Financial Characteristics and Classification of Production Companies Grouped by Relevance of the Logistic Metric

Jaroslava Pražáková, Martin Pech, Petra Kosíková

Abstract: The main aim of the paper is to present the classification of production companies created on the basis of the logistic metric. Companies are grouped into clusters by (with) relevance of the logistic metric dimensions. In the paper two of the most popular clustering techniques are presented in the framework of the data recovery approach (agglomerative hierarchical clustering and k-means for partitioning). The basic characteristics of explored companies are used for juxtaposition of the separated clusters. In results four clusters of production companies are presented: Cluster of up and down stream cooperation companies, Cluster with Companies focused on down-stream cooperation, Cluster with companies focused on reporting by indicators and Cluster of companies which consider indicators are not important. Results bring new questions and direction for further research on demonstration of the dependence between logistic indicators monitoring, information sharing and financial performance of the companies.

Key words: Supply Network · Information Flow · Finance Indicators · Cluster Analysis · Logistic Metrics

JEL Classification: L60 · L14 · M21

1 Introduction

Understanding the link between supply chain performance metrics and the overall metrics used to measure the company’s financial performance is essential to align Supply Chain processes’ performance to the company’s financial strategic goal (Elgazzar, Tipi et al. 2012). Many researchers have proposed various performance measurement systems to measure supply chain performance. However several criticisms were raised against these systems. Amongst the most widely highlighted criticisms of current performance measurement systems in supply chain management are: the failure to make integration between financial and non-financial measures and the lack of system thinking (Chan 2003). The challenge for many companies is that the alignment of performance measurements between supply chain and financial functions is still rather poor (Elgazzar, Tipi et al. 2012).

The main reason for this is that supply chain performance metrics and financial performance metrics are defined in different ways which creates difficulty to translate supply chain operational measures, with their focus on day to day operations, into financial targets (Camarinelli & Cantu 2006). Many times is possible to see, that companies use particular parts of financial performance indicators as a core structure for their logistic metrics. On the other hand, the process very often runs in both directions. The Supply Chain Reference Model (SCOR Model) can be stated as a one of the most common used examples of mentioned phenomenon (Poluha 2007).

In the case of Czech companies, researchers very often find that especially small and middle sized companies do not deal with this problem. Work on the long-term plans and strategies creating were often destroyed during the ongoing economic crisis and its aftermath. Companies changed the routine management practices and instead of development activities they focused on costs reductions and maintaining of existing market positions. Development activities become very rare and carried out only in exceptional cases. That is the main reason why the presented research is focused strictly on logistic metric used in almost every Czech production companies and is permanently and long-term monitoring, and not on the detection systems evaluating supply chain management as a whole, which is mostly related to substantial investment in the development of internal information systems and systems used for interconnecting the Tier 1 Suppliers and Tier 1 Customers (commonly on supply chain interfaces). The presented paper aims to answer whether it is even possible to determine the classification of the Czech production companies with respect to their prevalent dimension of logistic metric and whether it at least partly depends on the size of company, financial situation or categorization of industry.

1 Ing. Jaroslava Pražáková, Ph.D., University of South Bohemia in České Budějovice, Faculty of Economics, Department of Accounting and Finance, Studentská 13, 370 05 České Budějovice, smoloj@ef.jcu.cz

Ing. Martin Pech, Ph.D., University of South Bohemia in České Budějovice, Faculty of Economics, Science and research department, Studentská 13, 370 05 České Budějovice, mpechac@ef.jcu.cz

Petra Kosíková, University of South Bohemia in České Budějovice, Faculty of Economics, Studentská 13, 370 05 České Budějovice
2 Material and methods

The main aim of the paper is to present the classification of production companies created on the bases of the logistic metric. Companies are grouped into clusters with relevance to the logistic metric dimensions. Afterwards the main cluster characteristics with regard to company size, industry categorization and financial features are determined.

2.1 Cluster Analysis

Cluster analysis divides data into groups (clusters) that are meaningful, useful or both. The goal is that the objects within a group are similar (or related) to one another and different from (or unrelated to) the objects in other groups. The greater the similarity (or homogeneity) within a group and the greater the difference between groups, the better or more distinct the clustering is (Tan, Steinbach et al. 2006). The cluster analysis allowed the separation of 93 explored companies into groups based on the correlation found between logistic metric dimensions. Used logistic metric dimensions are divided into five main groups (Pech & Smolova 2010, 2011):

- New supplier selection (N),
- Evaluation of suppliers (E),
- Storage (S),
- Customers (C),
- Transport (T).

Two clustering methods are used in paper: agglomerative hierarchical clustering (AHC) and k-means clustering. Hierarchical clustering is the major statistical method for finding relatively homogeneous clusters of cases based on measured characteristics. It starts with each case as a separate cluster, i.e. there are as many clusters as cases, and then combines the clusters sequentially, and reducing the number of clusters at each step until only one cluster is left (Burns & Burns 2009). The clustering method uses the dissimilarities or distances between objects when forming the clusters (in paper it is Euclidean, Bhattacharya, Mahalanobis and Manhattan distance). K-means clustering is a method for finding clusters and cluster centres (called centroids) in a set of unlabelled data. One chooses the desired number of cluster centres, say \( k \) and the \( k \)-means procedure iteratively moves the centres to minimize the total within cluster variance (Hastie, Tibshirani et al. 2009). The \( k \)-means algorithm uses information about the desired number of cluster (obtained by AHC).

2.2 Companies and cluster characteristics

The basic characteristics of explored companies are used for juxtaposition of the separated clusters: for example company size (according to EU terms) and company industry categorization. The available data were obtained from Albertina database. More than 20 common used financial indicators were calculated to set detailed specification of the clusters (i.e. indicators of profitability, solvency, liquidity, stability, other indicators). On the basis of available data on 93 Czech production companies from the 5 years period (from 2009 to 2013), only seven indicators were selected for depiction of the clusters. These indicators are defined as follows:

**Days in inventory**\(^1\): The indicator represents the number of days in the period divided by the inventory turnover ratio. We calculated it on an annual basis. This formula is used to determine how quickly a company is converting their inventory into sales. A slower turnaround on sales may be a warning sign that there are problems internally, such as brand image or the product, or externally, such as an industry downturn or the overall economy.

**Days’ Sales Outstanding (DSO)**: A measure of the average number of days that a company takes to collect revenue after a sale has been made. A low DSO number means that it takes a company fewer days to collect its accounts receivable. A high DSO number shows that a company is selling its product to customers on credit and taking longer to collect money. We calculated this formula only with business receivables.

**Creditors payment period** (days): The Creditor Payment Period is a 'performance ratio' and it indicates the efficiency of a business. Efficiency and performance are linked, as efficient businesses are usually more profitable.

**Value added per one employee** (in thousands of CZK per month): Added value is the positive difference between sales prices of goods with purchasing prices of goods purchased to produce goods (Müftüoğlu in Savas, Özal et al. 2002). The indicator is calculated as a ratio of value added of the company and recalculated average number of employees.

**Share of equity to total capital** (in %): The term equity is used for the value of owner interest in company. It is the opposite value of overall indebtedness. Table X presents the share of equity to total capital in per cents.

---

\(^1\) FinanceFormulas.net. *Days in Inventory* [online]. Available on web: http://www.financeformulas.net/Days-in-Inventory.html
Ratio of business receivables to total assets (in %): Only short term business receivables were used for construction of this indicator, which might be used as indicator for potential risk of insolvency due to high share of not paid receivables.

Ratio of inventory to total equity (in %): this indicator is very important due to making an effort of almost every company against immobilisation of liquid funds. Low ratio of inventory is good sight which shows well function of current assets management.

3 Research results
Companies with high positive correlations are grouping together and segregate from those with negative correlation. Because we usually don’t know the number of clusters that will be optimum for our sample, two stage cluster analysis is used.

3.1 Agglomerative hierarchical clustering (AHC)
The purpose of AHC in paper is to determine number of desired clusters for k-means clustering phase. In agglomerative hierarchical clustering we link more and more companies together and create larger and larger clusters of increasingly dissimilar elements. After the last step, all companies are joined together as one cluster. The companies (rows) are clustered according to the dimensions (average values of dimensions). Result can show a hierarchical tree diagram (dendrogram). Distance among objects (companies) can be measured in a variety of ways. All clustering algorithms have the measurement of mathematical distance between observations as their primary purpose. The XLStat software that we use include for example: dissimilarity criterion Euclidean distance, Aggregation criterion Ward’s method and data have been standardized by columns. For this case, the proposed method employs classification of four clusters. The automatic truncation is (manual of XLStat software) based on the entropy and tries to create homogeneous groups.

Table 1 Number of clusters according to automatic truncation function

<table>
<thead>
<tr>
<th>Dissimilarity criterion</th>
<th>Number of clusters according to aggregation criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single linkage</td>
</tr>
<tr>
<td>Euclidean distance</td>
<td>&gt;5</td>
</tr>
<tr>
<td>Bhattacharya distance</td>
<td>&gt;5</td>
</tr>
<tr>
<td>Mahalanobis distance</td>
<td>5</td>
</tr>
<tr>
<td>Manhattan distance</td>
<td>4</td>
</tr>
</tbody>
</table>

Source: software XLSTAT

In Table 1, the results of three aggregation criterions (single linkage, strong linkage, Ward’s method) in conjunctions with several dissimilarity methods, such as Euclidean, Bhattacharya, Mahalanobis and Manhattan distance are depicted. The result of single linkage for Euclidean and Bhattacharya distance brings too many clusters, so we insert “ >5 ” as number of desired clusters into the table. There might be no definite or unique answer the question: How many groups are optimal? We used result of number of clusters with the highest frequency. Four clusters are also chosen for next phase of k-means clustering as optimal.

3.2 K-means clustering
The k-means method refers to simple technique, which begins with choose k initial centroids (in our paper, it is four according to result of AHC), which specify the number of clusters desired. The centroid of each cluster is then updated based on the points assigned to the cluster. This type of clustering is iterative. So we repeat the assignment until the centroids remain the same in order to choose the optimal solution.

Table 2 Number of clusters according to automatic truncation function

<table>
<thead>
<tr>
<th>Variable</th>
<th>Analysis of Variance</th>
<th>Cluster Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Between class</td>
<td>Within class</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evaluation of suppliers (E)</td>
<td>0.4257</td>
<td>3.4081</td>
</tr>
<tr>
<td>New supplier selection (N)</td>
<td>1.4679</td>
<td>4.3719</td>
</tr>
<tr>
<td>Customers (C)</td>
<td>6.7077</td>
<td>2.2813</td>
</tr>
<tr>
<td>Storage (S)</td>
<td>0.5283</td>
<td>2.4535</td>
</tr>
<tr>
<td>Transport (T)</td>
<td>2.4831</td>
<td>4.6620</td>
</tr>
</tbody>
</table>

Source: Statistica software
In the paper, the $k$-means clustering method has following parameters entered in software Statistica: number of clusters = 4; iterations = 10 and the data have been standardized by columns. The distances between the objects and the $k$ centers are calculated and the objects are assigned to the nearest centres. Table 2 shows results of clustering and basic statistical characteristics of gained clusters. Initial centroids are redefined from the assigned objects to the various classes. According to analysis of variance, all variables are significant (table 2, column “p”).

For more illustrative description of clusters characteristics, the cluster means are examined. Table 2 contains average values in the last four columns clusters which have different features expressed by dimensions. Strong linkages of dimensions to clusters are depicted in bold (the values higher than 0.5). We have identified one specific cluster with very strong linkages to all evaluated dimensions (cluster 3), cluster with weak linkages (cluster 4) and two clusters that have partial strong dependence on evaluation of dimensions (cluster 2 with Evaluation of suppliers, New supplier selection and in case of cluster 1 linkage to Customers dimension too).

3.3 The characteristics of the particular clusters

Based on cluster analysis four different groups of companies focused on the most used logistic indicators are determined. The characteristics of the particular clusters follow.

**Cluster 1.** The cluster consists of 27 companies (it represents 29% of all examined companies). More than 45% of all these companies are focused on engineering (almost 50% of all asked engineering companies). Seven members of this cluster fulfill EU terms for big companies and the others are small and middle sized companies. 18 companies, more than one third of asked consumer goods producers is the next important group in the cluster 1. Remaining companies are from others asked groups of production companies. More than 52% of all big companies through the all asked branches are grouped in cluster 1.

Average number of employees in cluster 1 is 228 and the value added per one employee exceeds 63 thousands of CZK every month (see Table 3). Cluster 1 seems to be the strongest in terms of economic effectiveness, however more than 23% of its members is in the red. Cluster 1 is strange, among the others, because the best reached values of inventory turnover (22 days), days' sales outstanding (36) or Inventory to total equity (6.5%).

Almost all these companies are interconnected to more than 2 well organised supply networks often with foreign activities. Supplier partnerships and strategic alliances refer to the co-operative and more exclusive relationships between organisations and their upstream suppliers and downstream customers (Gunasekaran, Patel et al. 2004). That is one of the reasons for such significant monitoring of logistic indicators focused on up and down stream cooperation.

With respect to finding results, it is possible to say, that almost big companies are focused on up and down stream cooperation regardless of branches. Storage and transport are not usually so important with respect to using of outsourcing or subcontracts. Other reasons for less importance of storage and transport indicators for this group of companies are: very specific and narrow production program or job-order manufacturing. On the other hand, there is a big group of SME’s too. This group of companies is very often close to customers and their production consists mainly of job-order manufacturing. Companies belonging to the cluster are strictly oriented on up and down stream cooperation.

**Table 3 Clusters characteristics**

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Cluster 1 ($n = 27$)</th>
<th>Cluster 2 ($n = 32$)</th>
<th>Cluster 3 ($n = 26$)</th>
<th>Cluster 4 ($n = 8$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Days in inventory</td>
<td>21.877</td>
<td>37.393</td>
<td>31.465</td>
<td>12.742</td>
</tr>
<tr>
<td>Days' Sales Outstanding</td>
<td>36.037</td>
<td>82.313</td>
<td>54.846</td>
<td>40.875</td>
</tr>
<tr>
<td>Creditors payment period</td>
<td>47.259</td>
<td>58.219</td>
<td>49.654</td>
<td>65.500</td>
</tr>
<tr>
<td>Value added per one employee (thousands of CZK per month)</td>
<td>63.259</td>
<td>24.313</td>
<td>27.346</td>
<td>19.000</td>
</tr>
<tr>
<td>Share of Equity to total capital (%)</td>
<td><strong>44.450</strong></td>
<td><strong>45.259</strong></td>
<td><strong>50.034</strong></td>
<td><strong>38.25</strong></td>
</tr>
<tr>
<td>Ratio of business receivables to total assets (%)</td>
<td>17.239</td>
<td>22.369</td>
<td>23.389</td>
<td>6.46</td>
</tr>
<tr>
<td>Ratio of inventory to total equity (%)</td>
<td>6.529</td>
<td>11.853</td>
<td>9.827</td>
<td>12.82</td>
</tr>
</tbody>
</table>

Source: authors

**Cluster 2.** Second cluster is composed of 32 production companies. It includes enterprises concentrated on production of consumer goods (almost 30% of the cluster), building companies (26% of cluster 2 companies) and engineering industry (18% of cluster 2 companies). Only 5 of these 32 companies fulfil EU terms for big companies. Average number of employees is the lowest of all determined clusters and above that it reaches Value added per one employee only 24 thousands of CZK (only 38% of the cluster 1 value).
The cluster includes enterprises with stable economic condition. Only 12% of them were in red in observed five years period and it was only 1 company that does not show the profit in first quarter of this year.

Value of average Inventory turnover exceeds 37 days and maximum value in the cluster is 63 days. This value was reached by the company with very specific production program depending on deliveries from Southern Asia. The indicator Average Days` sales outstanding displays potential problems with customer payments (20% increasing in last 2 years). It might be partly caused by financial problems of all economy, however another clusters do not show similar effects.

Suppliers are very important especially for SME’s, these companies have only week bargain power to their suppliers, and on the other hand these companies are very sensitive to delivery price. They are oriented on quality of deliveries (for example buying materials and semi-finished products), customers and good downstream cooperation.

**Cluster 3.** Third cluster is composed of 26 companies mainly from food production sector (54%) and engineering companies (19%). More than 190 employees is average value of this cluster, which companies are focused on reporting by indicators in each of five dimensions.

There are two main groups of companies: First of them concentrates big companies with sophisticated evaluation systems of process and performance indicators. They have operated many years on the market or they are subsidiaries of traditional companies. Supply chain integration is needed to manage and control the flow in operating systems. Such flow control is associated with inventory control and activity system scheduling across the whole range of resource and time constraints. Supplementing this flow control, an operating system must try to meet the broad competitive and strategic objectives of quality, speed, dependability, flexibility and cost (Toni & Tonchia 2001). These big companies are mainly from food and engineering industry. Second group of companies are new firms, which try to create new information system for performance or process evaluation. This first step of information system creating brings time period, when companies monitored big amount of information and will precise their information system in future (Pech & Smolova 2011).

This cluster has big potential to sharing information in supply chain on condition that method of calculation sustains identical. Members of this cluster have the highest share of equity to total capital (average value 42.3%). Regarding the structure of the cluster, it is not surprising.

**Cluster 4.** This cluster is composed only of 8 companies. It does not carry too much information about specification of these companies due to their low number. In addition, four companies show long term loose and with respect to their size, they are not obliged to present all financial figures. Companies monitored only a few indicators, which are connected with accounting. Reasons for not using many indicators of these five dimensions are: very specific and narrow production portfolio (only 2 of 3 different products), short-run production system, and orientation on providing services (especially transport companies).

**4 Conclusions**

To the conclusion we present the classification of production companies created on the bases of the logistic metric. As an effect of cluster analysis four clusters with the following generalised descriptions are isolated: Companies in the Cluster 1 seem to be the strongest in terms of economic effectiveness. Almost all these companies are members of more than 2 supply networks often with stable structure and good economic positions. That is one of the reasons for such significant monitoring of logistic indicators focused on up and down stream cooperation. Companies belonging to the cluster 2 are mainly focused on downstream cooperation. The Cluster 2 includes mostly SMEs, these companies have only week bargain power to their suppliers, and on the other hand these companies are very sensitive to delivery price. They are oriented on quality of deliveries, customers and good relationships with suppliers. Companies in cluster 3 are focused on reporting by indicators and tend to be perfect in monitoring. There are two main groups of companies: First of them concentrates big companies with sophisticated evaluation systems of process and performance indicators. Second group of companies are new firms, which try to create new information system for performance or process evaluation. This cluster has big potential to sharing information in supply chain on condition that method of calculation sustains identical. Companies in cluster 4 consider indicators as not so important and monitor only a few indicators which are connected with accounting.

Based on the classification stated above, mainly the companies with parallel characteristics like a Cluster 3 members should be interesting for the future research. Other important question for next step of survey is to find if the membership in Cluster 3 (the group of new companies) will be changed in time (when companies reach the other stadium of their development) and they will be joined for example to the cluster 1 or 2. Further, we would like to focus on demon-
stration of the dependence between logistic indicators monitoring, information sharing and financial performance of the companies.

At this stage of the research process it is hard to express any specific political or economic implications. We can only estimate that strong impact on C2C cooperation will lead to creation of strength relationships and more linkages through the whole economy. The competitive companies will bring new waves of information sharing and needs in IT sector for example intelligent solutions for whole Supply chain or network.

Although is information initially shared, it must to be determined by recipient whether it provide visibility. It is more informed decision making that potentially leads to improved performance (Barratt and Oke 2007). In the agile framework we propose that up to four different demand/supply chain configurations will possibly exist in any given situation, with some clearly more dominant than others (Gattorna 2003). Collaborative supply chain is one of the four configurations.

Acknowledgement

This paper was supported by the Grant Agency of the University of South Bohemia GAJU 79/2013/S.

References


