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Typology of European Listed Companies' Reactions to Global Credit Crunch: Cluster Analysis of Share Price Performance

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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.

Keywords: stock prices, credit crunch, cluster analysis

1. Introduction

It is evident that the credit crunch that got its start in 2007 in the United States attacked severely also European companies. 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. Cluster analysis is one of the subtypes of data mining, and 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.

2. Related Literature

Cluster analysis has been used in earlier finance research, primarily in the context of bankruptcy and default prediction of banks and companies. Alam et al. (2000) use fuzzy clustering as well as self-organising neural networks for the purposes of bank failure analysis. Cheng et al. (2004) present a novel concept of generic self-organising fuzzy neural network in developing an early warning system for predicting bank failures. Murtuza and Shah (2000) use clustering as a part of their study of company failures. Having grouped companies based on their activity status (failed or active), they use historical three year data of these

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companies to construct a self learning algorithm to predict bankruptcy. Chen and Du (2008) use *k*-means clustering as a part of their study on financial distress prediction based on the data of companies listed on the Taiwanese stock exchange.

All the above papers have found clustering a promising method in identifying the special characteristics of 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 economic 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.

3. Data and Methodology

Our dataset covers 705 European listed companies as of 31 December 2008 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;
- EU12 – the "new" member states of the European Union which joined 2004 and 2007;
- 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 CIS (Russia, Ukraine, Kazakhstan, Byelorussia, Azerbaijan, Uzbekistan, Turkmenistan, Georgia, Armenia, Tajikistan, Kyrgyzstan and Moldova); and
- TC – Turkey and Croatia.

Despite the fact that "fundamentalists" suggest using direct economic indicators to explain changes in share prices (Stewart, 2003), 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 (Altman and Narayanan, 1997; Beaver, 1967; Ohlson, 1980; Shumway, 2001; Zmijewski, 1984; Männasoo, 2008; Hazak and Männasoo, 2010; Crouhy et al., 2001) 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 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 $\left\| x_i^{(j)} - c_j \right\|^2$ measures the distance between an observation $x_i^{(j)}$ and the mean of points c_j. 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 (2008) 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.

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. 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%.

4. Empirical Findings

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 C8 is not led by changes in stock price.

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
Number of companies	51	117	35	82	274	37	26	83
% of total sample	7%	17%	5%	12%	39%	5%	4%	12%

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.

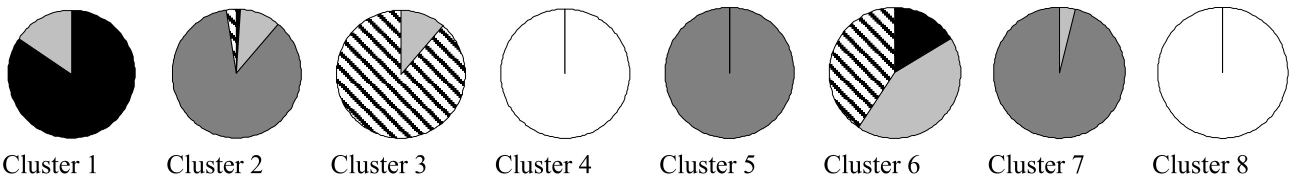

Fig. 1: Regional composition of clusters. ■ CIS □ EFTA ■ EU-15 ▧ TC □ EU-12

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 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 and the remaining 14% of the CIS companies, which belong to C6, 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. C7 ("winners") and C2 ("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 C2. 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.

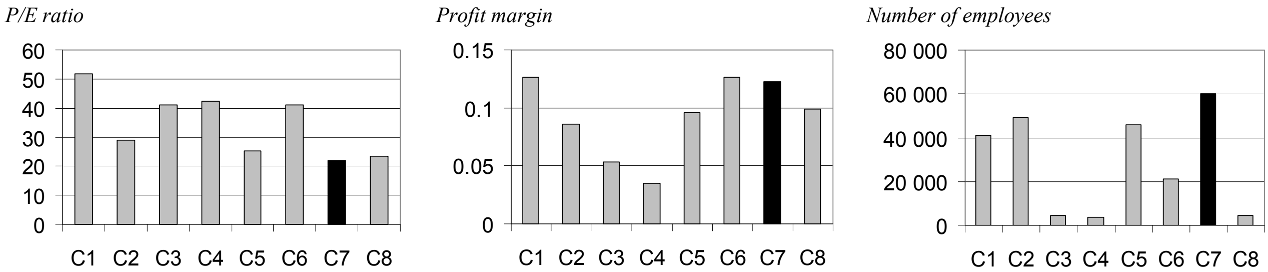

Fig. 2: Average P/E ratio, profit margin and number of employees by clusters.

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.2 we can also see a potential reason for shareholders' high expectations regarding companies in C1 and C6, 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 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.2 that C7 ("winners") and C2 ("other survivors") as well as C5, between which all the EU-15 companies are divided, comprise companies with the biggest average number of employees.

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

5. Conclusions

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). 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 depends 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.

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.

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