Detection of Breaks in a Capital Structure: a Case Study

Jaromír Antoch [1] | *Charles University, Prague, Czech Republic*
Daniela Jarušková [2] | *Czech Technical University, Prague, Czech Republic*

Abstract

The main goal of this paper is to present an analysis of financial quarterly time series describing the level of book leverage of U.S. companies selected from different industries in the period 1991–2014. The basic question is whether the sub-prime crisis 2007–2008 caused a change in the behavior of the respective companies. More generally, we are interested whether the time series may be considered stationary. Statistical methods suitable for the detection of breaks (changes) for individual and panel data are presented together with their pros and cons. Against our expectations, the analysis did not reveal a significant change due to the sub-prime crisis. On the other hand, all series contain at least one change, most of the changes occurring around the year 2000, thus offering room for an economic explanation.[3]

Keywords	***JEL code***
Change point problem; abrupt, gradual and multiple changes; stationarity in the mean; sum and maximal test statistics; panel data; book leverage	*C10, C23*

INTRODUCTION

Capital structure determines the relative ownership of the firm by creditors and equity holders, as represented by the relative weights of debt and equity in the company. Therefore, how a firm chooses its capital structure is one of the fundamental questions in corporate finance, and financial economic research focuses on variables that help explain capital structure decisions. For details see, e.g., seminal paper by Lemmon et al. (2008).

The key variable in capital structure is leverage, so that one of the basic research questions is whether the leverage, or any other key characteristic describing the capital structure, is time invariant or whether it contains a breaking point(s). If it does contain a breaking point(s), then the question is how to estimate them and how to decide which phenomenon is behind them.

In this paper we concentrate on selected issues from the change-point methodology and illustrate advantages and pitfalls of the selected approach on the analysis of real financial data. More specifically,

[1] Faculty of Mathematics and Physics, Department of Probability and Mathematical Statistics, Sokolovská 83, 186 75 Prague, Czech Republic. Corresponding author: e-mail: antoch@karlin.mff.cuni.cz.
[2] Faculty of Civil Engineering, Department of Mathematics, Thákurova 7, 166 29 Prague 6, Czech Republic. E-mail: daniela.jaruskova@cvut.cz.
[3] This article is based on contribution from the conference *Robust 2016*.

we are interested in breaks in the model describing the level of leverage of selected U.S. companies from different industries around the sub-prime crisis. Recall that the sub-prime crisis is generally defined between the fourth quarter of 2007 and the end of 2008, see Santos João (2011) and Dick-Nielsen et al. (2012) for details. Time span of the considered data covers the period from 1Q 1991 to 4Q 2014.

This paper is organized as follows. Section 1 describes statistical methods suitable for detection of changes in the underlying model. Section 2 describes the data and its analysis. Finally, Section 3 summarizes selected conclusions.

1 DESCRIPTION OF STATISTICAL METHODS USED

In the scope of mathematical statistics, whether an observed series has remained stationary or whether a change of a specific kind has occurred, the outcome is usually based on hypotheses testing. The null hypothesis claims that the process is stationary while the alternative hypothesis claims that the process is nonstationary and the stationarity was violated in a specific way. In our case we will mainly be interested in stationarity in the mean of the observed series.

We usually start the statistical inference process by analyzing information on one series describing the behavior of one company. We assume that the data $Y_1,..., Y_n$ was collected at time moments $t_1 < ... < t_n$, so that they form a time series. In our case the time moments can be, without a loss of generality, replaced by their indices $1,..., n$. When studying the data for one company, our goal is to decide whether the sequence $Y_1,..., Y_n$, is stationary or whether its mean has changed. We assume that a potential change of the analyzed series' mean occurred in a short, with respect to n, time period. Thus we can make a slight simplification dealing with time series models that contain a sudden shift in the mean at an unknown time point.

In our case the null hypothesis claims that the characteristic has not changed while the alternative claims that the analyzed characteristic has changed in an assumed manner. For testing which of these hypotheses is true we use statistics developed in the field of change-point detection. For more details and different approaches to the problem see, e.g., Csörgö et Horváth (1997), Bai et Perron (1998), Antoch et al. (2002, 2004, 2007, 2008), Antoch et Jarušková (2013) or Horváth et Rice (2014).

Recall that analogous methodology has been developed for gradual changes as well. Nevertheless, it is well known that procedures developed for detection of a sudden change also respond in the case of gradual changes, and vice versa. However, one must keep in mind that in such a case they lose a power. For details see, e.g., Antoch et al. (2002) or Jarušková (1998).

First let us explain how the test statistics applied in our paper are constructed. Suppose for a while that we know the position of a potential change point (break). In other words, if we know that a change occurred, then it certainly occurred at the time k. In such a case, for deciding whether or not the analyzed series has changed, one may use a classical two-sample test statistic for testing the equality of the mean of the first part $Y_1, ..., Y_k$ to the mean of the second part $Y_{k+1}, ..., Y_n$, of the original series. A natural estimate of the first mean is the average $\bar{Y}_k = \sum_{j=1}^{k} Y_j / k$ and, similarly, the estimate of the second mean is the average $\bar{Y}_k^0 = \sum_{j=k+1}^{n} Y_j / (n-k)$.

Supposing moreover that the variance σ^2 of the series remains the same over the entire time span $j = 1, ..., n$, then the test statistic T_k has the form:

$$T_k = \sqrt{\frac{k(n-k)}{n}} \frac{\bar{Y}_k - \bar{Y}_k^0}{\hat{\sigma}} = \sqrt{\frac{n}{k(n-k)}} \frac{\sum_{j=1}^{k} (Y_j - \bar{Y}_n)}{\hat{\sigma}}. \quad (1)$$

Notice that test statistic T_k may be obtained as the maximum likelihood estimator under the assumption that observations $\{Y_i\}$ are independent normally distributed random variables. For a detailed derivation see Section 3 in Antoch et al. (2002).

In Formula (1) the standard deviation of the analyzed time series has been replaced by its estimate, that can be calculated either as:

$$\hat{\sigma}_1 = \sqrt{\left[\sum_{j=1}^{k}\left(Y_j - \bar{Y}_k\right)^2 + \sum_{j=k+1}^{n}(Y_j - \bar{Y}_k^0)^2\right]/(n-2)},$$

or as:

$$\hat{\sigma}_2 = \sqrt{\sum_{j=1}^{n}(Y_j - \bar{Y}_n)^2 / n}.$$

In the situation where data is dependent and forms a linear process, σ must be estimated more carefully. A Bartlett type estimator adjusted to a possible change is usually recommended in the literature as the first choice. A detailed description can be found in Antoch et al. (1997).

In a case where the means of the first and second parts of the series coincide, the $\hat{\sigma}_1$ and $\hat{\sigma}_2$ do not differ substantially. If the means differ, then $\hat{\sigma}_1$ attains a smaller value than $\hat{\sigma}_2$ with a large probability, so that the test statistic using this value has a larger power for change point detection. It is well known that when k and $n - k$ are large, then the statistic T_k has approximately a standard normal distribution, and the hypothesis claiming that the means of the first and second parts are the same is rejected if $|T_k| > u_{1-\alpha/2}$ with $u_{1-\alpha/2}$ being the $(1 - \alpha/2)100\%$ quantile of $N(0,1)$.

If we do not know the position of a potential change point (break), then we calculate the value of the statistic T_k for all possible $k = 1, \ldots, n - 1$, and plot the sequence $\{|T_k|\}$ against time points $\{k; k = 1, \ldots, n - 1\}$. The plot provides us with important visual information about eventual change point(s). As the sequence $\{T_k\}$ is a standardized CUSUM sequence of residuals $\{Y_j - \bar{Y}_n\}$, which starts $(k = 0)$ and ends $(k = n)$ at zero. If a sudden shift occurs at a time k, the sequence $\{|T_k|\}$ attains a large value for such a k. A magnitude of this value is given by a difference between the means of the first and second parts of the series, i.e., by the size of a shift in the mean. If there are several sudden changes that are well separated, then the sequence $\{|T_k|\}$ has more peaks.

In addition to the sequence $\{T_k\}$ we may also compute a weighted sequence $\{w_k T_k\}$. The most frequently applied weights are:

$$w_k = \sqrt{k(n-k)/n^2},\ k = 1, \ldots, n-1, \tag{2}$$

leading to the statistic:

$$T_k^* = \sqrt{\frac{1}{n}}\frac{\sum_{j=1}^{k}(Y_j - \bar{Y}_n)}{\hat{\sigma}}. \tag{3}$$

As shown in James et al. (1987), the statistics T_k^* may be obtained using the modified likelihood principle.

It is not surprising that a decision on existence of a change point is based on the maximum of the statistics $\{|T_k|\}$, i.e.,

$$max_{1 \le k \le n-1} |T_k|, \tag{4}$$

respectively on the maximum of the statistics $\{w_k|T_k|\}$, i.e.,

$$max_{1 \le k \le n-1} |T_k^*|, \tag{5}$$

sometimes called a weighted maximum type test statistic. Notice that some authors use the term "penalized maximum type test statistic" here. However, the terminology is not uniform and we will use the term "weighted" throughout this paper.

Recall that besides test statistics (4) and (5) we might also use test statistics that are sums of $\{T_k^2\}$ or $\{(w_kT_k)^2\}$. Because we do not apply them in this paper, we refer to Antoch et al. (2002) and MacNeill (1974) for more details.

As an estimator of the time of change one usually takes that index $\hat{k}_0$, for which the sequence of the statistics $\{T_k\}$ attains its maximum, i.e.,

$$\hat{k}_0 = argmax_{1\le k\le n-1}\, |T_k|, \tag{6}$$

respectively, where the sequence of statistics $\{w_k|T_k|\}$ attains its maximum, i.e.,

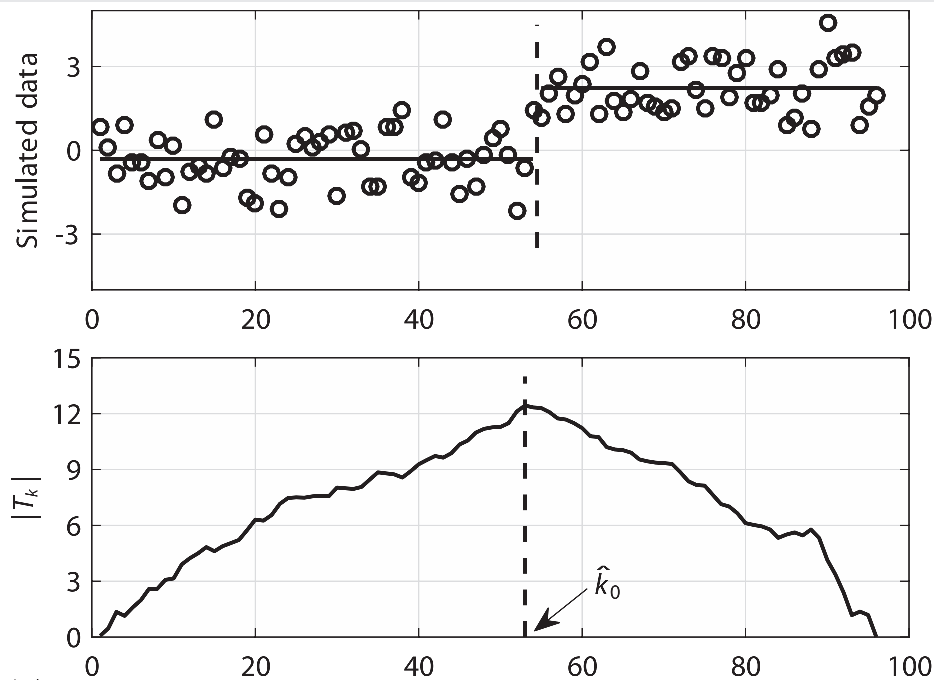
$$\hat{k}_0^* = argmax_{1\le k\le n-1}\, |T_k^*|. \tag{7}$$

If the maximum is not unique, so that a maximum is attained for a set of indices, we usually take as the estimator the smallest index of this set. Nevertheless, such an issue usually indicate that more than one change can be detected in the data, and one should deal with this issue. For details see, e.g., paper Antoch et Hušková (1998).

It is worth noticing that statistics (6) and (7) do not necessarily correspond to the location of a change provided the series exhibits a gradual instead of sudden change. In such a case, other estimators have to be used; for details see, e.g., Antoch et Hušková (1998) and Antoch et al. (2002). See also discussion in Section 2.

Clearly, the test statistic (5) detects more easily a change in the middle of the sequence while the statistic (4) detects more easily a change at the beginning or at the end of the series. As an illustration, Figure 1 shows a simulated time series with a shift in its mean and a corresponding behavior of the sequence $\{|T_k|\}$. Behavior of both sequences $\{|T_k|\}$ and $\{|T_k^*|\}$ when applied to the real data describing the level of the book leverage of U.S. companies selected from different industries, can be seen in Figure 2.

Figure 1 Simulated data and behavior of statistics $\{|T_k|\}$



Source: Authors

The exact distribution of statistics (4) and (5) is too complex; hence approximate critical values have to be applied. The approximate critical values may be obtained by simulations, where the observations $\{Y_i\}$ are taken from a standard normal distribution. These critical values may be applied to a broad class of distributions thanks to the invariance principle. For $n \approx 100$ the 5% critical value of statistic (4) is 3.17 and the 1% critical value is 3.70. For $n \approx 100$ the 5% approximate critical value of statistic (5) is 1.29, while the 1% approximate critical value is 1.55. As argued above, it is always useful to plot either statistics $\{|T_k|\}$ or $\{|T_k^*|\}$ against time points $\{k; k = 1, ..., n - 1\}$.

To get approximations to the distribution of the considered test statistics, different versions of the bootstrap were suggested in the literature. Because this issue goes far beyond the scope of this paper, we refer the reader to Antoch et al. (1995) and Horváth et Rice (2014) for details and additional references.

If the series contains more than one change, and the changes are well separated, the statistics (4) and (5) are able to reject the null hypothesis of stationarity in the means well. For estimating multiple change points, a sequential procedure proposed in Vostrikova (1981), and later modified by many other authors, may be applied. The basic idea may be described as follows. If a change is detected, the series is split into two parts, i.e., the part before the detected change point and the part after it. Then the same procedure is applied to both subseries recursively. Another possibility is to use the MOSUM approach discussed, e.g., in Antoch et al. (2002), or to employ a test statistic proposed for detecting several changes developed, e.g., in Antoch et Hušková (1994) and Antoch et Jarušková (2013).

The critical values for statistics (4) and (5) presented above were obtained under an assumption that $\{Y_i\}$ form a sequence of independent variables. When $\{Y_i\}$ form an ARMA sequence or, more generally, a linear process, the same test statistics may be applied, but σ^2 must be estimated more carefully and the critical values must be adapted. For more details see Antoch et al. (1997).

Finally, consider a situation when the data comes from I companies and are obtained during the same time moments $t_1 < ... < t_n$. We say that they form a so-called "panel". Suppose that $Y_j(i)$ denotes a value of variable of interest, e.g. book leverage, at time t_j for a company i. Then we can organize the data into a matrix with n rows and I columns. Moreover, we assume that if there is a change point k_0, then any series $\{Y_j(i), j = 1, ..., n\}$ either changes at time k_0 or does not change at all. For the i^{th} company we compute $\bar{Y}(i) = n^{-1}\sum_{j=1}^{n} Y_j(i)$ and $s(i) = \sqrt{n^{-1}\sum_{j=1}^{n}\left(Y_j(i) - \bar{Y}(i)\right)^2}$. Then for the i^{th} company and for $k = 1, ..., n$ we compute either

$$t_k(i) = \frac{n}{k(n-k)}\left(\sum_{j=1}^{k}\frac{Y_j(i)-\bar{Y}(i)}{s(i)}\right)^2,$$

or

$$v_k(i) = \frac{1}{n}\left(\sum_{j=1}^{k}\frac{Y_j(i)-\bar{Y}(i)}{s(i)}\right)^2.$$

Notice that for the i^{th} company $t_k(i) = T_k^2$ and $v_k(i) = (w_k T_k)^2$, where w_k are defined in (2). Further, for any time point $k = 1, ..., n$ we compute statistics:

$$U_k = I^{-1}\sum_{i=1}^{I}(t_k(i) - 1),$$

or a test statistic:

$$Z_k = I^{-1}\sum_{i=1}^{I}\left(v_k(i) - \frac{k(n-k)}{n}\right).$$

Similar to the one-dimensional case, the resulting panel test statistic can be either the maximum or sum of statistics $\{U_k\}$, respectively $\{Z_k\}$. We will not discuss here the details of either the appropriate normalization or finding the corresponding critical values, because such considerations go beyond the scope of this paper, being technically too complicated. The interested reader can find a detailed description and more about the analysis of panel data in Hušková et Horváth (2012) or, e.g., Baltagi (2013), Antoch (submitted).

Analogous to the case of statistics $\{T_k\}$ and $\{T_k^*\}$, the plot of $\{U_k\}$ and/or $\{Z_k\}$ provides us with important visual information about an eventual change point for panel data. Values of statistics of $\{U_k\}$ and $\{Z_k\}$, when applied to our book leverage data, can be seen in Figure 7.

2 DESCRIPTION OF DATA AND ITS ANALYSIS

To illustrate our approach, quarterly accounting data describing behavior of more than 300 U.S. companies from different industries was selected from the well-known FAMA/FRENCH database. At the beginning of our analysis we had at our disposal financial quarterly time series describing, among others, the level of book leverage collected during the period 1Q 1983 to 4Q 2014. Note that all financial indicators are in USD. After careful inspection, however, only 46 companies remained for subsequent change-point analysis. Both rough and detailed industry classification according to the SIC Code of the respective companies can be found in Tables 2 and 3. The main reasons why we could not include data about remaining companies into our analysis were the following:

1. A company disappeared from the market before the end of the year 2014.
2. The data series was too short for the purposes of our analysis.
3. There were too many values missing from the data series for a given company.

If only a few observations were missing, we replaced them by their estimates obtained by combining neighboring observations. In practice we used linear interpolation. In this way we obtained a panel of 46 companies observed during the last 24 years, more precisely 96 quarters of the period 1Q 1991 through 4Q 2014. The variable of interest was the book leverage, i.e., the size of the debt with respect to debt plus shareholders' equity. These data will be used to illustrate our approach. Complete data we worked with is available upon request from the authors of this paper.

Table 1 Identifiers of analyzed companies

1004	1078	1104	1161	1166	1173	1230	1300	1327	1356
1380	1408	1468	1585	1602	1613	1618	1678	1686	1704
1728	1773	1783	1823	1864	1913	1920	1926	1968	1988
2044	2049	2055	2061	2086	2136	2154	2184	2220	2269
2282	2282	2285	2290	2312	2403	2411			

Source: Authors

Table 2 Rough categories of analyzed companies according to the SIC Code

SIC Code	Standard Industrial Classification	#
10–14	Mining	2
20–39	Manufacturing	32
40–49	Transportation & Public Utilities	3
50–51	Wholesale Trade	3
52–59	Retail Trade	3
70–89	Services	4

Source: Authors

Table 3 Detailed categories of analyzed companies according to the SIC Code

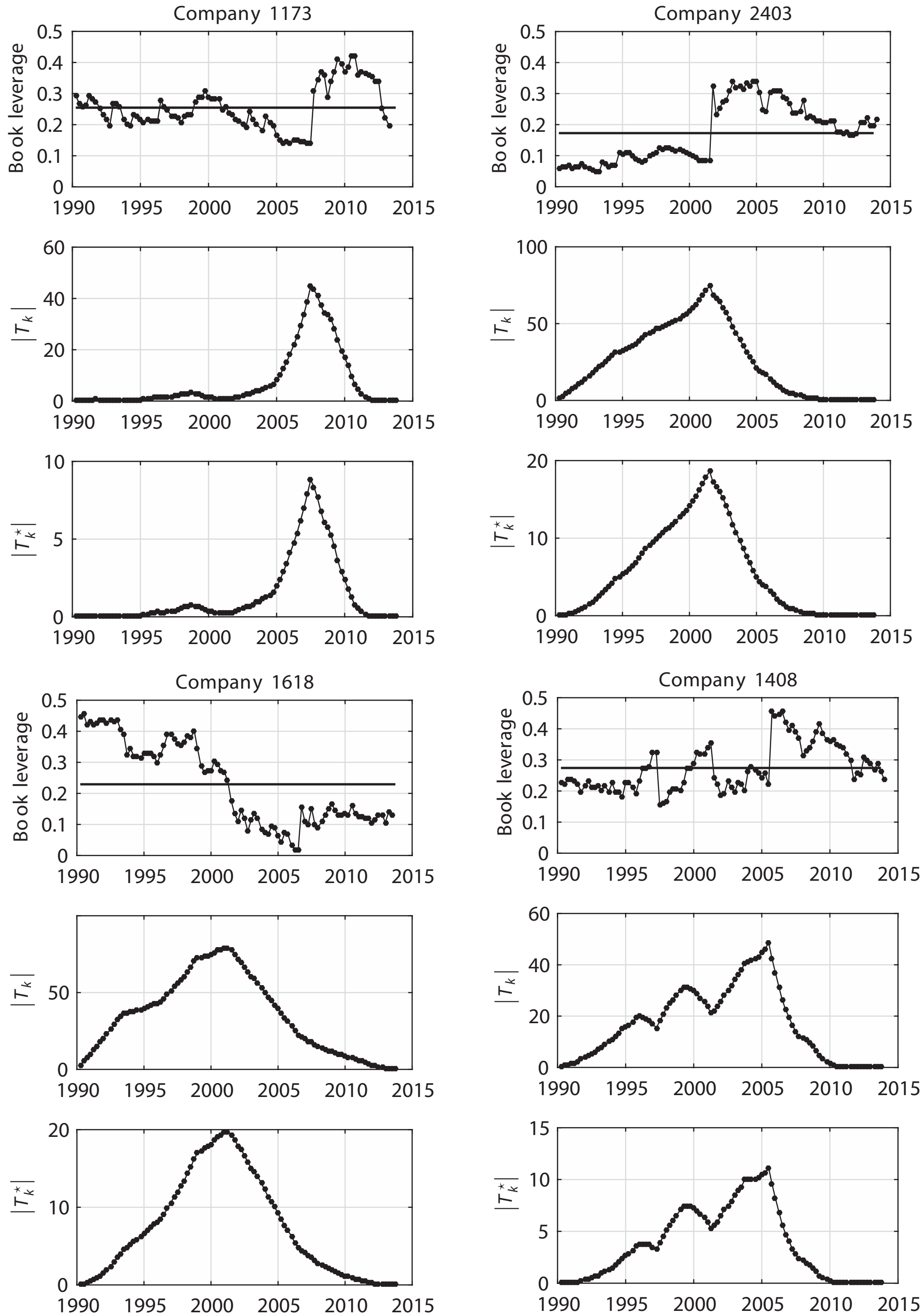
SIC Code	Standard Industrial Classification	#
10	Metal Mining	1
13	Oil and Gas Extraction	1
20	Food and Kindred Products	1
26	Paper and Allied Products	2
27	Printing, Publishing, and Allied Industries	1
28	Chemicals and Allied Products	7
29	Petroleum Refining and Related Industries	1
31	Leather and Leather Product	1
32	Stone, Clay, Glass, and Concrete Products	1
33	Primary Metal Industries	1
34	Fabricated Metal Products, except Machinery and Transportation Equipment	4
35	Industrial and Commercial Machinery and Computer Equipment	3
36	Electronic and other Electrical Equipment and Components, except Computer Equipment	4
37	Transportation Equipment	1
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks	5
45	Transportation by Air	1
48	Communications	2
50	Wholesale Trade-Durable Goods	2
51	Wholesale Trade-Nondurable Goods	1
54	Food Stores	1
57	Home Furniture, Furnishings, and Equipment Stores	1
58	Eating and Drinking Places	1
72	Personal Services	1
73	Business Services	2
80	Health Services	1

Source: Authors

Typical representative behavior of the analyzed data can be seen in Figure 2. As an illustration, we included here companies exhibiting different financial strategies. While some studied time series exhibit a sudden shift in book leverage as in the case of companies 1173 and 2403, some others exhibit gradual change, such as in the data of company 1618. A typical example of several sudden changes is given by the data of company 1408. Finally, different levels of the average book leverage are illustrated by companies 1988 and 2184.

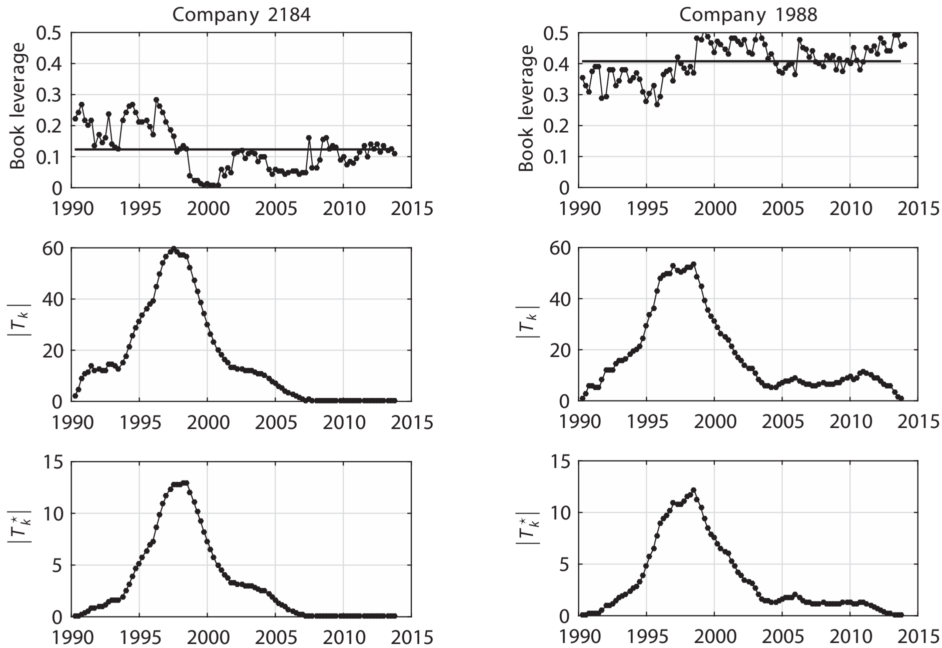
Notice that the scale for the book leverage is the same in all subfigures. On the other hand, this is not true for the scale of the values of the test statistics $\{|T_k|\}$ and $\{|T_k^*|\}$. The reason is a very high variability of the values of respective test statistics; if the same scale were used, then some figures would become unreadable.

Figure 2 Typical representatives of the analyzed data



Source: Authors

Figure 2 Typical representatives of the analyzed data – continuation

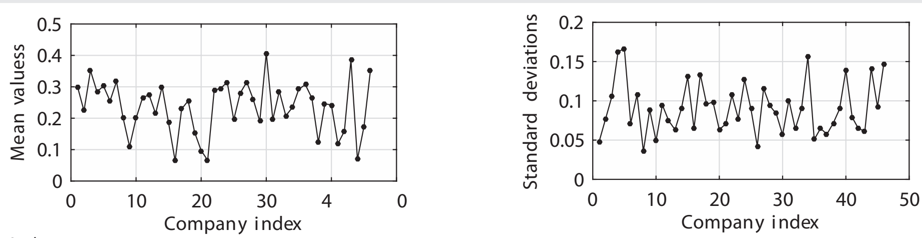


Source: Authors

First, the data passed a "visual inspection", which gave us an initial idea about the "behavior patterns" of individual companies. It is worth noticing that statistics $\{T_k\}$ and $\{T_k^*\}$ constructed for detection of sudden changes indicate a break also when the data exhibits a gradual change, as is the case of company 1618, see Figure 2. However, in such a case one must be careful when interpreting a course of $\{T_k\}$ and/or $\{T_k^*\}$, because the locations of corresponding maxima, i.e., statistics (6) and (7), do not necessarily correspond to the location of a change in behavior of the studied time series. For more details show to proceed in such a case see, e.g., papers Antoch et Hušková (1998) and Antoch et al. (2002).

Second, the mean value and standard deviation of the book leverage of each individual company has been calculated. The results can be seen in Figure 3. It appears that the mean values do not contain any outliers and follow our expectations. The same holds for the standard deviation values.

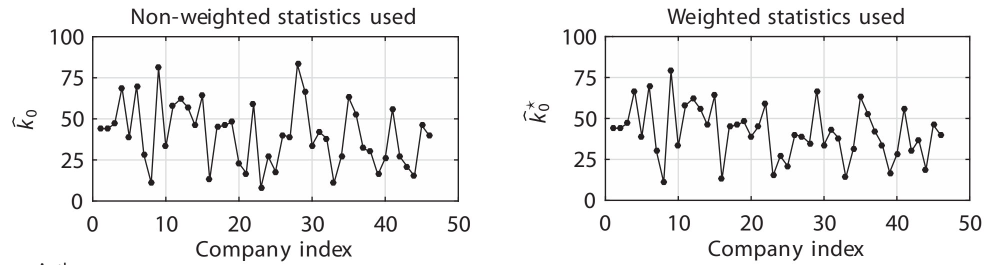
Figure 3 Mean values and standard deviations of the book leverage for individual companies



Source: Authors

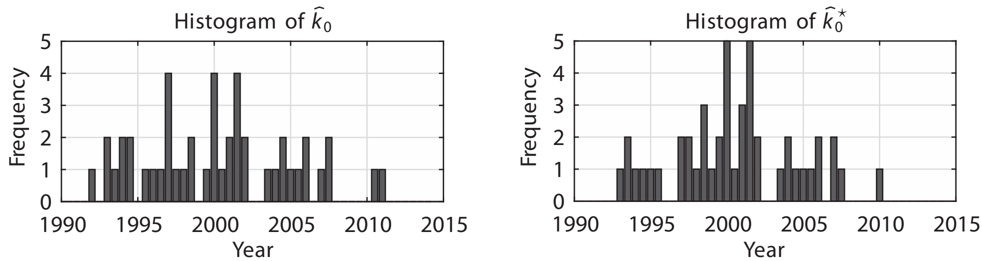
Third, test statistics (4) and (5) suggested for the detection of a sudden change in the behavior of individual time series have been calculated for each company. It was a bit surprising that all test statistics for individual series are statistically significant on the 5% level for non-weighted statistic (4), and all but two test statistics for individual series are statistically significant on the 5% level when weighted statistic (5) has been used. Several companies exhibited two to three detectable changes. Therefore, we estimated the times of the change for each individual data time series using both statistic (6) and (7). Estimated change points are presented in Figure 4, and summarized using histograms in Figure 5. From Figures 4 and 5 we can see that the most change points have been detected around the year 2000, followed by the years 1997 and 2005. Against our expectations, this analysis has not shown any breaks around the time of the sub-prime crisis.

Figure 4 Estimated individual change points using Formulas (6) and (7) ($\widehat{k}_0 = 1$ corresponds to 1Q 1983, while $\widehat{k}_0 = 100$ corresponds to 4Q 2015)



Source: Authors

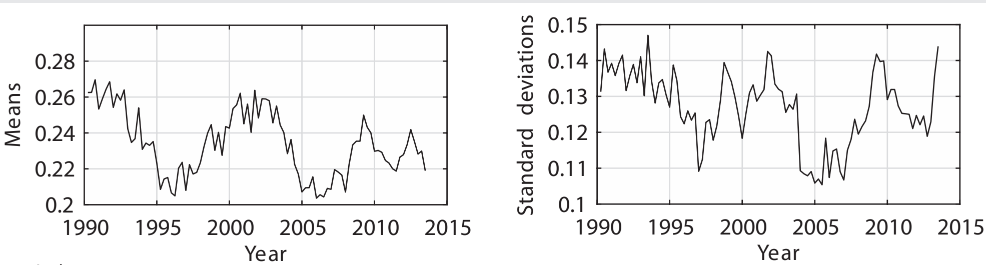
Figure 5 Histograms of estimated change points for estimators based on both non-weighted and weighted test statistics



Source: Authors

We also calculated averages and standard deviations of the set of analyzed companies during the period 1Q 1991 through 4Q 2014. The results are plotted in Figure 6. It is very interesting that the character of both means and standard deviations changes practically at the same time when many individual companies exhibited a sudden change in their book leverage levels.

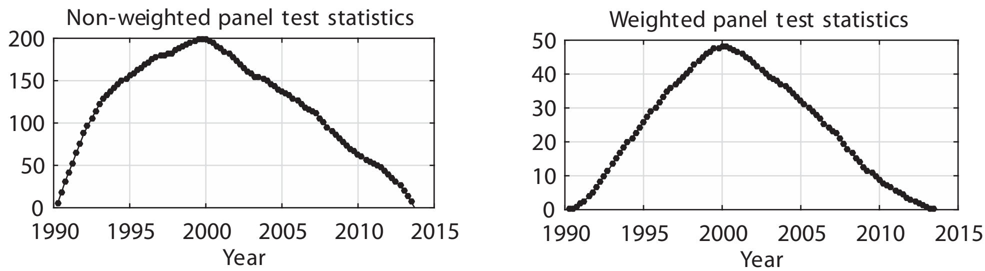
Figure 6 Average book leverage of actual portfolios during the time and the corresponding standard deviations



Source: Authors

Finally, we calculated panel test statistics (8) and (9). The results are presented in Figure 7. Both statistics indicate the change around the year 2000. The non-weighted panel test statistic also reflects the changes in the individual behavior of each company around the year 1997, compare Figures 4 and 5. The courses of both considered test statistics correspond to the analysis of individual companies.

Figure 7 Panel test statistics



Source: Authors

CONCLUSIONS

In our paper we describe analysis of stationarity (in the mean) of the book leverage data of 46 U.S. companies selected from different industries, see Tables 2 and 3. First, we analyzed each company separately, and then we analyzed all companies together using methods suggested for analysis of panel data. Moreover, we assumed that if there is a change at time k_0, then any series either changes at time k_0 or does not change at all.

Change point methods for panel data are proposed for deciding which of two hypotheses holds true. One hypothesis claims that the series do not change while the second claims that the series change at a certain unknown time. In the case of our data, none of these hypotheses seems to be true because each series exhibits a change, but at a different time. Most series changed near the year 2000, some also around 1997 and 2005, and as a consequence the hypothesis that all series are stationary was rejected.

The changes during the period 1997–2000 may reflect the Asian financial crisis that gripped much of East Asia, beginning in July 1997 and raised fears of a worldwide economic meltdown due to financial contagion. The Asian "flu" had also put pressure on the United States and Japan. Their markets did not collapse, but they were severely hit. On 27 October 1997, the Dow Jones industrial plunged 554 points or 7.2%, amid ongoing worries about the Asian economies. The New York Stock Exchange briefly suspended trading. The crisis led to a drop in consumer and spending confidence. Indirect effects included the dot-com bubble, and years later the housing bubble and the sub-prime mortgage crisis. Recall that many economists believe that the Asian crisis was created not by market psychology or technology, but by policies that distorted incentives within the lender-borrower relationship. For more details see, e.g., Goldstein (1998) or Muchhala (2007).

Another important goal of our analysis was to decide whether a sub-prime crisis in the period 2007–2008 caused a significant change in companies' behavior. Even though few analyzed series changed within this time period, see, e.g., company 1173, most series exhibit significant changes at some other times. Therefore, the panel statistics do not show a change in the period 2007–2008. We conclude that we did not discover a change of analyzed book leverage data of the selected U.S. companies due to the sub-prime crisis.

The fact that all 46 companies included in our study existed at least during 24 consecutive years, i.e., 1Q 1991 through 4Q 2014, and were able to report regularly, indicates that they represent rather powerful companies. Therefore, one should be careful about making sweeping generalizations on the whole U.S. economy, because in addition to these strong companies, many weaker ones were also present on the market.

ACKNOWLEDGEMENT

The work was supported by the Czech Science Foundation under Grant No. P403/15/09663S. The authors would like to thank Professor Jan Hanousek from CERGE and two unknown referees for their valuable comments that helped considerably improve the contents of the paper.

References

ANTOCH, J., GREGOIRE, G., HUŠKOVÁ, M. Tests for continuity of regression functions. *J. of Statistical Planning and Inference*, Vol. 137, 2007, pp. 753–777.

ANTOCH, J., GREGOIRE, G., JARUŠKOVÁ, D. Detection of structural changes in generalized linear models. *Statistics & Probability Letters*, Vol. 69, 2004, pp. 315–332.

ANTOCH, J., HANOUSEK, J., HORVÁTH, L., HUŠKOVÁ, M., WANG, S. Structural breaks in panel data: Large number of panels and short length time series. *Econometric Reviews* (submitted).

ANTOCH, J. AND HUŠKOVÁ, M. Procedures for detection of multiple changes in series of independent observations. In: HUŠKOVÁ, M., MANDL, P. eds. *5th Prague Symp. on Asymptotic Statistics,* Physica-Verlag, Heidelberg, 1994, pp. 3–20.

ANTOCH, J., HUŠKOVÁ, M., VERAVERBEKE, N. Change-point problem and bootstrap. *J. of Nonparametric Statistics*, Vol. 5, 1995, pp. 123–144.

ANTOCH, J. AND HUŠKOVÁ, M. Estimators of changes. In: GHOSH, S. AND DEKKER, M. *Nonparametrics, Asymptotics and Time Series*, New York: M. Dekker, 1998, pp. 533–578.

ANTOCH, J., HUŠKOVÁ, M., JANIC, A., LEDWINA, T. Data driven rank test for the change point problem. *Metrika,* Vol. 68, 2008, pp. 1–15.

ANTOCH, J., HUŠKOVÁ, M., JARUŠKOVÁ, D. Off-line statistical process control. In: LAURO et al. eds. *Multivariate Total Quality Control,* Springer/Physica-Verlag, Heidelberg, 2002, pp. 1–86. ISBN 3-7908-1383-4.

ANTOCH, J., HUŠKOVÁ, M., PRÁŠKOVÁ, Z. Effect of dependence on statistics for determination of change. *J. of Statistical Planning and Inference,* Vol. 60, 1997, pp. 291–310.

ANTOCH, J. AND JARUŠKOVÁ, D. Testing for multiple change points. *Computational Statistics*, Vol. 30, 2013, pp. 2161–2183.

BAI, J. AND PERRON, P. Estimating and testing linear models with multiple structural changes. *Econometrica*, Vol. 66, 1998, pp. 47–78.

BALTAGI, B. H. *Econometric Analysis of Panel Data.* 5th Ed. New York: John Wiley, 2013.

CSÖRGŐ, M. AND HORVÁTH, L. *Limit Theorems in Change-Point Analysis*. New York: J. Wiley, 1997.

DICK-NIELSEN, J., FELDHŰTTER, P., LANDO, D. Corporate bond liquidity before and after the onset of the subprime crisis. *J. of Financial Economics*, Vol. 103, 2012, pp. 471–492.

FAMA, E. F. AND FRENCH, K. Common risk factors in the returns on stocks and bonds. *J. of Financial Economics,* Vol. 33, 1993, pp. 3–56.

FAMA-FRENCH DATABASE [online]. <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.htm>.

GOLDSTEIN, M. *The Asian Financial Crisis: Causes, Cures, and Systemic Implications.* Institute for International Economics, 1998. ISBN 0-88132-261-X.

HORVÁTH, L. AND RICE, G. Extensions of some classical methods in change point analysis. With discussion. *Test*, Vol. 23, 2014, pp. 219–290.

HUŠKOVÁ, M. AND HORVÁTH, L. Change-point detection in panel data. *J. of Time Series Analysis*, Vol. 33, 2012, pp. 631–648.

JAMES, B., JAMES, K. L., SIEGMUND, D. Tests for a change-point. *Biometrika*, Vol. 74, 1987, pp. 71–83.

JARUŠKOVÁ, D., Testing appearance of linear trend. *J. of Statistical Planning and Inference*, Vol. 70, 1998, pp. 263–276.

LEMMON, M. L., ROBERTS, M. R., ZANDER, J. F. Persistence and the cross-section of corporate capital structure. *J. of Finance*, Vol. 63, 2008, pp. 1575–1608.

MAC NEILL, I. B. Tests for change of parameter at unknown time and distribution of some related functionals of Brownian motion. *Annals of Statistics,* Vol. 2, 1974, pp. 950–962.

MUCHHALA, B. *Ten Years After: Revisiting the Asian Financial Crisis*. Woodrow Wilson International Center for Scholars, Asia Program, 2007. ISBN 1-933549-24-6.

SANTOS JOÃO, A. C. Bank corporate loan pricing following the subprime crisis. *Review of Finance Studies,* Vol. 24, 2011, pp. 1916–1943.

SIC CODE [online]. <http://siccode.com/en/siccode/list/directory>.

VOSTRIKOVA, L. Detecting disorder in multidimensional random processes. *Soviet Mathematical Doklady*, Vol. 24, 1981, pp. 55–59.