countries, i.e., Australia, Austria, Belgium, Czech Republic, Denmark, Finland, Greece, Iceland, Ireland, Netherlands and New Zealand, in our empirical study. The data set is obtained from the OECD Main Economic Indicators at `http://stats.oecd.org/mei/`. For all countries the data are monthly from different starting date but they are all end with 2007M5 or 2007M6. We begin by applying the augmented Dickey and Fuller (1981) unit root test to ascertain the order of integration of the variables. The key here is to account for serial correlation; we set $k = 12$, which is the lagged difference, and use the Schwarz Bayesian Criterion (BIC) to select the optimal lag length. We summarize the data description and the ADF unit root test results in Table 1. We find no additional evidence against the unit root hypothesis based on the ADF test in their level data. When we apply the ADF test to the first difference of these series, we must reject the null hypothesis of a unit root at the 5% level or better. This implies that the stock prices of these 11 OECD countries have a unit root.

Next, we examine whether we can reject the linear autoregressive model (H_0) in favor of a Markov Switching model (H_A), which assumes that each coefficient and variance are affected by the regime in which they remain. Accordingly, this hypothesis is equivalent to testing the homoskedasticity of variance and the equality of all autoregressive parameters across regimes. It is also similar to the test of the standard ADF regression, as compared with the MS-ADF regression.

As shown in Table 1, the likelihood ratio (LR) statistics for all countries are greater than the $\chi^2_{0.95}(4) = 9.487$ critical value, thus rejecting H_0 at the 5% level or better of significance. This implies that MS-ADF model is preferable to the linear, single-regime autoregressive model with a constant conditional variance. That is, the conventional ADF test is less powerful in the presence of switching coefficients and variances. In short, we cannot reject the MS-ADF model for the 11 OECD countries' stock prices.

There is one econometric issue in the use of LR, and that concerns $LR(H_0|H_A)$ reported in the last column of Table 1. Because the parameters p_{11} and p_{22} are not identified under the null hypothesis, the conventional LR test does not yield the standard asymptotic distribution.[1] Most researchers, however, still use the LR test to obtain valuable supporting evidence. The LR by itself, however, may not be suitable as a safe source of evidence with which to reject or not reject the null hypothesis. Throughout this paper, our LR tests are considered in the same way.

Given that the MS-ADF model is not rejected for the sample, we next test for the presence of a unit root in each regime. Table 2 reports the variances, the ADF test results and the durations for each regime. The estimated value of σ_1 is substantially larger than that of σ_2, and thus regime 1 corresponds to the high-volatility regime while regime 2 corresponds to the low-volatility regime. We conduct a Monte Carlo simulation to obtain critical values for the unit root test in the MS-ADF model since the distribution under the null hypothesis is not known.[2] The p values corresponding to the t-statistics of the null hypothesis of non-stationarity in both regimes $b(S_t = 1) = 0$ and $b(S_t = 2) = 0$ against the respective one-sided alternatives of stationarity $b(S_t = 1) < 0$ and $b(S_t = 2) < 0$ are obtained by estimating Equation (1) under the null hypothesis $b(S_t) = 0,\ S_t = 1,\ 2$, and then generating 1,000 samples of size T that follow this estimated DGP. To this end, the estimated transition probabilities are used to simulate a single series S_t. Then, 5,000 series for u_t are drawn from a $N(0, \hat{\sigma}^2(S_t))$ and the aforementioned estimates of the parameters under the null are used to generate data for q_t. We next fit (1) to each realization of q_t, thus obtaining two series of t-statistics for the parameter b, one for the high volatility regime and the other for the low. The resulting p-values are then the percentage of the generated t-ratios that are below the t-values

[1] The problem comes from two sources: under the null hypothesis, some parameters are not identified, and the values are identified as zero. Hansen (1992, 1996) proposed a bounds test that addressed these problems, but its computational difficulty has limited its applicability. See Hansen (1992, 1996) and Garcia (1998) for a detailed explanation of these problems.

[2] Readers are referred to Hall et al. (1999), Kanas and Genius (2005) and Kanas (2006) for details.

from the estimated model.

As shown in Table 2, first, in regime 1 (the high-volatility regime), the ADF statistics for Australia, Austria, Belgium, Finland, Iceland, Ireland, Netherlands and New Zealand, fail to reject the null hypothesis of the non-stationarity because the simulated p-values are greater than 0.126 or better. In regime 2 (the low-volatility regime), the ADF statistics also fail to reject the null hypothesis of a unit root because the simulated p-values are greater than 0.148 or better. The results indicate that the stock prices for these OECD countries are characterized in non-stationarity in both regimes. These findings support the fact that the stock price series are characterized by a unit root process, consistent with the efficient market hypothesis either the stock price is in the high-volatility regime or in the low-valoatility regime. Second, for Czech Republic, Denmark and Greece, the ADF statistics must reject the null hypothesis of a unit root in the high-volatility regime because the simulated p-values are smaller than 0.10 or lesser, indicating that the stock prices of the 3 countries are mean-reverting in the high-volatility regime. In the low-volatility regime, the ADF statistics fail to reject the null hypothesis of a unit root. The results indicate that the stock prices for Czech Republic, Denmark and Greece, stock prices are found to be highly persistent in the low-volatility regime, but have finite lives in the high-volatility regime. Thus shocks to stock prices may have differing effects depending on the initial regime of stock prices, the sign and size of the shocks, and whether or not the shock causes a transition across regimes. A shock to stock prices in the low persistence regime may have less effect than a shock of similar magnitude in the high persistence regime.[3]

Table 2 also reports the estimated durations of each regime, which show the length of each regime's occurrence.The average duration of each regime i is calculated using the formula $d_i = (1 - p_{ii})^{-1}$, where p_{ii} is the probability that the transition probability from regime i to regime i,

[3] The maximum likelihood estimation of Equation (1) yields the filter probabilities, representing the inference that the stock price is in regime i at date t. Furthermore, one could date the regime switches. Because of space limitations, we have omitted the figures for the filtered probabilities estimated by the MS-ADF model, but these are available upon request from the author.

simply put, the system will stay in regime i for two consecutive years. The results reveal that for Australia, Belgium, Denmark, Finland, Greece, Iceland, Ireland, Netherlands and New Zealand, the high-volatility regime prevails for a longer period than the low-volaility regime for which the non-stationary high-volatility regime occurs more frequently. For Austria and Czech Republic, the low-volatility regime prevails for a relatively longer period. Therefore, the high-volatility regime arises in most of the countries considered and it tends to prevail over a relatively long period.

4 Concluding Remarks

The purpose of this study is to re-investigate the issue of the non-stationarity and non-linearity of stock prices of 11 OECD countries by using a recent nonlinear unit root test. The MS-ADF test has the advantage of neither splitting the sample period into different sub-periods nor pre-imposing regime dates. In addition, it endogenously identifies each volatility regime, and the unit root test is conducted for each regime separately. Two important results emerge from our empirical analysis. First, we find that the stock prices in the OECD countries are non-linear series, a finding that is consistent with the evidence reported by Shively (2003) and Narayan (2005, 2006), who test a unit root for stock prices by employing Caner and Hansen's (2001) nonlinear threshold modeling technique. Second, we apply the MS-ADF test statistics for unit roots and find that stock prices of Australia, Austria, Belgium, Finland, Iceland, Ireland, Netherlands and New Zealand are characterized by a unit root process, consistent with the efficient market hypothesis either the stock price is in the high-volatility regime or in the low-volatility regime. For Czech Republic, Denmark and Greece, shocks to stock prices are highly persistent in one regime, while in the other regime stock price displays fairly rapid mean reversion. The high-volatility regime arises in most of the countries considered and it tends to prevail over a relatively long-term period.

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Table 1: Testing for the Markov Switching in the ADF regression

Country	Sample	ADF statistic	$LL(H_0)$	$LL(H_A)$	$LR(H_0\|H_A)$
Australia	1958M1–2007M5	-0.097	952.814	1031.722	157.816**
Austria	1957M1–2007M5	0.464	1031.348	1200.015	337.334**
Belgium	1985M4–2007M5	-1.017	484.813	504.726	111.826**
Czech Republic	1994M1–2007M6	0.471	223.413	237.055	27.284**
Denmark	1983M1–2007M5	-0.623	486.397	501.461	30.128**
Finland	1957M1–2007M6	0.213	941.064	1022.039	51.436**
Greece	1985M1–2007M6	-2.441	287.452	315.991	161.950**
Iceand	1993M1–2007M6	0.689	285.074	295.170	20.192**
Ireland	1956M1–2007M6	-0.070	1018.460	1103.623	170.326**
Netherlands	1957M1–2007M6	-0.255	1108.030	1140.079	64.098**
New Zealand	1967M1–2007M6	-1.113	788.769	848.537	119.536**

The estimated model under the H_0 is $\Delta q_t = a + b\Delta q_{t-1} + \sum_{k=1}^{p} \gamma_k \Delta q_{t-k} + u_t$.

The estimated model under the H_A is $\Delta q_t = a(S_t) + b(S_t)\Delta q_{t-1} + \sum_{k=1}^{p} \gamma_k(S_t)\Delta q_{t-k} + u_t$.

LL denotes the log-likelihood value.

LR denotes the likelihood ratio test.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 2: The Markov Switching ADF Unit Root Test

	ADF statistic						Average regime duration	
Country	Regime 1	Regime 2	σ_1	σ_2	p_{11}	p_{22}	Regime 1	Regime 2
Australia	−0.525	0.013	0.105**	0.035**	0.980**	0.832**	50.00	5.95
	[0.475]	[0.726]	(0.012)	(0.001)	(0.009)	(0.075)		
Austria	−1.711	1.972	0.057**	0.013**	0.947**	0.955**	18.87	22.22
	[0.161]	[0.976]	(0.003)	(0.001)	(0.022)	(0.023)		
Belgium	−1.909	1.068	0.053**	0.025**	0.948**	0.900**	19.23	10.00
	[0.126]	[0.888]	(0.005)	(0.002)	(0.035)	(0.071)		
Czech Republic	−3.273**	−0.560	0.063**	0.030**	0.915**	0.948**	11.76	19.23
	[0.032]	[0.471]	(0.004)	(0.003)	(0.045)	(0.031)		
Denmark	−2.090*	0.094	0.053**	0.029**	0.905**	0.892**	10.52	9.26
	[0.100]	[0.616]	(0.004)	(0.002)	(0.053)	(0.073)		
Finaland	−1.036	1.964	0.082**	0.034**	0.986**	0.960**	71.42	25.00
	[0.382]	[0.985]	(0.006)	(0.002)	(0.008)	(0.022)		
Greece	−2.301*	−1.649	0.108**	0.046**	0.963**	0.952**	27.03	20.83
	[0.064]	[0.148]	(0.009)	(0.003)	(0.024)	(0.037)		
Iceland	−0.226	1.797	0.068**	0.034**	0.947**	0.803**	18.86	5.07
	[0.538]	[0.956]	(0.011)	(0.002)	(0.033)	(0.120)		
Ireland	−1.194	1.268	0.068**	0.027**	0.974**	0.949**	38.46	19.60
	[0.241]	[0.933]	(0.004)	(0.001)	(0.011)	(0.023)		
Netherlands	−0.553	0.592	0.058**	0.029**	0.948**	0.802**	19.23	5.05
	[0.534]	[0.849]	(0.002)	(0.001)	(0.024)	(0.082)		
New Zealand	−0.028	−0.611	0.066**	0.029**	0.983**	0.971**	58.82	34.48
	[0.702]	[0.442]	(0.004)	(0.001)	(0.009)	(0.075)		

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Figures in parentheses are standard errors.

Figures in square brackets are simulated p-values of the unit root tests.