European Listed Companies' Share Price Reactions to Global Credit Crunch: Typology of Winners and Losers

Mari Männiste, Aaro Hazak, and Enn Listra

Abstract —The large variances in the share price reactions to the 2007 credit crunch appear to depend on the geographical region, size and financial performance of companies. In order to identify commonalities and idiosyncrasies in these influences, we perform cluster analysis of companies' share price performance and financial and structural data as of 31 December 2008 in comparison to the start of the credit crunch in July 2007 on a sample of 705 listed companies from 45 European countries. Employing k-means clustering, we recognise 8 distinct clusters, one of these comprising companies, which gained in stock prices under the credit crunch. Most of the "winners" tend to be large companies in the EU 15 old member states, showing a relatively low *ex ante* P/E ratio, high profit margin and moderate return on assets. However, companies having experienced biggest losses in share prices are the ones with highest *ex ante* P/E ratios and high return on assets, demonstrating a clear contrast between the overly optimistic expectations of shareholders and companies' actual ability to increase value prior to the credit crunch. Interestingly, belonging to a certain industry does not seem to have been a key driver of companies' stock price reactions to the credit crunch.

Index Terms—Stock prices, credit crunch, cluster analysis.

I. INTRODUCTION

It is evident that the credit crunch that got its start in 2007 in the United States attacked severely also European companies. The credit crunch in the USA became apparent when structured finance products based on mortgage loans turned out to be much riskier than would have been expected under declining real estate prices. This in turn caused a major decline in the ratings of several investment products, bringing along difficulties for companies in the finance and real estate sectors. The liquidity crisis and the consecutive credit crisis, accompanied by a crisis in trust, significantly affected stock prices.

The aim of this paper is to map a typology of European listed companies' share price reactions to the credit crunch by means of cluster analysis based on the financial and other data of these companies. In particular, we attempt to get insight into the "winners" group, i.e. to find out what are the characteristics of companies that gained in stock prices under the credit crunch. We also attempt to disclose the characteristics of companies that were the fastest losers in stock prices.

Cluster analysis is one of the subtypes of data mining. The aim is to detect certain regularities or patterns in a given data set by comparing the distance measures between the data objects, and organising the data into groups on the basis of these distances.

While the drivers and consequences of the 2007 credit crunch are receiving increasing attention in recent finance literature, the novel aspect of our study is identifying the key features that distinguish the "winners" from "losers" in terms of stock price reactions to the credit crunch and the consequent economic crisis.

The paper is structured as follows. Section 2 gives an overview of key related literature. The third section specifies the data and methodology for the research. Section 4 presents the empirical results and Section 5 concludes the paper. Preliminary findings of our study have been presented at the 2011 3rd International Conference on Information and Financial Engineering (Shanghai, China) and included in the conference proceedings [1].

II. RELATED LITERATURE

Cluster analysis denotes a wide variety of methods that aim to establish groupings or clusters in the set(s) of data (see e.g. [2] for a detailed overview). The method has been used in earlier finance research for a number of purposes.

Most notable has been the use of cluster analysis in the bankruptcy and default prediction of companies. Alam et al. [3] use fuzzy clustering as well as self-organising neural networks for the purposes of bank failure analysis. Using different financial indicators, they aim at identifying clusters and characteristics of potentially bankrupting banks as opposed to viable ones.

Cheng et al. [4] present a novel concept of generic self-organising fuzzy neural network in developing an early warning system for predicting bank failures. Their study incorporates elements of fuzzy clustering.

Murtuza and Shah [5] use clustering as a part of their study of company failures. Having grouped companies based on their activity status (failed and continuing companies), they use historical three year data of these companies to construct a self learning algorithm that would enable to predict bankruptcy.

Depending on the aim of a particular study, cluster analysis has sometimes been used in association with other methods

M. Männiste is with Financial Economics at the Department of Economics at Tallinn University of Technology, Ehitajate tee 5, Tallinn 19086, Estonia (e-mail: mari@kups.pri.ee).

A. Hazak is with the Department of Economics at Tallinn University of Technology, Ehitajate tee 5, Tallinn 19086, Estonia (e-mail: aaro.hazak@tseba.ttu.ee).

E. Listra is with Finance and Banking at the Department of Economics at Tallinn University of Technology, Ehitajate tee 5, Tallinn 19086, Estonia (e-mail: enn.listra@tseba.ttu.ee).

of analysis. Ba and Zhu [6] use it in association with factor analysis to study the price differences of two types of shares in Chinese stock markets. The same combination is used by Chen et al. [7] to investigate the performance of listed companies in Chinese pharmaceutical industry, by Sun et al. [8] in a study on the financial performance of listed real estate companies on the Chinese stock market. Zhu et al. [9] use cluster analysis in combination with discriminant analysis for the financial evaluation of companies, and Wei and Chen [10] in combination with principal components analysis to develop a financial pre-alarming system for companies. Liu et al. [11] apply the clustering method on Altman's [12] Z-scores of different time series in order to get a better insight into early-warning indicators of companies' financial risks. Chen and Du [13] use k-means clustering as part of their study on financial distress prediction based on the data of companies listed on the Taiwanese stock exchange.

In some cases of data sets the clusters are pre-determined by trivial and clear groupings in some dimensions of vector variables. The possible existence of trivial groupings makes cluster analysis unproductive in such cases. Some important results related to this problem, which is applicable also in the case of our paper, were outlined by Dahlstedt et al. [14] who showed based on a dataset of all Finnish publicly traded companies that companies demonstrate non-homogeneity of the industry classification categories in terms of financial ratios. One can expect that at least belonging to a particular industry will not pre-determine the clusters in this study.

All the above papers have found clustering a promising method in identifying the special characteristics of (e.g. potentially failing) businesses *ex post*. A limitation of cluster analysis, however, is that the results of clustering based studies are sample specific and the algorithms that have proved to be successful on a given sample might not function on a different dataset and in a different environment. In our study, we use clustering only for the purpose of *ex post* analysis and do not aim to make any predictions for the future.

III. DATA AND METHODOLOGY

Our dataset covers 705 European listed companies as of 31 December 2008 and 31 December 2007 in comparison to the start of the credit crunch in July 2007. The companies in the dataset originate from 45 different European countries. The dataset covers companies from all industries, except for the financial sector which we have excluded due to incomparability.

For the purposes of clustering we use the following data for each company: change in share price, location (economic region), industry classification (Global Industry Classification Standard, GICS), number of employees and various financial indicators. As regards the economic region, we have distinguished the following territories:

– EU15 – the "old" member states of the European Union (France, Germany, United Kingdom, Italy, Portugal, Spain, Ireland, Luxemburg, Austria, Belgium, Greece, Finland, Sweden, Denmark, and the Netherlands);

– EU12 – the "new" member states of the European Union (Estonia, Latvia, Lithuania, Poland, Slovenia, Slovakia, Czech Republic, Hungary, Malta, Cyprus, Bulgaria and Romania);

– EFTA – members of the European Free Trade Area that are not covered by the EU15 and EU12 groups (Iceland, Liechtenstein, Switzerland and Norway)

– CIS – (previous) members of the Commonwealth of Independent States (Russia, Ukraine, Kazakhstan, Byelorussia, Azerbaijan, Uzbekistan, Turkmenistan, Georgia, Armenia, Tajikistan, Kyrgyzstan and Moldova)

– TC – Turkey and Croatia.

Despite the fact that "fundamentalists" suggest using direct economic indicators to explain changes in share prices (Stewart, [15]), the more indirect accounting based approach has been frequently used in practice due to better data availability. Our study employs accounting information in the form of financial ratios to analyse share price changes. When selecting financial variables, we build on previous studies [12] and [16]–[22], which have aimed at identifying financial ratios which best discriminate between potentially failing or distressed companies from viable ones. Five financial ratios, which have historically demonstrated a good ability to capture company success, were selected to be included in the cluster analysis model – P/E ratio, profit margin, ROA, debt-to-equity ratio and current ratio.

When selecting an algorithm for the cluster analysis of the above dataset, k-means clustering appeared to fit best for our research. Our aim was to identify clusters of the dataset companies based primarily on the change in their stock price as well as their other structural and financial characteristics as outlined above. K-means clustering developed by MacQueen [23] has been a milestone in the use and advancement of the method. It aims to partition the *n* observations in the total dataset into *k* sets based on minimising the following function (within-cluster sum of squares):

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 ,$$

where measures the distance between an observation $x_i^{(j)}$ and the mean of points c_j. Ward's [24] method of using the sum of squares between the two clusters, summed over variables, has been widely used in clustering studies as the measure of distance.

We used the PASW Statistics 17.0 program for performing the cluster analysis exercise.

From the companies' perspective, the credit crunch refers to a severe shortage of available financing. We have used 31 July 2007 as the breakpoint date to mark the start of the credit crunch on European markets, drawing on the Brunnermeier [25] study. By approximately that time the signs of the seriousness and global reach of the credit crunch became evident. However, the most drastic consequences for financial institutions and for the European stock markets had not yet come about. 31 December 2008 was used as the reference date for calculating the change in a company's

share price in comparison to 31 July 2007. In order to grasp an alternative and slightly different perspective, we have used 31 December 2007 compared to 31 July 2007 to calculate companies' share price change in order to identify what kind of companies have been fast losers in share prices.

Typically to k-means clustering, the number of clusters has been determined on a trial basis. We have identified the optimal number of clusters to be eight in order to capture meaningful groups of companies depending on the specifics of their stock price performance. Before subjecting to clustering, we brought the data to a common scale employing the following formula:

$$x_z = \frac{x_i - \bar{x}}{\sigma},$$

where x_z is the common scale value of the variable, x_i is the original value, $\bar{x}$ is the mean value and σ is the standard error. Subsequently, the common scale values were translated into the range of 0...1 as follows:

$$x' = \frac{x_z - x_{min}}{x_{max} - x_{min}},$$

where x_{min} is the minimum common scale value of the variable and x_{max} is the maximum common scale value of the variable.

The location (economic region) and industry classification variables were incorporated in the model as binary dummy variables. Similarly, dummy variables were used for indicating the change in the share price of the company in the following five groups: share price change >0 (the "winners"), 0…-30%, -30…-60%, -60…-95% and <-95%.

IV. EMPIRICAL FINDINGS

A. Typology of Longer Term Winners and Losers

Our first clustering exercise aims to establish the typology of longer term stock price winners and losers. Out of the 8 clusters formed as a result of k-means clustering, the majority of the stock price winners are located in Cluster 7. As 79% of the companies included in our sample lost more than 30% in their stock value, in a broader context those 17% whose share price decline remained between 0% and -30 % (C2) were also survivors compared to others.

Companies with largest losses in stock prices appear to be gathered into clusters 1, 3, 4 and 5. The formation of Cluster 8 is not led by changes in stock price.

As we can see from Fig. 1, C7 (or the "winners") consists mostly (96%) of companies in the EU-15 region. EU-15 companies form also a majority in C2 (i.e. the "other survivors"). This may be explained by the relative maturity of the EU-15 economies, where the success of companies tends to depend on their intrinsic ability to add value and gain competitive advantages through innovation. Such elements of market competition, combined with relatively efficient stock markets, may have enabled certain companies to

demonstrate better resistance to the credit crunch and other cyclical effects in business activities.

TABLE I: CLUSTERS OF COMPANIES IN THE SAMPLE

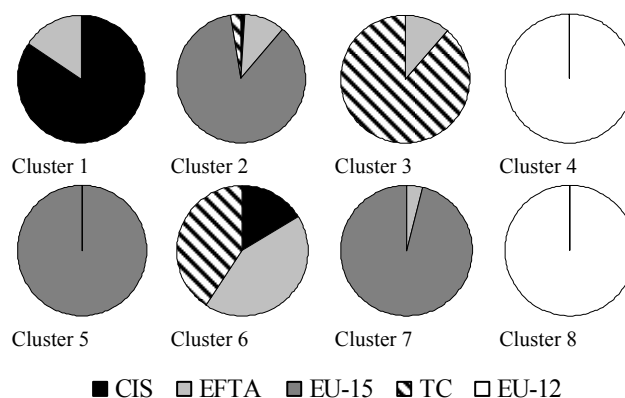| Cluster	C1	C2	C3	C4	C5	C6	C7	C8
Stock price change range	-60 … -95	0 … -30	-60 … -95	-60 … -90	-30 … -95	-30 … -60	>0	all
No. of companies	51	117	35	82	274	37	26	83
% of total sample	7%	17%	5%	12%	39%	5%	4%	12%

■ CIS ▦ EFTA ▦ EU-15 ▨ TC □ EU-12

Fig. 1. Regional composition of clusters.

Companies in Clusters 1, 3, 4 and 5 (i.e. the biggest losers in stock price) appear to be clustered according to the region they belong to. A large portion of EU-12 companies (cluster 4) included in our sample appears to have undergone a huge decline in share prices over the period under investigation. This may be explained by the emerging nature of these economies, where the success of businesses is largely based on achieving additional "quantity", i.e. their ability to meet emerging demand for products and services, as opposed to a competition based on additional "quality". As a consequence of the strong sensitivity of such business models to cyclical effects, the adverse changes in market expectations reflected in stock prices seem to have been more severe in the case of emerging markets compared to the relatively mature EU-15 and EFTA markets.

For a similar effect, we can note that most of the companies (86%) in the CIS region lost 60 to 95% in their stock price (Cluster 1) and the remaining 14% of the CIS companies, which belong to cluster 6, lost 30 to 60%. This means that there were no survivors or winners in the CIS region in terms of stock price reactions to the global credit crunch.

We find that almost all industry sectors are represented in each cluster. Cluster 7 ("winners") and Cluster 2 ("other survivors") are relatively homogeneous, however, and the best performing companies appear to be the ones in non-cyclical businesses. At the same time, we cannot clearly point out a sector in which the companies have lost most in share prices. Interestingly, belonging to a certain industry sector appears to have had no substantial effect on changes in a company's stock price due to the credit crunch.

As illustrated on Fig. 2, the lowest average

price-to-earnings (P/E) ratio was demonstrated by companies belonging to the "winners" cluster. P/E ratio was also relatively small in Cluster 2. This distinct feature of the better surviving companies indicates that the credit crunch and the subsequent economic crisis influenced more "gently" the share price performance of those companies the *ex ante* share prices of which relied more heavily on historical evidence on the ability of the company to generate profits, as opposed to expectations regarding future delivery of value.

For an opposite effect, companies in Clusters 1, 3 and 4 as well as 6 are characterised with high *ex ante* P/E ratios which shows the high expectations of the shareholders. Such a finding clearly demonstrates a strong contrast between the overly optimistic expectations of shareholders and companies' actual ability to increase value prior to the credit crunch.
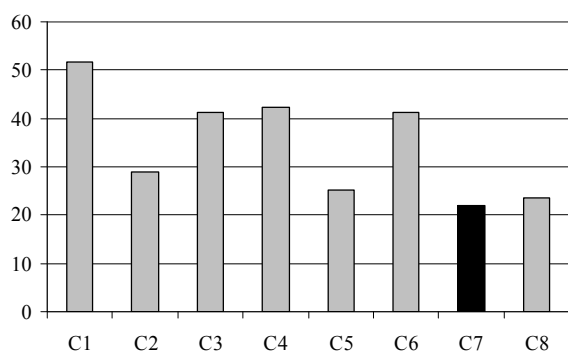

Fig. 2. Average P/E ratio by clusters (%).

Fig. 2 also indicates the main difference between Cluster 4 and Cluster 8, which both consists of companies in the EU-12 region – shareholders expected a higher future profit from the companies in Cluster 4 than from the companies in Cluster 8.

The companies in the "winners" cluster were among the ones with the highest average profit margin, whereby return on assets of the winner companies were relatively moderate compared to others. From Fig. 3 and Fig. 4 we can also see a potential reason for shareholders' high expectations regarding companies in Cluster 1 and Cluster 6, which is the high profit margins and relatively high return on assets (especially in C1).

It is of interest to note that the same clusters consisted mostly of companies of the CIS region and demonstrated high P/E ratios, meaning that highly profitable (and therefore expectedly risky) companies were able to convince shareholders prior to the peak of the credit crunch of their ability to deliver even higher profits in the future. After the start of the credit crunch, the bubble of such overly optimistic expectations appears to have become evident, leading to this type of companies experiencing huge declines in share prices.

We use the number of employees as a proxy variable for company size. It appears from Fig. 5 that Cluster 7 ("winners") and Cluster 2 ("other survivors") as well as Cluster 5, between which all the EU-15 companies are divided, comprise companies with the biggest average number of employees. Fig. 5 also indicates an important difference between the clusters with the biggest declines in share prices (i.e. Clusters 1, 3 and 4). Namely, companies in

Cluster 1 have a relatively high average number of employees whereas companies in Clusters 3 and 4 are relatively small based on the number of employees. All EU-12 region companies, divided between Clusters 4 and 8, are relatively small compared to others.
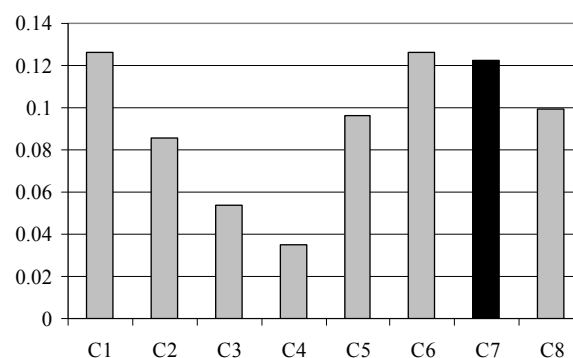

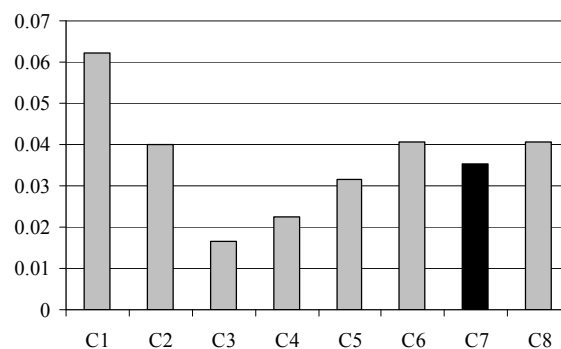Fig. 3. Average profit margin by clusters.
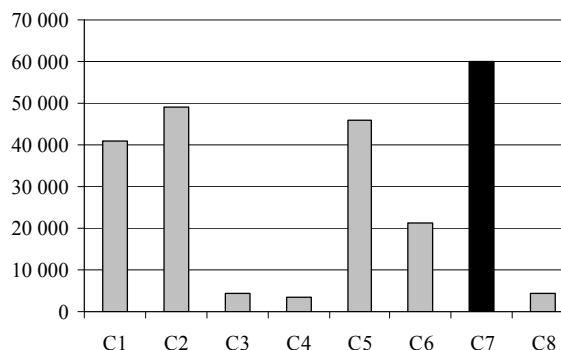

Fig. 4. Average ROA by clusters.

Fig. 5. Average number of employees by clusters.

We find that debt-to-equity ratio and current ratio do not differ substantially in the eight clusters.

B. Typology of Short Term Winners and Losers

As an alternative to the longer term view, we also studied the same population of companies with the aim of identifying the fastest losers and winners in stock prices. For these purposes we calculated stock price changes for 31 July 2007 compared to 31 December 2007 and strived to identify the types of companies which were most sensitive to the crisis and had lost in their stock prices already by the end of 2007.

The method and process of clustering remained the same as described above. However the optimal number of clusters appeared to be 6 for this clustering exercise due to the fact

that, compared to 31 December 2008, by 31 December 2007 there were fewer companies whose stock price had significantly dropped.

As can be seen from Table II, the fastest losers appear in clusters S2, S4 and S5 and the winners whose stock prices had gone up despite the crisis are in clusters S1 and S6. Nearly a half of the sample companies had lost in their stock prices by the end of 2007 compared to five months before.

TABLE II: CLUSTERS OF COMPANIES IN THE SAMPLE

Cluster	S1	S2	S3	S4	S5	S6
Stock price change range	>0%	0…-45%	all	0…-46%	0…-77%	>0%
No. of companies	73	52	70	217	105	188
% of total sample	10%	7%	10%	31%	15%	27%

As at 31 December 2007 all industry sectors were represented in both the winners and losers clusters. Therefore, similarly to the clustering results discussed in the previous subsection, belonging to a particular industry does not seem to have been a key driver of stock price changes in this period.

It is interesting to note that in the fastest losers clusters (clusters S2, S4 and S5) were represented all economic regions and companies of different sizes (defined by the number of employees).
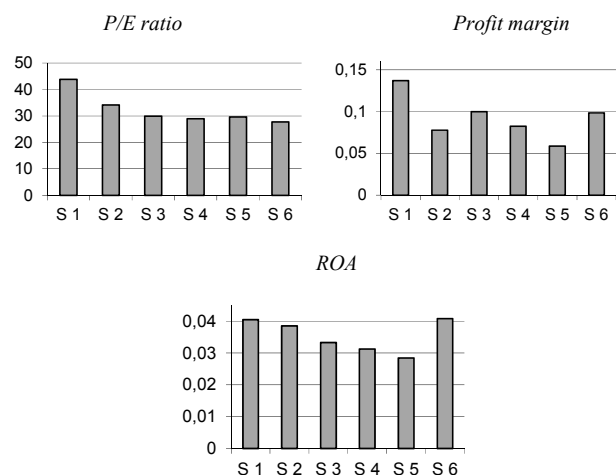

Fig. 6. Average P/E ratio, profit margin and ROA by clusters.

Differences between the stock price winners and losers as at 31 December 2007 are formed mostly on the basis of financial position of the companies. Namely, as illustrated on Fig. 6, the fastest losers in stock prices tend to have lower average *ex ante* ROA and profit margins compared to the winners. P/E ratios do not, however, differ substantially between the six clusters.

This reveals that already in a short time from the start of the credit crunch, companies which had not been historically able to deliver profits on the investments made, became subject to investors' skeptical expectations, reflected in decreased stock prices. However, the bubble of (overly optimistic) expectations regarding the future, as reflected in the P/E ratio, had not started to burst yet by 31 December 2007.

Fig. 7 reveals that although by 31 December 2008 there were no companies from the CIS region in the group of winners and a large portion of them had undergone a serious decrease in stock prices, as at 31 December 2007 only 12% companies of the CIS region had experienced a drop in stock prices.

This illustrates the time lag in markets realising the seriousness and global reach of the credit crunch, the signs of which were quite clear already by the end of year 2007.
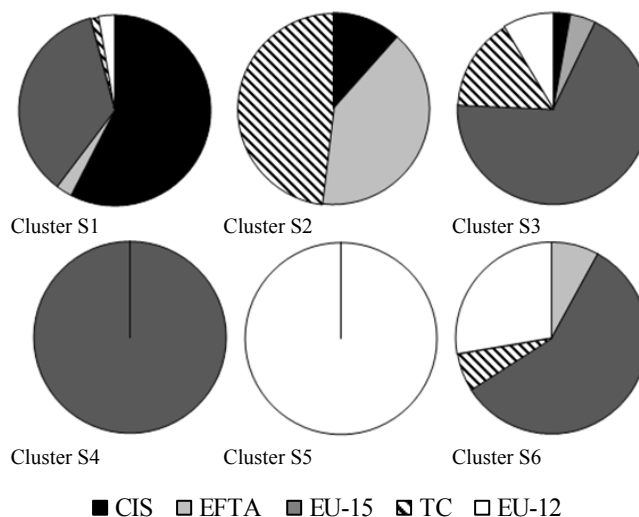

Fig. 7. Regional composition of clusters.

V. CONCLUSION

Our clustering analysis made a clear distinction between the companies the stock price of which had risen as of 31 December 2008 compared to the beginning of the credit crunch (31 July 2007). As a result of our k-means clustering study, 8 different clusters were formed based on companies' share price dynamics, location (economic region), industry sector, number of employees and five financial indicators – P/E ratio, profit margin, ROA, debt-to-equity ratio and current ratio.

Most of the "winner" companies belonged to the "old" member states of the European Union (EU-15) and could be characterised by a relatively low price-to-earnings ratio, a relatively high average profit margin and a large number of employees prior to the crisis. Thus, the "winner" group was primarily formed by such large EU-15 companies which exhibited stability and had demonstrated the ability to deliver profits by the beginning of the credit crunch. This may be partially explained by the relative maturity of the EU-15 economies, where the success of companies tends to depend on their intrinsic ability to add value and gain competitive advantages through innovation. Such elements of market competition, combined with relatively efficient stock markets, may have enabled those companies to demonstrate better resistance to the credit crunch and other cyclical effects.

In contrast, a typical "loser" in stock price after the credit crunch appears to be a company whose shareholders had high expectations (reflected in a high P/E ratio), but due to

operating on an emerging market or due to the company's weak potential those expectations did not materialise.

We can note that a large portion of the "new" European Union member states (EU-12) and CIS companies included in our sample have undergone a huge decline in share prices over the period under investigation. This may be explained by the emerging market nature of this region, where the success of businesses is largely based on achieving additional "quantity", as opposed to a quality based competition. As a consequence of the strong sensitivity of such business models to cyclical effects, the adverse changes in market expectations reflected in stock prices seem to have been more severe in the case of emerging markets.

The alternative clustering exercise, carried out to find the fastest "losers" and "winners" in stock prices as a result of the credit crunch, demonstrated that by 31 December 2007, in comparison with the beginning of the credit crunch (31 July 2007), the clusters of "losers" contained already about a half of all the companies included in our sample. As a result of k-means clustering, 6 clusters were formed based on companies' share price dynamics, location (economic region), industry sector, number of employees and five financial indicators (same as the ones discussed above).

The clusters of fastest "losers" contained companies of different economic regions and of different sizes, while the differences compared to the "winners" cluster as of 31 December 2007 were primarily due to variances in companies' financial performance. Namely, a fast stock price decline was experienced primarily by these companies the *ex ante* return on assets of which was relatively low.

Interestingly, belonging to a certain industry sector appears to have had no substantial effect on changes in a company's stock price due to the credit crunch.

REFERENCES

[1] M. Männiste, A. Hazak, and E. Listra, "Typology of European listed companies' reactions to global credit crunch: Cluster analysis of share price performance", In: Tao, F. (Ed.): *Information and Financial Engineering*. International Proceedings of Economics Development and Research, IACSIT Press, vol. 12, pp. 565-569, 2011.

[2] Data Mining VII: *Data, Text and Web Mining and Their Business Applications*, no. 37, pp. 35-44.

[3] P. Alam, D. Booth, K. Lee and T. Thordarson, "The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study," *Expert Systems with Applications*, vol. 18, pp. 186-199, 2000.

[4] P. Cheng, C. Quek, and W. L. Tung, "GenSo-EWS: a novel neural-fuzzy based early warning system for predicting bank failures," *Neural Networks*, vol. 17, pp. 567-587, 2004.

[5] M. Murtuza and J. Shah, "A neural network based clustering procedure for bankruptcy prediction," *American Business Review*, vol. 18, no. 2, pp. 80-86, 2000.

[6] S. S. Ba and Y. Q. Zhu, "Price difference between A-share and H-share in segmented Chinese stock markets: Influencing factor analysis using cluster analysis and panel data model," In Modern Finance and Global Trading Cooperation: Proceedings of the 5th International Annual Conference on WTO and Financial Engineering, 2008, pp. 441-451.

[7] H. B. Chen, Y. Ji, and H. J. Wang, "Positive analysis on enterprise performance of listed companies in Chinese pharmaceutical industry," *Comprehensive Evaluation of Economy and Society with Statistical Science*, pp. 221-225, 2009.

[8] W. B. Sun, B. Xi, and H.W. Shang, "Stock investment value analysis with factor and cluster analysis for listed company of real estate," In Proceedings of 2007 International Conference on Construction & Real Estate Management, 2007, pp. 1050-1053.

[9] J. Zhu, Y. Hao, Q. Guo, and S. Han, "Financial evaluation of the listed companies," Proceedings of 2009 International Conference of Management Science and Information System, 2009, pp. 1093-1097.

[10] Z. S. A. Wei and Z. Y. Chen, "Principal components analysis on financial crisis in listed company of China," In MoT2009: Proceedings of Zhengzhou Conference on Management of Technology, 2009, pp. 712-716.

[11] Y. Z. Liu, G. X. Hu, and L. Gao, "Clustering and comparative analysis on Z scores time series of public listed companies in non-ferrous metal industry," In Ninth Wuhan International Conference on E-Business, 2010, pp. 1591-1597.

[12] E. I. Altman and P. Narayanan, "An international survey of business failure classification models," *Financial Markets, Institutions and Instruments*, vol. 6, No. 2, pp. 1-57, 1997.

[13] W. S. Chen and Y. K. Du, "Using neural networks and data mining techniques for the financial distress prediction model," *Expert Systems with Applications*, vol. 36, pp. 4075-4086, 2008.

[14] R. Dahlstedt, T. Salmi, M. Luoma and A. Laakkonen, "On the usefulness of standard industrial classifications in comparative financial statement analysis," *European Journal of Operational Research*, vol. 79, no. 2, pp. 230-238, 1994.

[15] G. B. Stewart, "Market myths," In: Stern, J. M., Chew, D.H. (Eds), *The Revolution in corporate finance.* Oxford, UK: Blackwell Publishing, 1989.

[16] W. Beaver, "Financial ratios as predictors of failure," Empirical Research in Accounting: Selected Studies 1966, *Journal of Accounting Research*, Supplement to vol. 4, pp. 71-111, 1967.

[17] M. Crouhy, D. Galai and R. Mark, "Prototype risk rating system," *Journal of Banking and Finance*, Vol. 25, pp. 47-95, 2001.

[18] A. Hazak and K. Männasoo, "Indicators of corporate default – EU based empirical study," *Transformations in Business & Economics*, Vol. 9, No. 1, pp. 62-76, 2010.

[19] K. Männasoo, "Determinants of firm sustainability in Estonia," *Eastern European Economics*, Vol. 46, No. 4, pp. 27-42, 2008.

[20] J. Ohlson, "Financial ratios and the probabilistic prediction of bankruptcy," *Journal of Accounting Research*, Vol. 18, No. 1, pp. 109-131, 1980.

[21] T. Shumway, "Forecasting bankruptcy more accurately: A simple hazard model," *Journal of Business*, Vol. 74, No. 1, pp. 101-124, 2001.

[22] M. E. Zmijewski, "Methodological issues related to the estimation of financial distress prediction models," *Journal of Accounting Research*, Supplement to Vol. 22, pp. 59-86, 1984.

[23] J. B. MacQueen, "Some methods for classification and analysis of multivariate observations," Lucien M. LeCam and Jerzy Neyman (eds), Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability, Vol. 1, *Theory of Statistics.* Berkeley, University of California Press, 1967, pp. 281-297.

[24] J. H. Ward, Jr., "Hierarchical grouping to optimize an objective function," *Journal of the American Statistical Association*, 48, 236-244, 1963.

[25] M. K. Brunnermeier, "Deciphering the liquidity and credit crunch 2007–2008," *Journal of Economic Perspectives*, Vol. 23, No. 1, pp. 77-100, 2009.