

The duration analysis of structural breaks: is stability destabilizing?

Park, J. S.

Author post-print (accepted) deposited in CURVE June 2016

Original citation & hyperlink:

Park, J. S. (2015) The duration analysis of structural breaks: is stability destabilizing? Applied Economics, volume 47 (9): 940-954.

<http://dx.doi.org/10.1080/00036846.2014.985370>

Publisher statement: This is an Accepted Manuscript of an article published by Taylor & Francis in Applied Economics on 28th November 2014, available online: <http://www.tandfonline.com/doi/abs/10.1080/00036846.2014.985370>.

Copyright © and Moral Rights are retained by the author(s) and/ or other copyright owners. A copy can be downloaded for personal non-commercial research or study, without prior permission or charge. This item cannot be reproduced or quoted extensively from without first obtaining permission in writing from the copyright holder(s). The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the copyright holders.

This document is the author's post-print version, incorporating any revisions agreed during the peer-review process. Some differences between the published version and this version may remain and you are advised to consult the published version if you wish to cite from it.

CURVE is the Institutional Repository for Coventry University

<http://curve.coventry.ac.uk/open>

Duration analysis of structural breaks: Is stability destabilizing?

Jin Suk Park

Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, UK

Email: j.s.park@durham.ac.uk

Abstract

This paper investigates how the duration of a regime affects the likelihood of a permanent structural break by devising the duration-dependence in structural break (DDSB) method, which combines a structural break test and a duration dependence test. First, the locations of structural breaks are identified by Bai and Perron (1998)'s method. Then, it is estimated how a hazard rate changes in duration between structural breaks by parametric duration analysis using the Weibull and the log-logistic hazard functions.

This study reveals the evidence of positive duration dependence in 13 out of 27 international stock indices and the pooled data. In other words, as one regime continues over time with unchanged parameter values, a new structural break is more likely to occur. This method discloses a lower degree of duration dependence than the duration-dependence Markov-switching (DDMS) model (Durland and McCurdy, 1994) that considers temporary switches between a limited number of regimes. Also, some new patterns are emerged, e.g., more predominant positive duration dependence in bear markets, the secondary stock exchanges of a country and developing countries.

I. Introduction

A ‘structural break’ is defined as the permanent and non-reverting change in the parameter values of a data generating process and thus invalidates an existing data generating process. Voluminous work has been carried out on the methods of detecting the positions and the number of structural breaks (Zeileis *et al.*, 2003; Perron, 2006).

However, the change in the likelihood of a structural break over one regime has not been fully investigated. This probability is technically interpreted as a hazard rate in duration analysis. If a hazard rate does not depend on the duration of a regime (i.e. time length after the last structural break), the distribution of duration will follow exponential distribution. However, if a hazard rate changes depending on the duration, it will significantly deviate from the exponential distribution. This is defined as ‘duration dependence in structural breaks’ in this study.

Two types of duration dependence can be specified in terms of structural breaks. First, *positive* duration dependence in structural breaks implies that the structural breaks are more likely to occur as the same regime continues. In other words, the probability that any price run ends becomes higher over time. Second, *negative* duration dependence is equivalent to the decreasing likelihood of a new structural break in duration. If this is the case, the ongoing price regime is more likely to persist as it continues.

The analysis of duration dependence itself is not new in economics and finance. It was first brought in for economic analysis of unemployment duration (Kiefer and Neumann, 1979; Kiefer, 1988) and then to the study of economic growth and business cycles, e.g., Durland and McCurdy (1994), Lam (2008) and Ozun and Turk (2009) among many others. Financial studies such as rational bubbles also utilized duration dependence (McQueen and Thorley, 1994). For example, a stock bubble is the phenomenon of negative duration dependence where the probability that a positive run terminates (i.e. a crash) becomes lower as the run extends, but the size of the crash is larger. Since McQueen and Thorley (1994) found evidence of a

bubble in the US stock market, other researchers discovered the evidence of a bubble or duration dependence (Harman and Zuelke, 2004; Mokhtar *et al.*, 2006; Zhang, 2008; Bhaduri and Mahima, 2009; Yuhn *et al.*, 2010). A similar topic, the transition between bull and bear markets i.e., market cycle, also extensively used duration analysis (Maheu and McCurdy, 2000; Lunde and Timmermann, 2004; Chen and Shen, 2007; Chong *et al.*, 2010; Castro, 2012).

However, duration dependence in structural breaks has not been studied before. The research on structural breaks mostly focuses on revealing unknown breakpoints e.g. methodological survey by Perron (2006) or other examples like Kramer *et al.* (1988) and Rapach and Wohar (2006) among many others. On the other hand, the duration analysis does not usually consider the possibility of a structural break as it assumes one data generating process is effective over entire sample periods e.g. studies on rational bubbles.

The closest approach to the duration analysis of structural breaks is the duration-dependence Markov-switching (DDMS) model (Durland and McCurdy, 1994). Markov switching models (Hamilton, 1989) or more general state-space Markov switching models (Kim, 1993) analyze the probabilistic transition between two or more regimes. The DDMS model studies the impact of the duration of a regime on transition probabilities commonly between economic expansion and contraction or bullish and bearish markets. For example, Lam (2004) reveals positive duration dependence in an economic expansion and negative duration dependence in a contraction. Pelagatti (2008) reports that positive duration dependence is stronger in a recession than an expansion. Chen and Shen (2007) show positive duration dependence in East Asian stock exchanges. Castro (2012) discovers positive duration dependence in the Portuguese stock exchange. However, a temporary regime switch between a limited number of regimes is fundamentally different from a permanent structural break to a new regime. Also, the DDMS models do not utilize hazard functions unlike conventional duration analysis and treat all switches as endogenous.

This paper presents a two-stage method to identify duration dependence in structural breaks, namely the DDSB method, which allows for an unlimited number of regimes and exogenous breaks. Particularly, it specifies the dates of structural breaks using a separate structural break test by Bai and Perron (1998). Then, it investigates the impact of duration on the hazard rate of a regime. This study employs the weekly data of 27 stock price indices across 23 countries. Additionally, it examines the differences in duration dependence between bull and bear markets, developed and developing economies and the primary and secondary stock exchanges of a country.

Then, it compares the results with the duration-dependence Markov-switching (DDMS) model (Durland and McCurdy, 1994). However, methodological issues regarding the choice between structural breaks and unit roots or their interplay (Perron, 2006) are not within the scope of this research. The rest of the paper is structured as follows. Section II explains the theoretical background of both the DDSB method and the DDMS method. Section III presents the empirical results and discusses the findings. Section IV concludes.

II. Methodology

The duration-dependence in structural break (DDSB) approach is a two-stage method. Its first stage is the Bai and Perron method (1998) that retrieves the best timings of structural breaks and provides duration data as the time length between adjacent structural breaks. The second stage is parametric duration analysis (i.e. survival analysis) on the duration data. On the other hand, the duration-dependence Markov switching (DDMS) method is essentially a state-space Markov switching model that investigates whether transition probabilities between regimes rely on the duration of a regime.

Two methods provide alternative views on the changes in data generating processes. The DDSB method supposes structural breaks are exogenous with permanent jumps between numerous regimes. It implicitly assumes a trend-stationary process of price has structural breaks and implements piecewise regression. The DDMS method regards structural breaks as

endogenous and temporary switches between two or more regimes. It supposes a unit-root process of price and examines transition probabilities in a Markov chain.

Structural breaks

Several methods to detect structural breaks have been proposed. If the date of a structural break is known a priori, a Chow breakpoint test (Chow, 1960) can be conducted. If the date is unknown, the F statistics of all possible break dates can be used to date and test for a structural break. Andrews (1993) provided Wald, Lagrange and likelihood tests for this purpose.

Bai and Perron (1998) generalized dating and testing methods for multiple unknown breakpoints, which were further developed by allowing stochastic parameters of trend and structural changes in vector autoregressive models (Hansen, 2000; Hansen, 2003; Hungnes, 2010). Elliott (2003) suggested a test that allows for random, serially correlated or clustered breaks. On the other hand, CUSUM (cumulative sum) tests, which use accumulated errors (Brown *et al.*, 1975), are also available (Stock, 1994), but Kramer (1988) showed they did not contain power against zero-mean regressors (Clements *et al.*, 2006). Kuan (1995)'s general fluctuation test can be used to identify a structural break by interpreting increasing fluctuation as evidence. Perron (2006) summarized the tests for structural breaks in further detail.

This study employs the Bai and Perron (1998) method since it is a parsimonious approach to analyze a time series of mean values. Their method provides the algorithm to specify the number and locations of multiple structural breaks based on a piecewise regression model. It is different from spline regression models (Marsh and Cormier, 2002) as Bai and Perron's method allows for jumps between segments.

Their method assumes that a data generating process of price (P) is linear in time (t) and the parameter values (c and λ) change at certain structural breaks.

$$P_{j,t} = c_j + \lambda_j t + \varepsilon_{j,t} \tag{1}$$

where j is the index of a regime or a price partition between structural breaks and ε is the error term.

Each linear price partition represents a time trend in that particular time period. Thus, one time variable (t) is enough to characterize price runs (Zeileis *et al.*, 2002). The model can represent a non-linear behaviour while an individual partition maintains linearity (Campbell *et al.*, 1997).

However, the timing of structural breaks is usually unknown and thus must be first considered. Suppose t_1, \dots, t_m are the breakpoints in T total observations, the locations of breakpoints are estimated by the following algorithm by Bai and Perron (1998):

$$t_1, \dots, t_m = \arg \min_{t_1, \dots, t_m} [RSS(t_1, \dots, t_m)] \quad (2)$$

where $\arg \min$ is the argument of minimum and RSS is the residual sum of.

The aim is to find the global minimizers of the above objective function. Minimization can be accomplished using a grid search. Starting from a case of one breakpoint ($m=1$), piecewise linear regressions are repeated on all possible sets of sub-samples. At each repetition, a different position of the breakpoint is chosen. This whole procedure is repeated for all possible cases of different numbers of breakpoints from one to the maximum number of breakpoints until the best locations of breakpoints for each number of breakpoints are identified. The case of no structural break is additionally estimated. Finally, the best set of the number and locations of breakpoints, i.e. optimal breakpoints in Bai and Perron (1998, 2003), is selected by comparing information criteria. The number of breakpoints is known to be consistent over different model specifications (Liu *et al.*, 1997).

The burden of calculation can be minimized by the dynamic programming algorithm (Bai and Perron, 2003; Zeileis *et al.*, 2003). The optimal breakpoints are obtained by solving the recursive problem:

$$RSS(T_{m,T}) = \min_{mk \leq b \leq T-k} [RSS(T_{m-1,b}) + RSS(b+1, T)] \quad (3)$$

where $RSS(T_{m,T})$ is the residual sum of squares with optimal m breakpoints using T observations, $RSS(b+1,T)$ is the residual sum of squares from a price run ($b+1$ to T), k is the maximum number of breaks and b is the position of the previous breakpoint. The idea is to find the optimal previous partner for each breakpoint b (Zeileis *et al.*, 2003).

The decision of the minimum length of a price partition, i.e. minimum duration, is important. It is commonly specified as the minimum proportion (q) of the sample size (T). Then, the maximum number of breaks (k) is $(T/qT)-1$. If the minimum duration is not properly chosen, some of the breakpoints will be missed out or appear at wrong locations. Basically, it should be chosen to be smaller than the reasonably shortest distance between two adjacent potential breaks. However, it must be meaningfully large to improve economic implications and reduce computation burden.

Duration dependence in structural break

The duration data is essentially the collection of time length between adjacent structural breaks identified in the first step. This study employs parametric duration analysis because the estimation is easier and complicated econometric analyses are more applicable than non-parametric methods such as the Kaplan-Meier method (Kaplan and Meier, 1958) and Cox's (Cox, 1972) semi-parametric method.

The empirical test of duration dependence (Durland and McCurdy, 1994) investigates whether a hazard rate (i.e. a termination probability) increases, decreases or remains constant when the duration of a regime increases. Suppose f is the probability distribution function of a random variable (D) that represents the time length (i) after which a particular regime terminates or equivalently that of the duration of a regime. Then, the cumulative distribution function (F) is the probability that a regime ends before i .

$$\begin{aligned} f_i &= \text{prob}(D = i) \\ F_i &= \text{prob}(D < i) \end{aligned} \tag{4}$$

A hazard rate (h) is defined as the conditional probability of a regime terminating at time i given the regime lasts until time i .

$$h_i = \frac{f_i}{1 - F_i} \quad (5)$$

If positive duration dependence exists, the hazard rate increases as i goes up, but it decreases under negative duration dependence.

For statistical inference, its functional form needs to be specified. The Weibull and the log-logistic hazard function are two common choices as in Kiefer (1988) and McQueen and Thorley (1994)'s original studies.

First, the Weibull hazard function following Kiefer (1988)'s specifications is:

$$h_i = \gamma \delta i^{\delta-1} \quad (6)$$

where γ is a scale parameter and δ is a shape parameter. It is a generalized form of the exponential distribution and monotonically increases or decreases with duration i . Specifically, the hazard rate increases in duration i if $\delta > 1$, i.e. positive duration dependence, and decreases if $\delta < 1$, i.e. negative duration dependence. Where $\delta = 1$, the hazard rate is constant and the distribution of duration becomes the exponential distribution.

Second, the log-logistic hazard function is specified as:

$$h_i = \frac{\gamma \delta i^{\delta-1}}{(1 + \gamma i^\delta)} \quad (7)$$

where both γ and δ are positive. It can be a non-monotonic function in i unlike the Weibull hazard function. If $\delta > 1$, the hazard function is a bump shape that is suitable where positive duration dependence is expected to exist only in the lower range of duration.. If $0 < \delta \leq 1$, it monotonically decreases in duration.

The coefficients γ and δ are estimated by the maximum likelihood estimation (McQueen and Thorley, 1994). Then, the likelihood ratio (LR) test specifies whether duration dependence exists using the restriction of $\delta=1$ and the LR statistic:

$$LR = 2[\ln L_{UR} - \ln L_R] \sim \chi^2_{(1)} \quad (8)$$

where $\ln L_{UR}$ is the log likelihood value of the unrestricted model and $\ln L_R$ is that of the restricted model.

The duration-dependence Markov-switching model

On the other hand, the DDMS model explains how duration affects transition probabilities between multiple regimes. If a random variable r_t is subject to parametric switches depending on state S_t that has integer values. Then, the process of r_t can be specified as.

$$r_t = \mu(S_t) + \sigma(S_t)u_t \quad (9)$$

where $\mu(S_t)$ and $\sigma(S_t)$ are mean and variance equations of S_t , respectively. u_t follows i.i.d $N(0,1)$.

$\mu(S_t)$ and $\sigma(S_t)$ can be further specified as a linear equation of S_t for simplicity.

$$r_t = \mu_0 + \mu_1 S_t + (\sigma_0^2 + \sigma_1^2 S_t)^{1/2} u_t \quad (10)$$

where μ_0 , μ_1 , σ_0 and σ_1 are parameters.

To fully describe the process of r_t in this state-space model, how S_t evolves must be specified. A first-order Markov process is commonly employed to avoid computational burden and the excessive consumption of the degree of freedom in the higher-order Markov process (Durland and McCurdy, 1994). The conditional distribution of S_t depends on its immediate previous value, which is equivalent to knowing all of its past history.

$$\text{Prob}(S_t = s | S_{t-1}) = \text{Prob}(S_t = s | S_{t-1}, S_{t-2}, \dots, S_1) \quad (11)$$

where Prob is probability. It is usually assumed that two states ($s = 1$ or 0) exist. Then, all transition probabilities in a two-state first-order Markov process can be defined (Kim and Nelson, 1999):

$$\begin{aligned}
\text{Prob}(S_t = 1 | S_{t-1} = 1) &= p_{11} \\
\text{Prob}(S_t = 0 | S_{t-1} = 1) &= 1 - p_{11} \\
\text{Prob}(S_t = 0 | S_{t-1} = 0) &= p_{00} \\
\text{Prob}(S_t = 1 | S_{t-1} = 0) &= 1 - p_{00}
\end{aligned} \tag{12}$$

Suppose a latent continuous variable S_t^* decides the value of S_t .

$$\begin{aligned}
\text{Prob}(S_t = 1) &= \text{Prob}(S_t^* > 0) \\
\text{Prob}(S_t = 0) &= \text{Prob}(S_t^* < 0)
\end{aligned} \tag{13}$$

where S_t^* evolves as:

$$\begin{aligned}
S_t^* &= \alpha_0 + \alpha_1 S_{t-1} + \xi_t \\
\xi_t &\sim N(0,1)
\end{aligned} \tag{14}$$

α_0 and α_1 are parameters.

Then, the transition probabilities can be specified using a probit model:

$$\begin{aligned}
p_{11} &= \text{Prob}(\xi_t > -\alpha_0 - \alpha_1) = 1 - \Phi(-\alpha_0 - \alpha_1) \\
p_{00} &= \text{Prob}(\xi_t < -\alpha_0) = \Phi(-\alpha_0)
\end{aligned} \tag{15}$$

where Φ is a cumulative standard normal distribution.

On the other hand, the transition probabilities can be time-varying. Then, S_t is now conditional on the vector of explanatory variables, \mathbf{x} .

$$\text{Prob}(S_t | S_{t-1}, \mathbf{x}_{t-1}) \tag{16}$$

The duration-dependence Markov switching (DDMS) model assumes that duration (D) of a state can be representative of \mathbf{x} as it contains the entire history of the Markov process (Durland and McCurdy, 1994). Consequently, the transition probabilities are:

$$\text{Prob}(S_t | S_{t-1}, D_{t-1}) \quad (17)$$

where they progress through a Markov chain (S_t, D_t) . Meanwhile, duration growth is defined:

$$D_t = \begin{cases} (D_{t-1} + 1) & \text{if } S_t = S_{t-1} \\ 1 & \text{otherwise} \end{cases} \quad (18)$$

In Pelagatti (2008)'s the two-state example with duration, the transition probabilities are:

$$\begin{aligned} \text{Prob}(S_t = 1 | S_{t-1} = 1, D_{t-1} = i) &= p_{11,i} = 1 - \Phi(-\beta_1 - \beta_2 i) \\ \text{Prob}(S_t = 0 | S_{t-1} = 0, D_{t-1} = i) &= p_{00,i} = \Phi(-\beta_3 - \beta_4 i) \\ \text{Prob}(S_t = 0 | S_{t-1} = 1, D_{t-1} = i) &= 1 - p_{11,i} \\ \text{Prob}(S_t = 1 | S_{t-1} = 0, D_{t-1} = i) &= 1 - p_{00,i} \end{aligned} \quad (19)$$

where β 's are unknown parameters.

Pelagatti (2008) utilizes Bayesian inference on the model's unknown parameters by the iteration of the Gibbs sampler. In his method, β_2 and β_4 specify duration dependence. In state 1, positive duration dependence exists if $\beta_2 < 0$ and negative duration dependence exists if $\beta_2 > 0$. In state 0, positive duration dependence exists if $\beta_4 > 0$ and negative duration dependence exists if $\beta_4 < 0$.

III. Empirical Results

The empirical analysis is based on 27 stock price indices across 23 countries. They include 19 out of 20 of the largest stock exchanges in terms of market capitalisation in 2012 and some selected stock exchanges in developing countries. The data covers from 13 June 1984 or the earliest possible on the Datastream database to 31 December 2012. Weekly averages are employed since they can avoid excessive noise in daily data for structural break analysis and Markov-switching modelling and provide enough observations for duration analysis compared with monthly data. The maximum number of observations is 1,543. The next table presents the descriptive statistics of all 27 stock indices.

[*Insert Table 1 here*]

The first stage in the two-step DDSB method is to transform stock price index data to duration data. All index series are first de-trended to control for a long-term trend, as Canova (1999) confirmed the robustness of the identified structural breaks regardless of a de-trending method. Then, the Bai and Perron method is used to identify the optimal number and positions of structural breaks as in Zeileis (2002). the minimum duration (k) is 10 week.

Each price index series is divided at identified optimal breakpoints. The first and last price partitions are removed since they are censored i.e. start or end date is not known. An individual price partition between adjacent optimal structural breaks becomes a separate regime. The average number of regimes in individual stock index series is approximately 55. The duration data is finally obtained by counting the number of observations in each regime. The mean duration is 23.0 weeks. The descriptive statistics of the duration data are summarized in the following table.

[*Insert Table 2 here*]

The second stage is to test for duration dependence in the derived duration data. Both Weibull and Log-logistic hazard functions are estimated. In addition, the duration data are separately tested depending on the slope of a regime. A regime with a positive slope of price is interpreted as the period of a bull market and that with a negative slope is specified as the period of a bear market. The results are presented in the next table.

[*Insert Table 3 here*]

The estimated hazard function that is a better fit for each duration series is interpreted as a representative result. In general, the Weibull hazard function is a better fit. The values of Akaike Information Criteria are calculated by $AIC = 2 \times n - 2 \log L$ where n is the number of parameters (n=2).

[Insert Table 4 here]

In summary, 13 out of 27 price indices (48%) show duration dependence in any of the positive, negative or total price regimes at the 5% significance level. All of the discovered duration dependence is positive duration dependence ($\delta > 1$). In Weibull hazard functions, it means that as a regime continues with the same parameter values, a new structural break is more likely to arise. Where the log-logistic hazard function is a better fit, positive duration dependence will eventually turn into negative duration dependence in a larger duration. Two examples of estimated hazard functions are shown in the following figure.

[Insert Figure 1 here]

On the other hand, the bear markets are more affected by positive duration dependence than the bull markets: 9 versus 4. This result may indicate that a structural break more likely to arise in bear markets than bull markets given the duration. Another finding is that the secondary stock exchanges of a country tend to have stronger positive duration dependence, e.g., the NYSE and the NASDAQ, the Tokyo 1st and 2nd Section, the Bombay Stock Exchange and the National Stock Exchange, and the Shanghai Stock Exchange and the Shenzhen Stock Exchange. This may be because the secondary stock markets are inherently more prone to

structural breaks than the primary markets. Meanwhile, the stock exchanges in developing economies show stronger duration dependence (7 out of 12, 58.3%) than those in developed economies (6 out of 15, 40.0%).

In addition, the pooled data of all 27 duration series are analyzed for duration dependence in structural breaks. The following table confirms the existence of positive duration dependence in all positive, negative and total regimes of pooled data. Since the Weibull function is a better fit in all cases, it can be concluded that hazard rates decrease monotonically with duration.

[Insert Table 5 here]

Both estimated hazard functions are illustrated in the following figure. The magnitude of the change is smaller than that of the individual price index due to the weak duration dependence in some indices.

[Insert Figure 2 here]

On the other hand, the duration-dependence Markov-switching (DDMS) method is employed to analyze the identical price index data. Following Chen (2007) and Castro (2012), year-to-year percentage returns are used and thus the number of observations is 12 less than the DDSB method. As in Durland and McCurdy (1994), two regimes are assumed to exist: high-return and low-volatility bull markets and low-return and high-volatility bear markets. A state variable evolves through the first-order Markov process as in Equations 11 and 12. Maximum duration is set at 52 weeks. Pelagatti (2008)'s Bayesian inference is utilized to estimate unknown parameters in Equation 19.

As seen in the next table, the DDMS method also indicates dominant positive duration dependence in the stock exchanges. In other words, one regime is more likely to switch to the other regime if it persists over time except the Brazilian stock exchange where exists negative duration dependence.

[Insert Table 6 here]

Strong evidence of positive duration dependence is consistent with the previous results by the DDSB method. However, in the latter DDMS method, the percentage of stock exchanges with positive duration dependence is fairly higher and more positive duration dependences are identified in the bull markets than the bear markets. The differences between developed and developing markets and between the primary and secondary markets are barely identifiable as shown in the next table.

[Insert Table 7 here]

These results may be because the DDMS restricts the number of regimes and treats potentially different regimes as either of two regimes. Then, it may over-estimate the probability of switching and indicate stronger positive duration dependence, in more price indices. On the other hand, the difference can be partly explained by methodological dissimilarities. Each method investigates duration dependence from different perspectives. Then, the preference of the method may depend on the belief between a trending regressor with structural breaks or a unit root process. However, there remain methodological issues in distinguishing between the two (Perron, 2006).

The evidence of duration dependence discovered needs to be interpreted with a little caution. First, the limitation on the length of duration may have affected the results. The DDSB method restricts minimum duration and the DDMS method constrains maximum duration. It inevitably leads to some censored duration data. However, minimum duration (10 weeks) in the DDSB method used in this study is far from the mean duration (23.0), and maximum duration (52 weeks) in the DDMS method seems reasonable in weekly data. Next, both methods assume that only duration affects hazard rates or transition probabilities. Although duration analysis is able to incorporate other explanatory variables (Kiefer, 1988), duration itself could be a reasonable approximation of the others (Durland and McCurdy, 1994). Thus, the impact of these limitations may be minimal.

IV. Concluding Remarks

This study conducted the duration analysis of structural breaks using the new two-step DDSB method, which combines a structural break test and a parametric duration dependence test, on the price index data of 27 international stock exchanges. It first identifies optimal breakpoints by the Bai and Perron method and obtains duration data by counting the length of each regime. Then, it examines the changes in hazard rates in duration by estimating hazard functions.

In summary, this study discovered strong evidence for positive duration dependence in structural breaks in 13 out of 27 individual stock price indices as well as the pooled data. A significant positive relationship exists between the duration of a regime and the conditional probability of a new structural break. In other words, as one regime continues with the same parameter values, the probability of a new structural break becomes higher. This tendency is stronger in bear markets, the secondary stock exchanges of a country and developing countries. The existence of positive duration dependence was also supported by the duration-dependence Markov-switching (DDMS) method, which examines transition probabilities between two regimes. However, the DDMS method may over-estimate the degree of positive duration dependence since it uses a limited number of regimes. These results provided new insights in

understanding structural breaks, in particular the changes in the likelihood of structural breaks in duration; but there remain some methodological issues regarding the comparison between structural breaks and unit root processes, or the analysis of their interplay as summarized in Perron (2006). They remain on the agenda for future research.

V. References

- Andrews, D. W. K. (1993) Tests for Parameter Instability and Structural Change With Unknown Change Point. *Econometrica*, **61**, 821-856
- Atella, V., Centoni, M., Cubadda, G. (2008) Technology shocks, Structural Breaks and the Effects on the Business Cycle. *Economics Letters*, **100**, 392-395
- Bai, J., Perron, P. (1998) Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, **66**, 47-78
- Bai, J., Perron, P. (2003) Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics*, **18**, 1-22
- Bhaduri, S. N., Mahima, R. (2009) Bubble in the Indian Stock Market: Myth or Reality. *Macroeconomics & Finance in Emerging Market Economies*, **2**, 79-92
- Brown, R. L., Durbin, J., Evans, J. M. (1975) Techniques for Testing the Constancy of Regression Relationships over Time (with Discussion). *Journal of the Royal Statistical Society: Series B*, **37**, 149-192
- Campbell, J. Y., Lo, A. W., MacKinlay, C. A. (1997) *The Econometrics of Financial Markets*. Princeton University Press, Princeton.
- Canova, F. (1999) Does Detrending Matter for the Determination of the Reference Cycle and the Selection of Turning Points? *The Economic Journal*, **109**, 126-150
- Castro, V. (2012) The Portuguese Stock Market Cycle. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, **2012**, 1-23
- Chen, S. W., Shen, C. H. (2007) Evidence of the Duration-Dependence from the Stock Markets in the Pacific Rim Economies. *Applied Economics*, **39**, 1461-1474
- Chong, T. T.-L., Li, Z., Chen, H., Hinich, M. (2010) An Investigation of Duration Dependence in the American Stock Market Cycle. *Journal of Applied Statistics*, **37**, 1407-1416
- Chow, G. C. (1960) Tests of Equality Between Sets of Coefficients in Two Linear Regressions. *Econometrica*, **28**, 591-605
- Clements, M. P., Hendry, D. F., G. Elliott, C. W. J. G., Timmermann, A. (2006) *Forecasting with Breaks*. In: Handbook of Economic Forecasting. Elsevier, pp. 605-657.
- Cox, D. R. (1972) Regression Models and Life-Tables (with discussion). *Journal of Royal Statistical Society*, **34**
- Durland, J. M., McCurdy, T. H. (1994) Duration-Dependent Transitions in a Markov Model of U.S. GNP Growth. *Journal of Business & Economic Statistics*, **12**, 279-288
- Elliott, G., Müller, U. K. (2003) Optimally Testing General Breaking Processes in Linear Time Series Models. *UCSD Economics Working Paper*, **2003-07**

- Hamilton, J. D. (1989) A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, **57**, 357-384
- Hansen, B. E. (2000) Testing for Structural Change in Conditional Models. *Journal of Econometrics*, **97**, 93-115
- Hansen, P. R. (2003) Structural Changes in the Cointegrated Vector Autoregressive Model. *Journal of Econometrics*, **114**, 261-295
- Harman, Y. S., Zuelke, T. W. (2004) Duration Dependence Testing for Speculative Bubbles. *Journal of Economics and Finance*,
- Hungnes, H. A. (2010) Identifying Structural Breaks in Cointegrated Vector Autoregressive Models. *Oxford Bulletin of Economics and Statistics*, **72**, 551-565
- Kaplan, E. L., Meier, P. (1958) Nonparametric Estimation from Incomplete Observations. *Journal of the American Statistical Association*, **53**, 457-481
- Kiefer, N. M. (1988) Economic Duration Data and Hazard Function. *Journal of Economic Literature*, **26**, 646-679
- Kiefer, N. M., Neumann, G. R. (1979) An Empirical Job-Search Model, with a Test of the Constant Reservation-Wage Hypothesis. *Journal of Political Economy*, **87**, 89-107
- Kim, C.-J. (1993) Unobserved-Component Time Series Models with Markov-Switching Heteroscedasticity: Changes in Regime and the Link between Inflation Rates and Inflation Uncertainty. *Journal of Business & Economic Statistics*, **11**, 341-349
- Kim, C.-J., Nelson, C. R. (1999) *State-Space Models with Regime Switching*. MIT Press.
- Kramer, W., Ploberger, W., Alt, R. (1988) Testing for Structural Change in Dynamic Models. *Econometrica*, **56**, 1355-1369
- Kuan, C. M., Hornik, K. (1995) The Generalized Fluctuation Test: A Unifying View. *Econometric Reviews*, **14**, 135-161
- Lam, P.-S. (2004) A Markov-Switching Model of GNP Growth with Duration Dependence. *International Economic Review*, **45**, 175-204
- Liu, J., Wu, S., Zidek, J. V. (1997) On Segmented Multivariate Regression. *Statistica Sinica*, **7**, 497-525
- Lunde, A., Timmermann, A. (2004) Duration-Dependence in Stock Prices: An Analysis of Bull and Bear Markets. *Journal of Business and Economic Statistics*, **22**, 253-273
- Maheu, J. M., McCurdy, T. H. (2000) Identifying Bull and Bear Markets in Stock Returns. *Journal of Business & Economic Statistics*, **18**, 100-112
- Marsh, L. C., Cormier, D. R. (2002) *Spline Regression Models*. SAGE Publications, Thousand Oaks.

- McQueen, G., Thorley, S. (1994) Bubbles, Stock Returns, and Duration Dependence. *The Journal of Financial and Quantitative Analysis*, **29**, 379-401
- Mokhtar, S. H., Nassir, A. M., Hassan, T. (2006) Detecting Rational Speculative Bubbles in the Malaysian Stock Market. *International Research Journal of Finance and Economics*,
- Ozun, A., Turk, M. (2009) A Duration-Dependent Regime Switching Model for an Open Emerging Economy. *Journal for Economic Forecasting*, **0**, 66-81
- Pelagatti, M. M. (2008) *Duration Dependent Markov-Switching Vector Autoregression: Properties, Bayesian Inference, Software and Application*. In: Nagakawa T (Ed.) *Business Fluctuations and Cycles*. Nova Science Publishers, Hamburg, pp. 43-46.
- Perron, P. (2006) *Dealing with Structural Breaks*. In: Palgrave Handbook of Econometrics.
- Rapach, D. E., Wohar, M. E. (2006) Structural Breaks and Predictive Regression Models of Aggregate U.S. Stock Returns. *Journal of Financial Econometrics*, **4**, 238-274
- Stock, J. H. (1994) *Unit Roots, Structural Breaks and Trends*. In: Engle RF & McFadden DL (Eds.) *Handbook of Econometrics*. North-Holland, Amsterdam, pp. 2739-2841.
- Yuhn, K.-H., Kim, S. B., Nam, J. H. (2010) Is a Financial Market Bubble Closely Related to a Real Asset Bubble? In: *Changes in the Financial Markets after the Financial Crisis*. Korea Institute of Finance
- Zeileis, A., Kleiber, C., Kramer, W., Hornik, K. (2003) Testing and Dating of Structural Changes in Practice. *Computational Statistics & Data Analysis*, **44**, 109-123
- Zeileis, A., Leisch, F., Hornik, K., Kleiber, C. (2002) strucchange: An R Package for Testing for Structural Change. *Journal of Statistical Software*, **7**
- Zhang, B. (2008) Duration Dependence Test for Rational Bubbles in Chinese Stock Market. *Applied Economics Letters*, **15**, 635 - 639

Table 1. Descriptive statistics of stock index prices

Region	Country	Index	Obs.	Start Date	Mean	Maximum	Minimum	SD
US & Canada	US	NYSE Composite	1543	13/06/1983	4691.98	10256.20	906.49	2661.87
		NASDAQ 100	1543	13/06/1983	1110.89	4704.73	99.45	921.80
	Canada	Toronto Comp.	1543	13/06/1983	6908.54	14984.20	2090.20	3659.75
Europe	UK	FTSE100	1543	13/06/1983	3961.73	6930.20	916.70	1735.51
Developed	Germany	Frankfurt MDAX	1305	04/01/1988	4815.81	11994.32	923.00	2884.79
	Spain	Madrid General	1543	13/06/1983	633.88	1716.89	50.97	425.28
	France	Paris CAC40	1330	13/07/1987	3276.08	6922.33	911.80	1401.36
	Italy	FTSE MIB	783	05/01/1998	29 767.86	50 108.56	12 620.57	9009.16
	Swiss	Swiss Market	1279	04/07/1988	5072.65	9487.50	1287.60	2310.11
	Sweden	Stokholm OMX	1409	06/01/1986	605.18	1537.33	87.65	374.73
	Japan	Tokyo TOPIX	1543	13/06/1983	1369.04	2884.80	640.22	466.10
Asia Developed		Tokyo 2nd Sec.	1543	13/06/1983	2389.15	5531.09	1042.22	818.75
	Hongkong	Hang Seng	1543	13/06/1983	10 743.34	31 586.90	715.01	7038.89
	Korea	KOSPI200	1200	08/01/1990	127.36	295.35	33.19	66.13
	Taiwan	Weighted	1543	13/06/1983	5688.35	12 424.53	636.04	2526.51
BRICS	Brazil	Bovespa	1202	25/12/1989	23 338.61	73 438.00	0.01	23 080.44
Developing	Russia	MICEX	798	22/09/1997	822.15	1956.14	18.53	615.00
	India	Bombay MSE100	1357	05/01/1987	1921.97	6675.78	120.56	1829.92
		NSE CNX500	1148	07/01/1991	1824.54	5500.15	343.74	1444.78
	China	Shanghai A	1096	06/01/1992	1820.62	6330.48	298.77	1034.32
		Shenzhen B	1057	05/10/1992	291.10	875.26	44.98	224.95
Other	Poland	Warsaw General	1133	22/04/1991	23 368.17	67 288.81	660.30	16 047.18
Developing	Turkey	Istanbul 100	1305	04/01/1988	18 291.10	78 208.44	3.62	21 853.11
	Mexico	IPC35	1305	04/01/1988	11 610.82	43 705.83	87.42	12 552.10
	Argentina	Mervel	1211	23/10/1989	1074.86	3631.80	15.89	859.99
	South Africa	JSE All	914	26/06/1995	16 225.92	39 250.24	4359.51	10 221.72
	Indonesia	IDX Composite	1543	13/06/1983	941.51	4375.17	61.58	1089.33

Note: this table shows the descriptive statistics of 27 weekly average stock price indices of 23 countries. The end dates are 31 Dec 2012 for all series. Obs. and SD stand for the number of observations and standard deviation, respectively.

Table 2. Descriptive statistics of duration data

Region	Country	Index	Obs.	Mean	Median	Max.	SD	Skewness	Kurtosis
US & Canada	US	NYSE Composite	62	23.7903	20	70	14.5322	1.4359	4.6356
		NASDAQ 100	60	24.7833	23	59	12.7000	1.0350	3.4218
	Canada	Toronto Comp.	69	21.3913	18	58	11.4419	1.2984	4.3507
Europe Developed	UK	FTSE100	71	21.0563	16	63	11.8525	1.5630	5.3575
	Germany	Frankfurt MDAX	53	23.8302	21	61	12.6183	1.3698	4.5511
	Spain	Madrid General	70	21.2571	19	67	12.3695	2.0030	7.3311
	France	Paris CAC40	50	25.8600	21	95	15.5446	2.1727	9.3982
	Italy	FTSE MIB	38	19.8158	16	57	11.6546	1.5037	4.7509
	Swiss	Swiss Market	52	23.6923	21	55	13.4070	0.7665	2.4600
	Sweden	Stokholm OMX	60	22.8167	18	70	14.1894	1.5635	4.7563
	Japan	Tokyo TOPIX	66	22.8030	21	64	12.6128	1.4394	5.0026
Asia Developed		Tokyo 2nd Sect.	74	20.4730	19	62	9.2028	1.8350	8.0878
	Hongkong	Hang Seng	71	21.1268	18	71	11.5807	1.6218	6.5854
	Korea	KOSPI200	53	21.6226	20	42	9.7216	0.5757	2.2058
	Taiwan	Weighted	63	23.5079	20	75	14.5012	1.6832	5.9636
	Brazil	Bovespa	42	27.5000	24	71	16.8599	0.8315	2.6873
BRICS Developing	Russia	MICEX	31	24.2581	21	53	12.2365	0.9900	3.0399
	India	Bombay MSE100	62	20.9032	18	45	9.4794	0.8638	2.7420
		NSE CNX500	50	22.0800	21	46	9.3827	0.8708	3.1266
	China	Shanghai A	45	22.8444	19	51	11.2330	0.8555	2.8577
		Shenzhen B	49	20.8980	20	50	7.7278	1.5182	6.5676
Other	Poland	Warsaw General	41	26.1463	19	102	17.9173	2.1986	9.1523
Developing	Turkey	Istanbul 100	54	23.2963	19	84	15.8871	1.8019	6.4079
	Mexico	IPC35	57	21.6140	18	64	12.3053	1.9006	6.3810
	Argentina	Mervel	44	26.2955	20	82	16.5327	1.6655	5.3020
	South Africa	JSE All	35	24.3714	19	62	13.6707	1.2759	3.8426
	Indonesia	IDX Composite	62	23.0161	19	92	15.0687	2.6561	11.3878
Average			55	23.0019	19	66	12.8233	1.4554	5.2723

Note: this table shows the descriptive statistics of duration data that are derived by dividing the stock index data at optimal breakpoints. Minimum duration is 10 week. Obs. and SD stand for the number of observations in each duration series and standard deviation, respectively.

Table 3. Parametric duration dependence tests: individual indices

Stock	Type	Weibull					Log-logistic					Fit	Sig.
Market		γ	δ	LogL	AIC	p(LR)	γ	δ	LogL	AIC	p(LR)		
US	(+)	0.0450	1.0876	-133.50	271.01	0.5435	0.0280	1.4763	-136.66	277.32	0.0101	Wei	
NYSE	(-)	0.1080	0.9068	-94.36	192.72	0.4988	0.0809	1.3219	-95.32	194.64	0.0917	Wei	
	Total	0.0703	0.9876	-229.02	462.04	0.9007	0.0485	1.3753	-233.33	470.65	0.0042	Wei	
US	(+)	0.0123	1.4083	-118.81	241.61	0.0324	0.0049	1.8936	-121.99	247.98	0.0002	Wei	**
NASDAQ	(-)	0.0381	1.3292	-99.52	203.04	0.0669	0.0221	1.8340	-101.65	207.31	0.0003	Wei	*
	Total	0.0304	1.2353	-223.60	451.20	0.0492	0.0146	1.7309	-227.87	459.74	0.0000	Wei	**
Canada	(+)	0.0351	1.2134	-124.74	253.48	0.1723	0.0179	1.6961	-127.17	258.35	0.0008	Wei	
	(-)	0.1052	0.9804	-115.68	235.36	0.8801	0.0833	1.4062	-117.16	238.32	0.0201	Wei	
	Total	0.0674	1.0615	-242.48	488.96	0.5360	0.0459	1.4841	-246.95	497.89	0.0002	Wei	
UK	(+)	0.0612	1.0385	-139.57	283.15	0.7680	0.0357	1.5049	-141.38	286.76	0.0050	Wei	
	(-)	0.0787	1.1213	-106.06	216.12	0.4192	0.0584	1.5831	-107.75	219.50	0.0030	Wei	
	Total	0.0747	1.0357	-247.69	499.38	0.7056	0.0471	1.5136	-250.36	504.72	0.0001	Wei	
Germany	(+)	0.0227	1.3143	-127.23	258.46	0.0551	0.0080	1.9130	-129.03	262.07	0.0001	Wei	*
	(-)	0.0689	1.0639	-66.24	136.47	0.7301	0.0393	1.5685	-66.98	137.96	0.0303	Wei	
	Total	0.0367	1.1978	-194.62	393.24	0.1066	0.0165	1.7338	-197.56	399.13	0.0000	Wei	
Spain	(+)	0.0608	1.0679	-122.15	248.30	0.6232	0.0312	1.5906	-123.35	250.69	0.0030	Wei	
	(-)	0.0689	1.0917	-122.63	249.25	0.4889	0.0316	1.7488	-121.85	247.71	0.0002	Log	***
	Total	0.0655	1.0748	-245.12	494.24	0.4326	0.0322	1.6566	-245.66	495.32	0.0000	Wei	
France	(+)	0.0321	1.1223	-116.36	236.73	0.4383	0.0139	1.6153	-118.08	240.16	0.0048	Wei	
	(-)	0.0148	1.6412	-69.69	143.37	0.0131	0.0064	2.1703	-72.46	148.92	0.0004	Wei	**
	Total	0.0352	1.1626	-190.34	384.68	0.1776	0.0123	1.7656	-192.08	388.15	0.0000	Wei	
Italy	(+)	0.1165	0.8741	-77.30	158.60	0.4064	0.0990	1.2667	-77.92	159.84	0.1869	Wei	
	(-)	0.0850	1.1318	-49.94	103.88	0.5457	0.0680	1.5604	-51.00	106.00	0.0443	Wei	
	Total	0.1111	0.9355	-128.33	260.67	0.5899	0.0876	1.3725	-129.26	262.53	0.0230	Wei	
Swiss	(+)	0.0507	1.0696	-109.06	222.12	0.6646	0.0399	1.3816	-112.21	228.42	0.0449	Wei	
	(-)	0.1014	0.9036	-82.18	168.36	0.5331	0.0880	1.2580	-83.41	170.83	0.1891	Wei	
	Total	0.0716	0.9839	-191.73	387.46	0.8850	0.0596	1.3072	-196.23	396.46	0.0231	Wei	
Sweden	(+)	0.0690	0.9357	-128.16	260.31	0.6310	0.0528	1.2683	-130.78	265.56	0.1103	Wei	
	(-)	0.0361	1.4642	-83.09	170.18	0.0237	0.0189	2.0020	-85.90	175.80	0.0002	Wei	**
	Total	0.0734	0.9955	-217.55	439.10	0.9641	0.0431	1.4747	-219.61	443.23	0.0008	Wei	
Japan	(+)	0.0545	1.0526	-123.48	250.96	0.7148	0.0334	1.4520	-126.39	256.77	0.0181	Wei	
Tokyo	(-)	0.0636	1.0925	-114.98	233.95	0.5365	0.0484	1.4521	-118.13	240.25	0.0149	Wei	
	Total	0.0607	1.0584	-239.08	482.16	0.5681	0.0409	1.4434	-244.89	493.77	0.0008	Wei	
Japan	(+)	0.0472	1.2722	-121.47	246.95	0.0820	0.0294	1.7569	-124.11	252.22	0.0002	Wei	*
Tokyo 2nd	(-)	0.0252	1.3938	-127.95	259.90	0.0117	0.0045	2.3330	-126.91	257.83	0.0000	Log	***
	Total	0.0356	1.3205	-250.29	504.57	0.0035	0.0138	1.9690	-253.11	510.21	0.0000	Wei	***
Hong Kong	(+)	0.0385	1.1791	-143.61	291.21	0.2035	0.0191	1.6919	-145.47	294.95	0.0003	Wei	
	(-)	0.1224	0.9749	-101.28	206.56	0.8560	0.1173	1.3339	-103.31	210.62	0.0535	Wei	
	Total	0.0737	1.0384	-248.09	500.19	0.6895	0.0521	1.4522	-252.56	509.12	0.0003	Wei	
Korea	(+)	0.0863	0.9471	-93.76	191.52	0.7395	0.0887	1.1819	-96.90	197.80	0.3043	Wei	
	(-)	0.0136	1.6703	-88.81	181.62	0.0024	0.0037	2.4537	-89.93	183.86	0.0000	Wei	***
	Total	0.0437	1.2062	-186.11	376.22	0.1105	0.0307	1.5756	-192.07	388.14	0.0003	Wei	

Stock Market	Type	Weibull					Log-logistic					Fit	Sig.
		γ	δ	LogL	AIC	p(LR)	γ	δ	LogL	AIC	p(LR)		
Taiwan	(+)	0.0696	0.9784	-126.92	257.83	0.8689	0.0421	1.4203	-128.50	261.01	0.0210	Wei	
	(-)	0.0651	1.0436	-104.40	212.80	0.7747	0.0444	1.4422	-106.61	217.22	0.0263	Wei	
	Total	0.0684	1.0025	-231.51	467.01	0.9795	0.0432	1.4299	-235.14	474.29	0.0014	Wei	
Brazil	(+)	0.1166	0.7929	-87.18	178.36	0.1490	0.1130	1.0720	-88.81	181.63	0.6807	Wei	
	(-)	0.0147	1.3613	-74.91	153.82	0.1130	0.0055	1.8936	-76.25	156.51	0.0028	Wei	
	Total	0.0588	0.9749	-164.53	333.05	0.8396	0.0454	1.2841	-168.72	341.44	0.0598	Wei	
Russia	(+)	0.0495	1.0551	-65.07	134.14	0.7919	0.0383	1.3506	-67.17	138.33	0.1597	Wei	
	(-)	0.0114	1.6563	-47.62	99.23	0.0247	0.0010	2.9331	-46.48	96.97	0.0001	Log	***
	Total	0.0310	1.2430	-114.43	232.85	0.1467	0.0142	1.7557	-116.72	237.45	0.0008	Wei	
India	(+)	0.0458	1.2238	-102.74	209.48	0.1852	0.0274	1.7006	-104.86	213.72	0.0015	Wei	
Bombai	(-)	0.0377	1.2729	-110.59	225.19	0.1019	0.0193	1.8111	-112.39	228.78	0.0003	Wei	
	Total	0.0415	1.2485	-213.37	430.74	0.0363	0.0230	1.7551	-217.32	438.65	0.0000	Wei	**
India	(+)	0.0177	1.5066	-90.07	184.14	0.0170	0.0076	2.0717	-92.16	188.32	0.0001	Wei	**
National	(-)	0.0300	1.3228	-84.31	172.63	0.1039	0.0134	1.8766	-85.96	175.93	0.0011	Wei	
	Total	0.0234	1.4095	-174.56	353.11	0.0047	0.0101	1.9744	-178.23	360.46	0.0000	Wei	***
China	(+)	0.0358	1.2104	-69.72	143.44	0.3354	0.0245	1.5494	-72.24	148.47	0.0376	Wei	
Shanghai	(-)	0.0486	1.1515	-92.61	189.22	0.3802	0.0281	1.6159	-94.41	192.82	0.0073	Wei	
	Total	0.0431	1.1728	-162.44	328.88	0.2020	0.0271	1.5779	-166.83	337.66	0.0008	Wei	
China	(+)	0.0279	1.4210	-79.90	163.80	0.0363	0.0076	2.2308	-80.09	164.18	0.0001	Wei	**
Shenzhen	(-)	0.0060	1.9359	-81.38	166.77	0.0002	0.0007	2.9858	-82.34	168.68	0.0000	Wei	***
	Total	0.0146	1.6317	-162.35	328.70	0.0001	0.0030	2.5041	-163.84	331.68	0.0000	Wei	***
Poland	(+)	0.0662	0.9091	-84.53	173.07	0.5681	0.0434	1.2951	-85.55	175.10	0.1651	Wei	
	(-)	0.0244	1.3844	-70.37	144.74	0.0874	0.0091	1.9952	-71.74	147.48	0.0014	Wei	*
	Total	0.0536	1.0257	-157.49	318.98	0.8322	0.0256	1.5388	-158.68	321.36	0.0022	Wei	
Turkey	(+)	0.1106	0.9468	-87.07	178.14	0.7178	0.0883	1.3766	-87.90	179.80	0.0592	Wei	
	(-)	0.0729	0.9216	-108.50	220.99	0.5766	0.0501	1.2933	-110.29	224.57	0.1160	Wei	
	Total	0.0952	0.9015	-197.14	398.27	0.3153	0.0703	1.2995	-199.38	402.76	0.0246	Wei	
Mexico	(+)	0.0486	1.1218	-109.19	222.39	0.4139	0.0167	1.8044	-108.91	221.81	0.0006	Log	***
	(-)	0.0609	1.1474	-91.06	186.12	0.3670	0.0300	1.7458	-91.58	187.16	0.0018	Wei	
	Total	0.0560	1.1180	-200.89	405.79	0.2767	0.0229	1.7592	-200.99	405.98	0.0000	Wei	
Argentina	(+)	0.0408	1.0859	-93.79	191.58	0.6120	0.0195	1.5916	-94.71	193.41	0.0118	Wei	
	(-)	0.0316	1.2144	-74.72	153.43	0.2464	0.0044	2.2590	-72.30	148.59	0.0002	Log	***
	Total	0.0365	1.1412	-168.78	341.57	0.2597	0.0114	1.8296	-167.99	339.97	0.0000	Log	***
South Africa	(+)	0.0213	1.2875	-77.18	158.37	0.1672	0.0069	1.9379	-77.38	158.77	0.0014	Wei	
	(-)	0.0550	1.1627	-51.32	106.65	0.4637	0.0270	1.7615	-51.54	107.08	0.0170	Wei	
	Total	0.0364	1.1860	-129.84	263.68	0.2070	0.0144	1.8034	-130.20	264.40	0.0002	Wei	
Indonesia	(+)	0.0411	1.1271	-120.79	245.59	0.3946	0.0182	1.6543	-122.38	248.75	0.0020	Wei	
	(-)	0.0784	1.0303	-103.68	211.35	0.8167	0.0230	1.8501	-101.44	206.87	0.0004	Log	***
	Total	0.0588	1.0628	-225.49	454.98	0.5233	0.0225	1.7039	-225.12	454.25	0.0000	Log	***

Note: this table shows the results of parametric duration analysis of 27 duration series in Table 2 using two hazard functions: Weibull (Wei) and Log-logistic (Log). Each duration data is divided into three sub-groups depending on the slope of a trending regressor of each regime: positive, negative and total.

γ is a scale and δ is a shape parameter of hazard functions. In general, if $\delta > 1$, positive duration dependence exists. If $0 < \delta < 1$, negative duration dependence exists. logL is log likelihood values and AIC is the Akaike information Criteria. p(LR) is the p-value of the likelihood ratio test for $H_0: \delta = 1$. 'Fit' indicates which hazard function is a better fit. In 'Sig' column, *** represents the significance at 1%, ** represents the significance at 5% and * indicates significance at 10%.

Table 4. Summary: the duration dependence in structural break (DDSB) method

Category	Type	Num.	Sig 5%	
Market condition	Bull	27	3	(11.11%)
	Bear	27	9	(37.04%)
Economic development	Developed	15	6	(40.00%)
	Developing	12	7	(58.33%)
Market section	Primary	4	1	(25.00%)
	Secondary	4	4	(100.00%)
Total	All	27	13	(48.15%)

Note: this table summarizes the percentage of significant duration dependence in three different categories. ‘Num.’ represents the number of stock indices in the category. ‘Sig 5%’ indicates significance at the 5% level. The significance is measured by p-values in the LR tests reported in Table 3.

Table 5. Parametric duration dependence tests: pooled duration data

Type	Weibull					Log-logistic					Fit	Sig.
	γ	δ	LogL	AIC	p(LR)	γ	δ	LogL	AIC	p(LR)		
(+)	0.0525	1.0696	-2902.29	5808.59	0.0186	0.0304	1.5142	-2951.40	5906.80	0.0000	Wei	**
(-)	0.0567	1.1294	-2455.58	4915.17	0.0000	0.0295	1.6593	-2486.53	4977.05	0.0000	Wei	***
Total	0.0558	1.0860	-5371.01	10 746.02	0.0001	0.0306	1.5728	-5445.71	10 895.42	0.0000	Wei	***

Note: this table presents the results of the parametric duration dependence test of the pooled duration data of 27 stock price indices. The total number of identified regimes is 1484. The number of regimes with positive slope is 779 and that with negative slope is 705. The analysis employs two different distributions of hazard functions. Weibull (Wei) is monomotic and Loglogistic (Log) is a non-monotonic function. γ is a scale and δ is a shape parameter of hazard functions. If $\delta > 1$, positive duration dependence exists. If $0 < \delta < 1$, negative duration dependence exists. logL is log likelihood values and AIC is the Akaike information Criteria. p(LR) is the p-value of the likelihood ratio test for $H_0: \delta = 1$. 'Fit' indicates which function is a better fit. In 'Sig' column, *** represents the significance at the 1% level. ** represents the significance at the 5% level and * indicates significance at the 10% level.

Table 6. The duration-dependence Markov-switching models

Stock	Run				Stock	Run			
Market	Type	Beta	Dep.	Sig 5%	Market	Type	Beta	Dep.	Sig 5%
US	(+)	-0.0970	Pos	**	Taiwan	(+)	-0.0347	Pos	**
NYSE	(-)	0.0322	Pos	**		(-)	0.0571	Pos	**
US	(+)	-0.0498	Pos		Brazil	(+)	0.0061	Neg	
NASDAQ	(-)	0.0135	Pos			(-)	-0.0423	Neg	
Canada	(+)	-0.0184	Pos	**	Russia	(+)	-0.0455	Pos	**
	(-)	0.0503	Pos	**		(-)	0.0177	Pos	
UK	(+)	-0.1188	Pos	**	India	(+)	-0.0343	Pos	**
	(-)	0.0120	Pos		Bombai	(-)	0.0163	Pos	
Germany	(+)	-0.0492	Pos	**	India	(+)	-0.0774	Pos	**
	(-)	0.0714	Pos	**	National	(-)	0.0455	Pos	**
Spain	(+)	-0.0082	Pos		China	(+)	-0.0066	Pos	
	(-)	0.0091	Pos		Shanghai	(-)	0.0128	Pos	
France	(+)	-0.1220	Pos	**	China	(+)	-0.0372	Pos	**
	(-)	0.1259	Pos	**	Shenzhen	(-)	0.0600	Pos	**
Italy	(+)	-0.0801	Pos	**	Poland	(+)	-0.1474	Pos	**
	(-)	0.1131	Pos	**		(-)	0.1015	Pos	
Swiss	(+)	-0.0626	Pos	**	Turkey	(+)	-0.0236	Pos	**
	(-)	0.0211	Pos			(-)	0.0140	Pos	
Sweden	(+)	-0.0155	Pos		Mexico	(+)	-0.1035	Pos	
	(-)	0.0211	Pos			(-)	0.0796	Pos	**
Japan	(+)	-0.0093	Pos		Argentina	(+)	-0.0269	Pos	**
Tokyo	(-)	0.0572	Pos	**		(-)	0.0280	Pos	**
Japan	(+)	-0.0336	Pos	**	South Africa	(+)	-0.0002	Pos	
Tokyo 2nd	(-)	0.0099	Pos			(-)	0.0252	Pos	
Hong Kong	(+)	-0.0073	Pos		Indonesia	(+)	-0.0118	Pos	
	(-)	0.0212	Pos			(-)	0.0517	Pos	**
Korea	(+)	-0.0121	Pos						
	(-)	0.0329	Pos	**					

Note: this table presents the analysis results of the duration-dependence Markov-switching (DDMS) models on the year-to-year return data of the same 27 stock indices. ‘Beta’ indicates the value of β_2 in bull markets or that of β_4 in bear markets. ‘Dep.’ is the type of duration dependence where ‘Pos’ is positive and ‘Neg’ is negative. ** under ‘Sig 5%’ indicates the significance of β_2 or β_4 at the 5% level.

Table 7. Summary: the duration dependence Markov-switching model

Category	Type	Number	Sig 5%
Market condition	Bull	27	16 (59.26%)
	Bear	27	13 (48.15%)
Economic development	Developed	15	11 (73.33%)
	Developing	12	9 (75.00%)
Market section	Primary	4	3 (75.00%)
	Secondary	4	4 (100.00%)
Total	All	27	20 (74.07%)

Note: this table summarizes the percentage of significant duration dependence revealed by the DDMS method in three different categories. ‘Sig 5%’ indicates the significance of β_2 or β_4 at the 5% level. ‘Number’ indicates the number of indices in each category.

Figure 1. The estimated Weibull and log-logistic hazard functions: selected examples

The two graphs show the estimated Weibull hazard function of the positive runs of CNX500 of the National Stock Exchange in India and the estimated log-logistic hazard function of the negative runs of the Tokyo Stock Exchange 2nd Section Price Index. Both functions are a better fit for each specific stock price index. Y-axis is the hazard rate and X-axis is duration.

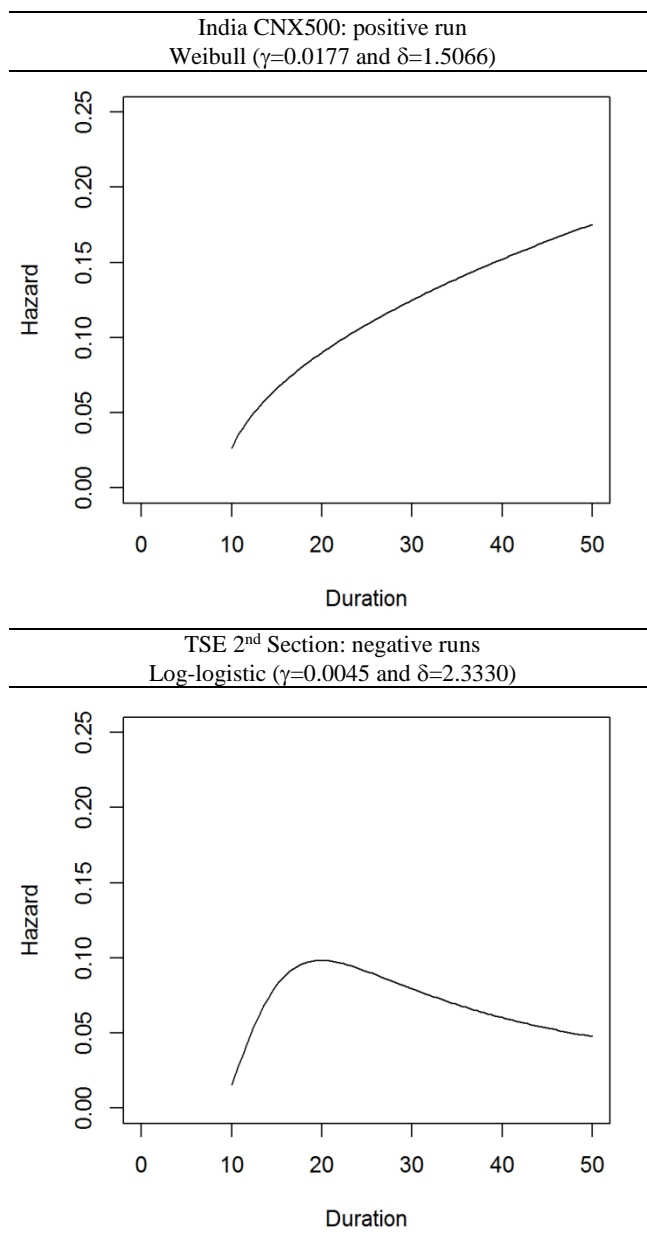


Figure 2. The estimated Weibull and log-logistic hazard functions: pooled duration data

The two graphs show the estimated Weibull and log-logistic hazard functions of the pooled duration data of 27 indices. The Weibull hazard function in the upper panel is a better fit. Y-axis is the hazard rate and X-axis is duration.

