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Mistakes in the Real-time Identification of Breaks

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Abstract

We study the mistakes that happen in the real-time identification of structural breaks in the selected aggregate-level of the U.S. financial data series. We are interested in the real time identification because of its relevance for forecasting. The level of noisiness of different data sets and techniques used for the identification of breaks affect the frequency of mistakes encountered in real time. We find that mistakes in not finding the true breaks and/or finding the wrong ones in real time are made more frequently in the case of a noisier financial data set. Moreover, the techniques for optimal break detection based on sequential learning of the Bai and Perron (2003) are found to make fewer mistakes than those based on Information Criteria (IC).

Keywords: Structural breaks, real-time, learning, mistakes, uncertainty

1. INTRODUCTION

Many economic and financial time series are subject to structural breaks or changes as a result of changes in tastes, technology or policy. The presence of breaks in time series, as widely recognized, if ignored, may lead to serious implications. 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). Moreover, breaks can pose a serious problem for forecasting. Pástor and Stambaugh (2012) also argue that "estimation risk" is one of the key components of long-horizon forecasting uncertainty.

Pástor and Stambaugh (2012) also argue that "estimation risk" is one of the key components of long-horizon forecasting uncertainty. There is a large literature on the developments of techniques for identifying breaks in a given data set (e.g. Alogoskoufis and Smith (1991); Stock and Watson (1996); Pesaran and Timmermann (2002); Stock and Watson (2003); Rapach and Wohar (2006); Breitung and Eickmeier (2011)). A recent literature has concurrently focused on developing approaches to forecasting under the presence of breaks. Rossi et al. (2012) review the empirical analyses that have been carried out on the advances in forecasting under the presence of breaks. A key question is what data set to employ to estimate the parameters of the forecasting model. Since forecasts are typically based on the assumption of the constancy of the model parameters, the potential for breaks implies that a key forecasting problem is to determine the data set to employ to estimate the parameters of the model that will generate future observations. This requires judging if and when there has been a break in the past data. If there is judged to be a recent break then there is a further question of whether the model should be solely estimated on post break data or whether there is any incremental information in pre-break data.

In this paper, we consider another aspect of this problem of forecasting in an environment where there are uncertain break dates. We study the problem of learning about break dates and examine the dynamics of how agents learn about the occurrence of breaks in real time. Intuitively, the problem for an agent in real time is judging

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whether an extreme observation is just an outlier from an unchanged structural model, or whether it is the first observation from a model with revised parameters. We investigate how often different techniques mistakenly identify breaks in real time, when we know with the hindsight of the full data set that no break occurred.

The liquidity crisis that arose in 2008 offers an example of this problem. It is so severe that at times confidence is eroded that this is just another shock drawn from the same distribution as shocks over the last 50 years. Many commentators argue that the future might resemble a 1930s style depression or to the low growth environment observed in Japan since the early 1990s. This would be an example of a potential structural break in the economy. Confidence has gradually returned that this is not a structural break but rather a very extreme observation in a given model. However at the time of writing there are still different views on this point. As more data accumulate, the apparent break turns out merely to have been a few extreme observations in an unchanged model. The nearly halving of stock prices in 2008 can only reflect the opinion of many investors that a structural break had occurred in 2008. The recovery of stock markets from that low point can be interpreted in the context of the ideas of this study as the result of a gradual revival of confidence that a permanent break had not occurred.

We obtain the aggregate-level financial data series i.e. dividends, earnings and prices from Shiller (2013). Following Timmermann (2001), we model the growth processes in dividends and the same for earnings and prices as well. The key results from our study of the real-time dynamics of breaks are summarised below:

- The breaks found with the benefit of hindsight are found linked to some major or significant events in the economic and financial history. This provides us with a good ground into assuming that these breaks are the true breaks in our study.
- In real time, it is more likely for mistakes to be made in the case of a noisier dataset, or dataset with higher volatility.
- For the four techniques for optimal break detection of the Bai and Perron (2003), Bayesian Information Criterion (BIC) reports the highest number of total false breaks found compared to the other techniques for optimal break selection; Sequential, Repartition and the modified version of Schwarz' criterion proposed by Liu et al. (1997) and abbreviated as LWZ.

2. DATA AND METHODOLOGY

2.1 Aggregate-level Data

The monthly data on dividend, earnings and price series, denoted by Dt, Et and Pt for the time period that begins from January 1881 until December 2013 are obtained from the continuously updated-data following Shiller (2013). The computation of 'Online Data Robert Shiller' on monthly dividend and earnings is from the S&P four-quarter totals for the quarter since 1926, with linear interpolation to monthly figures. The data on dividend and earnings before 1926 are compiled from Cowles (1939), with linear interpolation from the annual figures. Moreover, the monthly data on stock prices are computed from averaging the daily closing prices and the data on CPI (Consumer Price Index-All Urban Consumers) starting from 1913 are obtained from the Index (2011). For the years before 1913, the data on CPI are extracted from the CPI Warren and Pearson's price index (Warren and Pearson (1935))**.**

We convert the series of dividend, earnings and price into real dividends, earnings and price by using the Consumer Price Index (CPI) are obtained from the same source as well. The left-hand side or dependent variable in our structural break analysis in real time is the growth rate of real dividends, prices and earning. Thus, we model the change in logarithm of real dividend, earnings and price as the following:

1. $d_t = \Delta \log (D_t)$
2. $e_t = \Delta \log (E_t)$
3. $p_t = \Delta \log (P_t)$

Furthermore, we also consider the absolute value of the growth rate i.e. |dt|, |et| and |pt| in the above aggregate-level financial series which allows us to detect possible breaks in the volatility of the processes related to the above aggregate-level financial series.

2.2 Structural Break Analysis

We utilise the Bai and Perron (2003) program that allows for the construction of estimates of the parameters in models with multiple structural breaks. The algorithm of this program is based on the principle of dynamic programming and information criteria and sequential hypothesis testing give the optimal number of breaks. Besides that, it is also designed to construct confidence intervals and test for structural change. We can also estimate either pure or partial structural change models and choose the options whether to allow for heterogeneity and/or serial correlation in the data and the errors across segments or not.

The multiple linear regression models with m breaks (m+1 regimes) are described as the following:

$$\begin{aligned} y_t &= x_t'\beta + z_t'\delta_1 + u_t, && t = 1, \dots, T_1 \\ y_t &= x_t'\beta + z_t'\delta_2 + u_t, && t = T_1 + 1, \dots, T_2 \\ &\vdots \\ y_t &= x_t'\beta + z_t'\delta_{m+1} + u_t, && t = T_{m+1} + 1, \dots, T \end{aligned} \quad (1)$$

where yt is the observed dependent or response variable at time t; xt(p x 1) is the vector of variable(s), fixed throughout the analysis; zt(q x 1) is the vector of variable(s) subject to structural breaks at time t, β and δj(j = 1,...,m+1) are the vectors of coefficients of xt and zt respectively; ut is the error or disturbance at time t. The maximum number of breakpoints is given by m.
For the purpose of our structural break analysis, we consider two different (general) structural break models as the following:

- Trend-stationary break model (Model 1):

$$y_t = f(t) + u_t \quad (2)$$

where t is time, f is a deterministic (linear) function, in which f(t)= and ut is the disturbance at time t. The variable(s) subject to breaks is given by zt={f(t)} whereas xt={}. It is a trend stationary break model when f(t)= .

- Autoregressive break model (Model 2):

$$y_t = \alpha + y_{t-1} + u_t \quad (3)$$

where t is time, α is drift, yt-1 is the lag of dependent variable or unit root term and ut is the disturbance at time t. The variable(s) subject to breaks is given by zt={α, yt-1} whereas xt={}.

2.3 Real-time Analysis

In general, following Clements and Galvão (2013), we have access to the "vintage" T values of the observations on y up to time period T-1, where "vintage" is defined as the information set that one has available in hand at a given or specific date and the compilation of such vintage is the "real-time data set"(Croushore and Stark 2003). The T-vintage which can be written as {ytT}t=1,2,…T-1. This is also called the latest available T-vintage whereas the previous vintages, for example, the T-j vintage is {ytT-j} for j=1,2,3,…, and where t=1,2,…,T-j-1. When we have the full data set with hindsight, I have the T-vintage in which the true breaks are detected as in the previous chapter. The regression model for T-vintage with m breaks (m+1 regimes) of interest is

$$\begin{aligned} y_t^T &= x_t'^T\beta + z_t'^T\delta_1 + e_t^T, && t = 1, \dots, T_1 \\ y_t^T &= x_t'^T\beta + z_t'^T\delta_2 + e_t^T, && t = T_1 + 1, \dots, T_2 \\ &\vdots \\ y_t^T &= x_t'^T\beta + z_t'^T\delta_{m+1} + e_t^T, && t = T_{m+1} + 1, \dots, T\text{-}1 \end{aligned} \quad (4)$$

The true set of breaks is given by {Tk} where k=1,2,…,m where m is the maximum number of break allowed in the empirical exercise.

For the real time analysis, we carry out the structural breaks analysis of the Bai and Perron (2003) program by using all the previous vintages that I have, i.e. {ytT-j}for j=1,2,3,…, and where t=1,2,…,T-j-1.

$$\begin{aligned} y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_1 + e_t^{T-j}, && t = 1, \dots, T_1 \\ y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_2 + e_t^{T-j}, && t = T_1 + 1, \dots, T_2 \\ &\vdots \\ y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_{m+1} + e_t^{T-j}, && t = T_{m+1} + 1, \dots, T\text{-j-1} \end{aligned} \quad (5)$$

With the benefit of hindsight that a break had occurred at at 5% significance level, we would expect to find the same break at as more data arrive. For instance, we would expect to detect a break at a past date, at +1 by using +1-vintage, i.e. {ytT}t=1,2,…T-1. Similarly, we would always expect to detect the same break in the next periods as more data become available.

However, there are times that this happens not to be the case. The error in judgement in real time may present in the form of Type 1 and Type 2 error:

1. Type 1 error: This happens in the case of a rejection of the null hypothesis of no break when it is actually true i.e. a break was identified when there was no break.
2. Type 2 error: This happens in the case of a failure to reject the null hypothesis when it is actually not true i.e. a break was not identified when there was a break.

In the context of our structural break analysis in real time, if we were to explain judgement error in the form of Type 1 and Type 2 error as how it would naturally have been thought of, this would lead us to some confusion which can further lead to misleading analysis.

For the mistakes in detection of structural breaks in real time, the following would have been our set of hypotheses:

- Null hypothesis: There is no (true) break(s) at data point t
- Alternative hypothesis: There is a (true) break(s) at data point t

Essentially, we investigate the following:

- How often do we find or not find the wrong or true break(s) given different level of noisiness of the data set in real time respectively?

3. RESULTS

3.1 Structural Breaks in Aggregate-level Series in Hindsight

Bai and Perron (2003) method involves an extensive programming that allows the construction of the estimates of parameters in models with multiple structural changes (the main essence being a dynamic programming algorithm). By setting m=8, the maximum number of breaks allowed is 8 and by treating the number of breaks as known, Global Optimization procedure estimates the break dates for m=1, 2, 3, 4, 5, 6, 7, 8. The optimal number of breaks is estimated by using Information Criteria (BIC and LWZ), Sequential and Repartition test.

Timmermann (2001) tests the breaks in the endowment process by using the Gauss program provided by Bai and Perron (1998). The maximum number of breakpoints is set to 8 as well and by allowing the heteroscedasticity in the residuals; he presents the evidence of structural breaks in the U.S. dividend series. He utilises the monthly data of on dividends from 1871-1999 obtained from Shiller (2000). Dividends are converted into the real dividends by, D_t. The dependent or left-hand side variable is the change in the logarithm of D_t, i.e. the real dividend growth rate, dt = Δ log (Dt).

Timmermann (2001) presents the results for the following processes:

1. Dividend growth
2. Absolute dividend growth
3. Dividend growth with lag
4. Absolute dividend growth with lag

The same processes are included in our investigation together with some other processes of the aggregate-level time series of earnings and price as well. We demonstrate the results by applying different specifications in two different models. The first model is based on the univariate specifications with a drift or an intercept term as the regressor subject to structural breaks whereas the second model includes drift or the intercept term and a single lag of the dependent variable as the regressors subject to structural breaks.

Table 1 presents the estimated number of optimal breakpoints by the techniques for optimal break selection for all the processes for the two models. The estimated number of breakpoints by using the Bai and Perron (2003)method, which is the modified version of the Bai and Perron (1998) method applied by Timmermann (2001) for the above four processes are consistent with Timmermann (2001). Sequential and Repartition breakpoint tests use a significance level of 5%, while the two information criteria, BIC and LWZ are based on the penalized likelihood function. Sequential and Repartition fail to detect any break for most of the processes when there is only an intercept term included as the regressor but by including a single lag as another regressor, the estimated number of breakpoints reported by Sequential and Repartition is higher compared to BIC. LWZ is observed to be more stringent and the estimated number of breaks is always lower than BIC.

Table 1: The Estimated Number of Breakpoints, Bai and Perron (2003) Method

Process	Sequential	Repartition	BIC	LWZ
Model 1: Stationary Break Model				
Abs. dividend growth*	2	2	5	1
Abs. earnings growth	0	0	5	1
Abs. price growth	3	3	2	2
Dividend growth*	0	0	4	0
Earnings growth	0	0	0	0
Price growth	0	0	0	0
Model 2: Autoregressive Break Model				
Abs. dividend growth with lag*	6	6	4	1
Abs. earnings growth with lag	0	0	2	1
Abs. price growth with lag	3	3	2	2
Dividend growth with lag*	3	3	1	1
Earnings growth with lag	5	5	1	1
Price growth with lag	0	0	0	0

3.2 Mistakes in Real Time

Table 2 presents the descriptive statistics of the number of dates where we do not find an earlier true break in real time. We observe that for the absolute growth processes, the noisier a dataset is, the more dates we do not find a break at a date where there is indeed a true break. In terms of the comparison between the techniques for break detection, it is interesting to see that for the processes related to growth in dividend, BIC finds the highest number of dates that we do not find the true breaks followed by LWZ, and Sequential and Repartition for the processes related to growth in dividend. However, for the processes related to growth in price, this is not the case. Overall, the autoregressive model (Model 2) reports mostly higher number of dates at which the true breaks are not found compared to the stationary break model (Model 1).

Mistakes can also happen when we find a break at a past date where there is no true break at that date in real time. Table 3, on the other hand, presents the descriptive statistics of the number of dates where we do not find a break at a past date where there is no true break at that date in real time i.e. we correctly do not find the wrong breaks. BIC reports the highest number of total false breaks found compared to the other techniques for optimal break selection. Comparing the two break models, the autoregressive model (Model 2) reports lower number of dates at which the false breaks are not found especially noted for Sequential and Repartition techniques but the evidence is not conclusive for BIC and LWZ.

4. CONCLUSION

It is important to look at breaks from the real time perspective as this captures what could actually have been attained with the data that we have available at the present time. As more data become available, the view also changes accordingly. As said earlier, we could relate this to the recent financial crisis that arose in 2008. This would be a potential structural break in the economy. However, the techniques for optimal break selection considered in this paper do not find a break during this crisis. We offer an explanation to this situation from our point of view of the real-time learning about the dynamics of breaks. The availability of more data in the subsequent periods may reveal that some apparent breaks turn out merely to have been few extreme observations in an unchanged model.

In this paper, the breaks found in hindsight are assumed to be the true breaks for the purpose of real-time analysis. We observe links between these breaks and some major or significant events in the history. We find that in real time, it is more likely for mistakes to happen in the case of a noisier dataset. Bayesian Information Criterion (BIC) is observed to record the highest number of total wrong breaks found compared to the other techniques for optimal break selection; Sequential, Repartition and the modified version of Schwarz' criterion proposed by Liu et al. (1997) abbreviated as LWZ.

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Table 2: Mistakes in the Identification of Breaks in Real Time, Bai and Perron (2003) Program

Procedure	Process	Descriptive Statistics						
		Model 1: Stationary Break Model						
		N	Mean	Median	Std. Dev.	Min	Max	Range
Sequential	Absolute dividend growth	2	80	80	N/A	N/A	N/A	N/A
	Absolute price growth	3	304	307	263.51	39	566	527
Repartition	Absolute dividend growth	2	80	80	N/A	N/A	N/A	N/A
	Absolute price growth	3	523.33	692	353.58	117	761	644
BIC	Absolute dividend growth	5	233.25	132	277.59	27	642	615
	Absolute earnings growth	5	330.75	336.50	199.34	109	541	432
	Absolute price growth	2	371.50	371.50	297.69	161	582	421
	Dividend growth	4	613.25	628.50	92.96	492	704	212
LWZ	Absolute dividend growth	1	198	198	N/A	N/A	N/A	N/A
	Absolute price growth	2	428.50	428.50	350.02	181	676	495
		Model 2: Autoregressive Break Model						
Sequential	Absolute dividend growth	6	472.40	540	361.51	42	980	938
	Absolute price growth	3	764.67	1005	424.09	275	1014	739
	Dividend growth	3	591.67	267	590.92	167	1540	1373
	Earnings growth	5	763.60	636	335.26	511	1144	633
Repartition	Absolute dividend growth	6	417.40	248	369.16	42	980	938
	Absolute price growth	3	499	691	397.45	42	764	722
	Dividend growth	3	247.67	286	189.43	42	415	373
	Earnings growth	5	474	212	533.65	3	1215	1212
BIC	Absolute dividend growth	4	361.50	361.50	54.45	323	400	77
	Absolute earnings growth	2	812	812	216.37	659	965	306
	Absolute price growth	2	985	1135	518.53	251	1418	1167
	Dividend growth	1	671	671	N/A	N/A	N/A	N/A
	Earnings growth	1	1139	1139	N/A	N/A	N/A	N/A
LWZ	Absolute dividend growth	1	497	497	N/A	N/A	N/A	N/A
	Absolute price growth	2	399.50	399.50	54.45	361	438	77
	Dividend growth	1	905	905	N/A	N/A	N/A	N/A
	Earnings growth	1	1139	1139	N/A	N/A	N/A	N/A

Table 3: Correct Identification of Breaks in Real Time, Bai and Perron (2003) Program

Procedure	Process	Descriptive Statistics						
		Model 1: Stationary Break Model						
		N	Mean	Median	Std. Dev.	Min	Max	Range
Sequential	Absolute dividend growth	29	1333.69	1372	390.45	162	1705	1543
	Absolute price growth	36	1076.53	1017.50	486.44	263	1713	1450
Repartition	Absolute dividend growth	28	1426.29	1628	321.38	795	1708	913
	Absolute price growth	90	1058.07	1014	451.57	263	1713	1450
BIC	Absolute dividend growth	98	1201.80	1030.50	323.48	528	1709	1181
	Absolute earnings growth	179	1111.71	1052	424.87	123	1713	1590
	Absolute price growth	70	909.13	1088	528.26	86	1710	1624
	Dividend growth	112	1180.46	1110	299.36	739	1712	973
LWZ	Absolute dividend growth	20	1316.45	1636	424.24	779	1712	933
	Absolute price growth	34	1168.76	1016.50	350.24	760	1708	948
		Model 2: Autoregressive Break Model						
Sequential	Absolute dividend growth	29	1223.48	1219	493.41	201	1712	1511
	Absolute price growth	17	1001.12	945	571.18	42	1694	1652
	Dividend growth	28	1171.89	1155	422.80	42	1694	1652
	Earnings growth	72	36.80	17	128.84	1	754	753
Repartition	Absolute dividend growth	23	1143.65	1148	497.61	201	1711	1510
	Absolute price growth	27	1028.30	941	399.72	260	1694	1434
	Dividend growth	28	1227.18	1155	297.83	511	1694	1183
	Earnings growth	92	47.43	20	132.44	1	861	860
BIC	Absolute dividend growth	7	1528.57	1659	212.95	1035	1694	659
	Absolute earnings growth	16	1300.44	1216	323.99	829	1637	808
	Absolute price growth	23	1293.13	1193.50	171.10	1122	1646	524
	Dividend growth	0	N/A	N/A	N/A	N/A	N/A	N/A
	Earnings growth	4	1594.25	1640.5	102.13	1442	1654	212
LWZ	Absolute dividend growth	2	1366	1366	384.6661	1094	1638	544
	Absolute price growth	1	1323	1323	N/A	N/A	N/A	N/A
	Dividend growth	0	N/A	N/A	N/A	N/A	N/A	N/A
	Earnings growth	4	1594.25	1640.50	102.13	1442	1654	212