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How Stable is the Underlying Process of Stock Prices? Empirical Evidence of Structural Breaks in the Firm-Level Dividend of the U.S. Firms

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ABSTRACT

In this paper, we present empirical evidence of instability in the form of structural breaks in dividend at the firm level of the U.S. firms. We perform the Bai and Perron (2003) structural break program that estimates multiple breaks based on deterministic econometric approach. We also observe for links between any specific episodes in the economic and financial history of the U.S and structural breaks detected in the dividend process of the U.S firms.

JEL Classification:

Keywords: structural breaks, firm level, dividend

INTRODUCTION

The ability to forecast the return on stock market is dependent on whether or not the existing stock price has been fully incorporated and reflected by all the information available at present time. This is the idea behind one of the main propositions of modern finance theory, i.e. the Efficient Market Hypothesis (EMH). If the implication of EMH is correct, stock prices should equal the present value of expected future dividends.

Brennan (1998) questions the stability phenomenon observed when examining the average return on U.S stocks since 1926 despite the major changes happening in the economy, technology and social aspects over the years. In other words, in order to generate a

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comprehensive picture of asset prices, it is necessary to take into account the stability of the underlying process of the stock prices. This stability has also been put to the question by Timmermann (2001), who inquires, “Is the fundamentals process underlying U.S stock prices stable over several decades?” Most of the studies on empirical asset-pricing which assay present value models do not question the issue of stability.

However, there are evidences of instability in the process of dividends which serves as a violation to the assumption made by most studies regarding the fundamentals process of U.S stock prices. Shiller (1992), Froot and Obstfeld (1991) and Fama and French (1998) who, based on U.S. historical data, have remarked upon the fact that it is difficult to attribute the movement of stock prices to the process of underlying fundamentals during certain periods.

Proof of the structural changes in the U.S. dividend series was presented by Timmermann (2001) and Esteve *et al.* (2013). Other studies that have analysed structural changes have put particular emphasis on the aggregate or index level data (Perron 1989, Banerjee *et al.* 1992, Zivot and Andrews 1992, Dolmas *et al.* 1999, McConnell and Perez-Quiros 2000, Hansen 2001, Granger and Hyung 2004, Homm and Breitung 2012).

There are some notable studies that utilise the firm-level data among which are Borensztein and Lee (2002) and Comin and Philippon (2006). The former analyse the credit crunch following the recent financial crisis in Korea by using enterprise-level data whereas the latter investigates the causes and consequences of the widespread increase in firm-level volatility. Until now, we have not yet encountered any significant contribution that looks at the instability scenario in the underlying process of stock prices from the firm-level perspective. Thus, one of the objectives of this paper is to fill this gap.

The presence of structural breaks in the economic and financial time series may lead to serious implications if it is ignored. It is a crucial matter that needs to be dealt with special care and attention, or otherwise one may obtain spurious results as argued by Perron (1989).

As mentioned earlier, the studies such as Brennan (1998) and Timmermann (2001) question the stability of the fundamentals process underlying U.S. stock prices. They argue that it is vital to take into consideration the stability of this fundamental process in order to fully understand asset prices. Timmermann (2001), by using the aggregate level data of U.S. dividend series provided by Shiller (2013), provides evidence of instability in the processes related to aggregate-level dividend. Timmermann (2001) also explains that, breaks in dividend process give rise to either “persistence” or “information” effect in which the stock prices can be affected. The “persistence” effect is when the breaks create a long lasting effect whereas the “information” effect is directly linked to the beliefs of the investors.

Moreover, Timmermann (2001) differentiate breaks from ordinary shocks by explaining that the former leads to an effect that persists for a longer period of time as it does not happen often if compared to the latter. In his study, he applies two different econometric methods; deterministic and non-deterministic approach of regime switching.

Our study, guided and motivated by Timmermann (2001) but utilizes a different set of data series, i.e. by utilizing the firm-level data, while taking advantage of cross-firm variation in U.S. stock market. By using a program designed by Bai and Perron (2003), we test for the presence of structural breaks in the time trend and autoregressive models by using a collation of quarterly firm-level dividend series of the dividend series of U.S. firms

Evidently, we observe the presence of structural breaks at the firm-level. We utilize the method developed by Bai and Perron (2003) for our investigation in which the multiple structural change(s) models are estimated based on deterministic econometric approach.

The structural breaks in index-level data are observed to be associated with the specific episodes in the economic and financial history of the U.S. (Timmermann 2001). As for the firm-level data, the finding is different in the sense that breaks can possibly be due to, not only the external but also the internal factors of every individual firm in the sub-sample. We discuss

The rest of this paper is structured as follows: section 2 discusses the literature review and formulates the research question, section 3 describes the empirical data and model, section 4 discusses the methodology, section 5 discusses empirical results and section 6 concludes.

LITERATURE REVIEW

The existence of structural breaks in macroeconomic and financial time series can pose serious problems, if they are ignored, as documented by many empirical studies. They lead to spurious results as argued by Perron (1989). The implications that are related to structural breaks include the long memory effects as discussed by Lamoureux and Lastrapes (1990),Baillie (1996), Mikosch and Stărică (2004), Hillebrand (2005) among others and the existence of higher order unconditional moments e.g. kurtosis (Mikosch and Stărică, 2004; Andreou and Ghysels, 2009). Moreover, breaks can also lead to an adverse performance of forecasting as argued by several studies (e.g. Clements and Hendry, 1998, 2001; Stock and Watson, 2003; Pesaran and Timmermann, 2004; Pesaran et al., 2006). In the economy, the following studies discuss on the evidence of breaks in the following key macroeconomic variables: inflation (Alogoskoufis and Smith, 1991), interest rate (Ang and Bekaert, 2002) and output growth (Stock and Watson, 2004), among others. In financial market, for instance, some significant issues in relation to structural breaks are also raised. For instance, the issues on asset allocation by Pettenuzzo and Timmermann (2011), equity premium by Pástor and Stambaugh (2001), and credit risk by Andreou and Ghysels (2006).

Pesaran et al. (2006) view the phenomenon of structural breaks as follows: “Structural changes or “breaks” appear to affect models for the evolution in key economic and financial time series such as output growth, inflation, exchange rates, interest rates and stock returns. This could reflect legislative, institutional or technological changes, shifts in economic policy, or could even be due to large macroeconomic shocks such as the doubling or quadrupling of oil prices experienced over the past decades.”

It is common that most breaks identified at aggregate-level are linked to the external factors. Timmermann (2001), by using the fundamentals process underlying U.S. stock prices presented evidence of breaks at the aggregate-level as well. The motivation is supported by Brennan (1998) who argues that “there are good reasons to doubt that this parameter has remained constant for almost three quarters of a century which has witnessed the most dramatic economic, technological and social change of any comparable period in history.” Timmermann (2001), in his paper, questions “Is the fundamentals process underlying U.S. stock prices stable over several decades?” He utilizes the aggregate-level of the U.S. dividend series provided by Shiller (2000) and observes for the links between the breaks and major economic and financial events associated with the U.S history.

What about dividend process at the firm level? It would be interesting to look at the issue of structural breaks in the context of dividend process at the firm level. We argue that breaks at the firm level can be driven by not only by external but also the internal factors. At the time of writing, we have not yet encountered any studies that look at breaks in the dividend process of U.S. firms at the firm level. Traditionally, Miller and Modigliani (1961) discuss the 'information content of dividends' which means that any decisions on dividend will convey information regarding future earnings of the firms provided that the expectations on firms' future earnings can affect the current decisions on dividend.

Technically, structural breaks can be divided into two different types: discrete (deterministic) and non-discrete (non-deterministic). In our study, we view breaks as discrete (deterministic) and the tests for this type of breaks can be divided into three different types; (1) structural break tests for "known" breaks, (2) structural break tests for "unknown" breaks. For example, the classic Chow test proposed by Chow (1960) is the first type of test that allows us to test whether a break has occurred at a particular date. We have seen the evolution of the second type of test in the literature from tests that allow for a single "unknown" break to ones that allow for a multiple "unknown" breaks. In our study, we utilize the methodology proposed by Bai and Perron (2003) for the detection of multiple "unknown" breaks. Therefore, we formulate the research question for this paper as the following:

Is the firm-level dividend process of U.S. firms stable?

The hypothesis is given as the following:
The dividend processes at the firm level of U.S. firms are not stable and subject to structural breaks.

METHODOLOGY AND DATA

The structural break analysis is carried out on quarterly, compounded dividend series of 263 firms by implementing the program designed by Bai and Perron (2003). This program allows the users to set up their own data and options and they also have flexibility in choosing the length of dataset, the number of breaks and the number of regressors. The techniques for optimal breaks selection; Sequential, Repartition, the Bayesian Information Criterion (BIC) and the modified version of Schwarz' Criterion proposed by Liu *et al.* (1997), abbreviated as LWZ are utilised for the detection of structural breaks in the dividend process of the U.S firms.

The estimation of the unknown regression coefficients as well as the break points in Bai and Perron (2003) method is based on the method of least squares. The estimated values of β and δ_j are computed for each m-partition $(T_1,...,T_m)$ by minimising the sum of squared residuals, $S_T(T_1,...,T_m)$. The estimated break points are such that

$$\left(\hat{T}_1,\ldots,\hat{T}_m\right)=\operatorname{argmin}_{T_1,\ldots,T_m} S_T\,(T_1,\,\ldots,\,T_m), \tag{1}$$

where all the partitions $(T_1,...,T_m)$ are subject to minimization such that T_i-$T_{i-1} \geq q$. The model used here is a pure structural change model where it is obtained when p=0 and all the coefficients are subjected to shifts. When p>0, a partial structural change model is obtained.

The structural break analysis is divided into several parts. First, depending on the maximum number of breaks chosen by the users, Global Optimization computes the break dates as the global minimizers of the sum of squared residuals. The algorithm for the method of Global Optimization is based on the principle of dynamic programming. It is not a new or unfamiliar concept as we can find this in studies as early as Fisher (1958). Bai and Perron (2003) generalise the original method to a model of partial structural change.

The Bai and Perron (2003) program also reports the sup-F type test of no structural breaks (m=0) versus the alternative hypothesis of a fixed number of m=k breaks. The conventional F-statistic, $F^*_T$is for testing $\delta_1=...=\delta_{k+1}$ against $\delta_i \neq \delta_{i+1}$.

Let $(T_1,...,T_K)$ be a partition such that $Ti = [T\lambda_i]$ where i = (1,...,k) and R be a matrix such that $(R\delta)' = (\delta'_1-\delta'_2,...,\delta'_k-\delta_k+_1)$. Then, $F^*_T$is given by

$$F_T(\lambda_1,\ldots,\lambda_k;q)=\frac{1}{T}\left(\frac{T-(k+1)q-p}{kq}\right)\hat{\delta}'R'\left(R\hat{V}(\hat{\delta})R'\right)R\hat{\delta}), \tag{2}$$

where $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\delta}})$ is an estimate of the variance covariance matrix of $\hat{\boldsymbol{\delta}}$ that is robust to serial correlation and heteroscedasticity.

Then, the sup-F test is defined as

$$\sup F_T(k;q)=F_T(\lambda_1,\ldots,\lambda_k;q), \tag{3}$$

where$\lambda_1,\ldots,\lambda_k$minimize the global sum of squared residuals implying the maximization of F-test by assuming spherical errors.

In the presence of serial correlation, it would be easier to compute the asymptotically equivalent, $\sup F_T(k;q)$ by using the breakpoints estimated by the Global Optimization procedure.

Moreover, Bai and Perron (2003) include the double maximum tests of no structural breaks versus an unknown number of breaks given some upper bound M. The first version of the test is the equally weighted one given by

$$\text{UDmax}\, F_T(M,q)=\max_{1\leq m\leq M} F_T(\lambda_1,\ldots,\lambda_m;q) \tag{4}$$

where$\hat{\boldsymbol{\lambda}}_j = \hat{\mathbf{T}}_j/T$ and j = 1,...,m are the break dates estimated by the Global Optimization procedure as before.

The second version is the value-weighted given by

$$\text{WDmax}\, F_T(M,q)=\max_{1\leq m\leq M}\frac{c\ (q,\alpha,1)}{c(q,\alpha,m)} F_T(\lambda_1,\ldots,\lambda_m;q), \tag{5}$$

where $c(q,\alpha,m)$ is the asymptotic critical value of the $\sup_{\lambda_1,\ldots,\lambda_m \epsilon \Lambda \epsilon} F_T(\lambda_1,\ldots,\lambda_m;q)$ for a significance level α.

This version of test applies different weights to individual tests when marginal p-values are equal for all values of m.
The techniques discussed previously do not estimate the optimal number of breaks. The Bayesian Information Criterion (BIC) defined as

$$\mathrm{BIC}(m)=\ln\widehat{\sigma^2}(m)+p^*\ln(T)/T, \tag{6}$$

where $p^*=(m+1)q+m+p$ and $\widehat{\sigma^2}(m)=T^{-1}S_T(\widehat{T_1},\ldots,\widehat{T}_m)$.

and a modified version of Schwarz' criterion proposed by Liu *et al.* (1997) given by

$$\mathrm{LWZ}(m)=\ln\left(S_T(\widehat{T_1},\ldots,\widehat{T}_m)/(T-p^*)\right)+(p^*/T)c_0(\ln T)^{2+\delta_0}. \tag{7}$$

As argued by Perron (1997), BIC and LWZ produce a reliable estimate of the number of breaks in the presence of no serial correlation. However, both tend to overestimate the true value when that is not the case. Moreover, without the presence of serial correlation, BIC is not reliable in a situation where the coefficient of the lagged of dependent variable included as a regressor in the model is large. LWZ would be better but it will choose a lower value than the true value here.

The empirical investigation in this study focuses on the techniques for optimal break selection; the techniques based on sequential hypothesis testing i.e. Sequential and Repartition as well as the information criteria, BIC and LWZ. Sequential is recommended by Bai and Perron (2003) to be used in practice, as it works best in estimating the number of breaks on the whole. The $\sup F_T(l+1|l)$test as proposed by Bai and Perron (1998) is defined as

$$\sup F_T(l+1|l)=\Big\{S_T\big(\widehat{T_1},\ldots,\widehat{T}_l\big)$$

$$\min_{1\le i\le l+1}\ \inf_{\tau\epsilon\Lambda_{i,\eta}} S_T(\widehat{T_1},\ldots,\widehat{T_{i-1}},\tau,\widehat{T}_i,\ldots,\widehat{T}_l)\Big\}/\widehat{\sigma^2},$$

where

$$\Lambda_{i,\eta}=\{\tau;\ \widehat{T_{i-1}}+\big(\widehat{T}_i-\widehat{T_{i-1}}\big)\eta\le\tau\le\widehat{T}_i-(\widehat{T}_i-\widehat{T_{i-1}})\eta\}\ .$$

Under the null hypothesis, the consistent estimate of $\boldsymbol{\sigma^2}$ is denoted by$\widehat{\boldsymbol{\sigma^2}}$. Note that I have $S_T(\widehat{T_1},\ldots,\widehat{T_{i-1}},\tau,\widehat{T}_i,\ldots,\widehat{T}_l)$ equals to $S_T\big(\tau,\widehat{T_1},\ldots,\widehat{T}_l\big)$ for i=1 and equals to $S_T\big(\widehat{T_1},\ldots,\widehat{T}_l,\tau\big)$ for $i=\boldsymbol{\ell}+\mathbf{1}$respectively.

The first step in the Sequential application based on the $\sup F_T(l+1|l)$ involves estimating a model with no break or a small number of breaks before conducting the parameter-constancy tests for each subsample (obtained by dividing the sample at the estimated break dates). A rejection in favour of the alternative hypothesis of $(\ell+1)$ breaks in a subsample implies adding a break to it. This process will continue to be repeated until the null hypothesis of no additional structural changes can no longer be rejected.

Bai (1997) argues that it is likely that we would under or overestimate the break dates and hence this is where Repartition test comes useful. Assuming the T consistent estimators of a total of m breaks denoted by $\widehat{T}_j$ (j=1,...,m), the repartition procedure will estimate these breaks again. For instance, the subsample ($\widehat{T}_{j-1}$, $\widehat{T}_{j+1}$) is used to estimate $\widehat{T}_0$. The new break points are consistent and have the same limiting distribution as the single break model as well as the model of multiple breaks obtained from the simultaneous method. The main part is to set up the data in three parts:

1. The dependent variable (y),
2. The variable(s) whose coefficients are subjected to structural breaks (z, dimension q) and
3. The variable(s) whose coefficients are not subjected to structural breaks (x, dimension p).

In the empirical investigation, the assumptions concerning the nature of the errors in relation to the regressor are taken into account by not allowing for the presence of heteroscedasticity and serial correlation in the residuals.

We consider two different types of break models for our structural break analysis in this paper by utilising the firm-level data:
For the firm-level structural breaks and event study analysis, we define the variables based on the general form of multiple linear regression model in (3):

- Trend stationary break model (Model 1): The variables subject to structural break are the drift α and the time trend, t, i.e. $z_t=\{\alpha, t\}$ where t= 1,..., N and N is the total number of observations. Therefore, the first regression model with m breaks (m+1 regimes) of interest is

$$\begin{aligned} \log D_t &= \alpha+\beta_1 t+u_t, && t=1,\dots, T_1, \\ \log D_t &= \alpha+\beta_2 t+u_t, && t=T_1+1,\dots,T_2, \\ &\vdots \\ \log D_t &= \alpha+\beta_{m+1} t+u_{t,}, && t=T_m+1,\dots, T. \end{aligned} \quad (8)$$

For model 1, the sign of break is defined as

$$\text{Sign} = \begin{cases} \text{Positive (Upward)}, & \beta_t > \beta_{t-1} \\ \text{Negative (Downward)}, & \text{otherwise.} \end{cases} \quad (9)$$

- Autoregressive break model (Model 2): In order to capture the essential dynamics of the dividend series, we also test for breaks with an intercept and the lagged of dependent variable, i.e. $z_t=\{\alpha, \log D_{t-1}\}$. The regression model with m breaks (m+1 regimes) is given by

$$\begin{aligned} \log D_t &= \alpha_1+\log D_{t-1}+u_t, && t=1,\dots, T_1, \\ \log D_t &= \alpha_2+\log D_{t-1}+u_t, && t=T_1+1,\dots,T_2, \\ &\vdots \\ \log D_t &= \alpha_{m+1}+\log D_{t-1}+u_t, && t=T_m+1,\dots, T. \end{aligned} \quad (10)$$

The sign of break in Model 2 is given by

$$\text{Sign} = \begin{cases} \text{Positive (Upward)}, & \alpha_t > \alpha_{t-1} \\ \text{Negative (Downward)}, & \text{otherwise.} \end{cases} \quad (11)$$

The main variable of concern is the quarterly compounded 'adjodiv' downloaded from the Centre for Research in Security Prices (CRSP) database. 'Adjodiv' is defined by CRSP as the "ordinary cash dividends paid, adjusted using the price adjustment factor". The adjustment for split events allows for a direct comparison of a stock or security at different times. CRSP is set to list down all the firms listed on the New York Stock Exchange (NYSE) from the first quarter of 1926 until the last quarter of 2010, i.e. 1926:1-2010:4.

This huge dataset is filtered according to some criteria. First, all the firms which are no longer available in the very last month of the time period concerned, i.e. December 2010 is removed. Next, firms with time series data of less than 40 years are removed. There is no specific reason for choosing 40 years. As pointed out from the very beginning, the concern here is not the survivorship bias. The goal is to have a reasonable number of firms in the sub-sample in order to carry out the firm-level empirical analysis. Finally, all the firms with missing observations are also removed. The total number of firms obtained is 263.

The quarterly compounded 'adjodiv' series is converted into real value by dividing it with the Consumer Price Index (CPI) provided by Shiller (2013). The logarithm of quarterly compounded real 'adjodiv', log D_t is used as the dependent variable in throughout the analysis.

EMPIRICAL RESULT AND DISCUSSION

Is the firm-level dividend process of U.S. firms stable?

An investigation on each firm is conducted and the results are presented for the following regression models of interest respectively:

- Model 1: Trend stationary break model
- Model 2: Autoregressive break model

A problem of matrix singularity is encountered in the structural break analysis for the autoregressive break model (Model 2) and in order to ensure the accuracy of the results obtained; a total number of 45 firms are removed from the total of 263 firms selected for the firm-level dataset.

Table 1 reports the number of break points detected by the Bai and Perron (2003) method adapted to the logarithm of quarterly real dividends series of selected U.S. firms. For the first break model i.e. trend stationary break model, LWZ is observed to always select a lower number of breaks than BIC with about 6% of the sub-sample of firms shown to choose zero breaks. Overall, LWZ, BIC, Sequential and Repartition show that at least 94% of the sub-sample of firms has at least a single break in the quarterly compounded dividend series for the trend stationary break model (Model 1). Sequential and Repartition always select the same number of breaks almost every time. Overall, these procedures result in selection of mostly 3 to 4 breaks and none of them result in the maximum number of 5 breaks. Note that we specify the maximum number of breaks, m=5 for the structural break analysis in this paper. The second break model i.e. autoregressive break model selects a total of fewer breaks compared to the first break model i.e. trend stationary break model. There are about 18% and 6% of the subsample of firms with zero breaks as recorded by LWZ and BIC in Table 2. Again, Sequential and Repartition produce consistent results where both show that about 71%

of the subsample of firms fails to reject the null hypothesis of zero breaks. LWZ and BIC are shown to select mostly 1 and 2 breaks throughout the analysis whereas Sequential and Repartition result in the selection of mostly 3 breaks. None of these procedures are shown to select the maximum number of 5 breaks.

Table 1: Structural Break Analysis in U.S. Dividend Series 1926-2010

Specifications				
z_t={ α ,t}, p=1, q=1, ϵ=0.10, M=5, robust=0				
Procedures				
No. of breaks selected	Sequential	Repartition	BIC	LWZ
MODEL 1: TREND STATIONARY				
0	15 (5.70%)	15 (5.70%)	10 (3.80%)	16 (6.00%)
1	20 (7.60%)	20 (7.60%)	26 (9.89%)	45 (17.11%)
2	43 (15.97%)	42 (15.97%)	40 (15.21%)	57 (21.67%)
3	91 (33.84%)	89 (33.84%)	77 (29.28%)	85 (32.32%)
4	92 (33.84%)	89 (33.84%)	110 (41.83%)	60 (22.81%)
5	8 (3.04%)	8 (3.04%)	0 (0.00%)	0 (0.00%)
Total	787	767	777	654
MODEL 2: AUTOREGRESSIVE				
0	64 (29.36%)	64 (29.36%)	13 (5.96%)	40 (18.35%)
1	35 (16.06%)	35 (16.06%)	66 (30.28%)	82 (37.61%)
2	55 (25.23%)	55 (25.23%)	72 (33.03%)	71 (32.57%)
3	56 (25.69%)	56 (25.69%)	53 (24.31%)	23 (10.55%)
4	8 (3.67%)	8 (3.67%)	14 (6.42%)	2 (0.92%)
5	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Total	345	345	425	301

The method of detection of structural breaks, Global Optimization detects the maximum number of breaks, m pre-determined in the analysis. In this case, we have set a value of m=5 and thus, it will produce a total number of 5 breaks from the iteration based on the algorithm of dynamic programming every time. The method of selection of structural breaks, Sequential and Repartition select optimal number of breaks up to a maximum number of 5 breaks. The idea behind Repartition is it re-estimates the breaks detected by Sequential by producing the new break points, which are consistent, and the limiting distribution is the same as both the single and multiple break models. It can be observed here that Sequential and Repartition mostly produce a matching number and location of break points. On the other hand, the information criteria select optimal breaks based on the penalized maximum likelihood function.

Table 2 reports the number of break points detected by the Bai and Perron (2003) method adapted to the logarithm of quarterly real dividends series of selected U.S. firms in which the time period is divided into 10-year period. Most of the breaks are found by all the four method of selection of optimal breaks; Sequential, Repartition, BIC and LWZ in the following time periods: 1971-1980, 1981-1990, 1991-2000 and 2001-2010 which are associated with the episodes of inflation woes, deregulation and ergonomics, and the rise of globalisation and world superpowers. In the structural break analysis of index-level data, Timmermann (2001) found breaks mostly in the earlier time periods that could be linked to the period after World War I (WWI), the Great Depression, and the beginning and end of World War II (WWII). Some of the breaks found in other time periods are not linked to any major or significant episodes in the history. The likelihood and/or occurrence of breaks can possibly be related to, not only external but also the internal factors for every individual firm in the sub-sample. The internal factors, such as the dividend policies of the firm may have important implications to the likelihood of breaks.

Table 2: Structural Break Analysis in U.S. Dividend Series by 10-Year Period

Specifications				
	$x_t=\{\alpha\}$, $z_t=\{T\}$, $p=1$, $q=1$, $\epsilon=0.10$, $M=5$, robust=0			
Year	Sequential	Repartition	BIC	LWZ
MODEL 1: TREND STATIONARY				
1921-1930	0	0	0	0
	(0.00%)	(0.00%)	(0.00%)	(0.00%)
1931-1940	7	7	9	7
	(0.89%)	(1.17%)	(1.16%)	(1.07%)
1941-1950	42	40	46	40
	(5.08%)	(6.00%)	(5.93%)	(6.12%)
1951-1960	40	40	46	41
	(5.08%)	(6.00%)	(5.93%)	(6.27%)
1961-1970	92	94	89	67
	(11.94%)	(11.60%)	(11.47%)	(10.24%)
1971-1980	166	166	150	124
	(21.09%)	(19.56%)	(19.33%)	(18.96%)
1981-1990	189	181	180	150
	(23.00%)	(23.47%)	(23.20%)	(22.94%)
1991-2000	172	183	179	159
	(23.25%)	(23.34%)	(23.07%)	(24.31%)
2001-2010	79	56	77	66
	(7.12%)	(10.04%)	(9.96%)	(10.09%)
MODEL 2: AUTOREGRESSIVE				
1921-1930	0	0	0	0
	(0.00%)	(0.00%)	(0.00%)	(0.00%)
1931-1940	3	2	3	1
	(0.87%)	(0.58%)	(0.71%)	(0.33%)
1941-1950	26	28	23	16
	(7.54%)	(8.12%)	(5.41%)	(5.32%)
1951-1960	30	24	27	20

	(8.70%)	(6.69%)	(6.35%)	(6.64%)
1961-1970	37	39	43	26
	(10.72%)	(11.30%)	(10.12%)	(8.64%)
1971-1980	82	82	90	64
	(23.71%)	(23.77%)	(21.18%)	(21.26%)
1981-1990	74	71	93	65
	(21.45%)	(20.58%)	(21.88%)	(21.59%)
1991-2000	71	71	98	75
	(20.58%)	(20.58%)	(23.06%)	(24.92%)
2001-2010	22	28	48	34
	(6.38%)	(8.12%)	(11.29%)	(11.30%)

CONCLUSION

The detection of breaks by using the techniques for optimal break selection: Sequential, Repartition and the Information Criteria; BIC and LWZ. Sequential and Repartition when performed on the firm-level data of 263 selected U.S. firms are shown to consistently estimate mostly the same number and location of break dates every time. The latter, supposedly correct for the under or over estimation of structural breaks by the former. Global Optimization procedure is set to estimate the maximum number of 5 breaks for each firm.

In terms of the selection of the optimal number of break points, BIC works well with the presence of breaks whereas LWZ criterion is shown to work better under the null hypothesis by imposing a higher penalty. It records the lowest percentage of firms in the sub-sample that select zero breaks compared to the other procedures.

Overall, the structural break analysis provides substantial evidence on the presence of structural breaks in the dividend series at the firm level. Furthermore, the break model of trend stationary (Model 1) is shown to have a higher total number of breaks than the break model of autoregressive (Model 2). Therefore, this supports our hypothesis for this paper i.e. the underlying process of the stock price is not stable and subject to structural breaks. We also find significant links between breaks and the major episodes in the economic and financial history of the U.S

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