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CLUSTER ANALYSIS AND SEGMENTATION OF GLOBAL M&A TRANSACTIONS

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Abstract: The present thesis is the analysis a dataset of mergers and acquisitions (M&A) through a segmentation process by cluster analysis, to better understand combined explanatory variables and characteristics of global M&A transactions. Past researched has strongly focused on (A) whether or not M&A creates wealth for investors or (B) which factors and variables help explain value this wealth (des)creation. The present thesis is rather an attempt to reach a third leg of research which is that, by segmenting and understanding these "natural" groupings we may develop a richer understanding of this form of corporate transactions. The paper comprises a study-event dataset from global completed M&A since 1994 with high disclosure filters, a factor analysis that selected 7 out of 13 variables from previous literature review, preceded by a the cluster analysis for variable selection. The end result indicated a connection between several explanatory variables and the formation of clusters with economical meaning. Six clusters were formed under a two-step clustering process. The paper has three relevant highlights: (1) the application of cluster analysis in a M&A setting; (2) the selection of surrogate variables from the factor analysis, providing better economic representation and (3) a clustering method that automatically captures the natural grouping the dataset.

Keywords: Mergers and Acquisitions (M&A); Value Creation; Factor Analysis (FA); Cluster Analysis (CA); Segmentation.

Dedicated to Mom and Dad, for your constant love and support.

You have held my hand in difficult times and believed in me throughout my journey.

Thank you.

1. Introduction

As with the auto industry, where one cannot properly assess the overall sales or profitability of a car manufacturer's – in our case value creation from M&A transactions – without understanding that, for example, that sedan or compact vehicles have product but also have different target audiences, market dynamics and cost drivers.

That concept gave the paper its study hypothesis: can a segmentation process be done for M&A transactions due to its different characteristics, actors and large complexity? In order to apply the same idea, the present thesis contains the review of the right variables and metric that measures value creation, to then later adequately segment and interpret the results from the Cluster Analysis (CA). Methodologically, an event-study dataset is constructed from the Bloomberg M&A database, the Factor Analysis (FA) selects the variables for the clustering process and finally, the two-step CA is put in places based on a distance measure log-likelihood and a Schwarz's Bayesian Criterion (BIC) for clustering criterion. Following the *Literature Review* and *Methodology*, readers will find a section for commentary of the results, managerial implications and overall summary under the *Conclusion*.

The prime research objective of the paper in the attempt to properly classify M&A transaction is to bring to research areas of M&A and Value Creation a new paradigm and discussion level for both practitioners and research community.

2. Literature Review

The *literature review* for the present thesis undergoes the following order: (1) understand the selection of an event-study dataset, as well as its timeframe, metric of value creation and variables and (2) comment on research for the FA and CA which will detailed further on the *Methodology* section.

Robert F. Bruner (Bruner, 2002) found that out of that there are four research approaches employed to measure M&A value creation: event studies, accounting studies, surveys and clinical studies, of which event studies clearly dominated literature. Event studies examine abnormal returns for within a defined time horizon around the transaction (normally centered around the announcement date). From his paper came the decision to pursue a dataset based on event studies, allowing for more a representative sample and leveled playfield across all transactions. However, accounting studies require access to accounting statements and a common legal framework and accounting standards. Furthermore, survey to executives and clinical studies are specific to a small set of cases (firms and executives), which may bring some bias and unrepresentative view, especially when trying to grasp a broad overview of M&A transactions globally. His paper proved additionally important in the *Methodology* section as it as studies what it means for M&A to "pay" in review of 130 studies from 1971 to 2001.

The paper from McKinsey (Cyriac, Koller, & Thomsen, 2012) provides with the argument for using Excess Total Return to Shareholders as the adequate metric for measuring value that mergers and acquisitions create. Still, two other metrics were considered: (1) comparison of share prices before and after a deal is announced and (2) accounting metrics, example of Economic Profit. The first alternative, takes into account short-term investor reactions as an indicator, with the sole benefit of providing a measure of value unimpaired by other events due to the reduced term of the analysis, such as subsequent acquisitions or other corporate events post-acquisition. This metric however, relies on short-term market reaction to gauge value creation not allowing investors to "digest" adequately the value of a transaction. This is a major step in the research process, as not following this path implies not accepting as true the Efficient Market Hypothesis (EMH). The big reason is that, if it is plausible to infer that a great majority of transactions take a great deal of time and resources for corporations to analyze before a decision is made, than why would it not take at least the same amount of time for the investor community to assess such transaction before trading on the stock? Moreover, a short-term measure does not give investors time enough to evaluate the success of the post-merger process (Ikenberry, Lakoniskok, & Vermaelen, 1995). The second alternative would be through an accounting measure such as Economic Profit. As justified above, it is hard to put in practice, due to different accounting standards, legal framework and limited access to information. One would need to obtain for instance the combined Net Operating Profit After Taxes (NOPAT) from the deal, which would reduce substantially the sample. Moreover, Weighted Average Cost of Capital (WACC) and the Economic Capital employed (K) are variables affected by attritions such as the tax shield having a (likely) different and unknown target capital structure and new cost of debt will exist after the deal. Therefore, in order to adequately measure Economic Profit one would need to know the new cost of debt (k_d), which unlike the cost of equity, that can reflect changes in operational and financial leverage through leveraged beta, and have the target capital structure that would arise from the transaction, in most cases it is neither attainable nor is it scalable to such global M&A databases.

Asquith (1983) argues that measurement of wealth effects is insignificant around the consummation date. Furthermore, in order to fully understand wealth effects to the bidder's shareholders, it becomes paramount to measure before and after effects of a deal around the announcement date, where most of the abnormal returns are generated. Asquith gave us a clear perspective on how important the timeframe was for an adequate analysis. The period of return measurement defined for our study is one calendar year counting from the announcement date, further explained in the *Methodology*.

Datta, Pinches and Narayannan (1992) found that the relevant factors that determine M&A wealth creation are: regulatory changes, the number of bidders, the bidders approach (i.e. merger or tender offer), the mode of payment (i.e. cash, stock) and the type or motive of acquisition. Furthermore, the value chain, relationship and economic area of each M&A transaction are significant for wealth creation (Hoang & Lapumnuaypon, 2007). Value chain refers to: (1) vertical M&A, (2) horizontal M&A or (3) conglomerate M&A. Vertical M&A, is defined with a transaction which combines client and supplier or client and seller. Firms involved seek to reduce uncertainty and transaction costs by upstream and downstream linkages in the value chain and to benefit from economies of scope (Chen & Findlay, 2003); In the case of Horizontal M&A, both parties are competing firms in the same industry. In this case, eliminating competition, economies scale, acquiring or accessing a certain capability or technology is amongst the biggest are the biggest motives that justify this form of M&A. Lastly, in the attempt of reduce and diversify risk companies might engage in Çonglomerate M&A. Based on the findings of Megginson, Morgan and Nail (2004) “mergers that decrease focus result in significant losses in relative shareholder wealth, operating performance, and firm value over the three years following merger completion” as with mergers that preserve of increase focus these “result in marginal improvements in long-term performance”. Supported by the empirical evidence and references of the authors, it seemed rational to include the type of M&A as a variable to be analyzed. The relationship refers to the nature as with the transaction occurred, in simply termed “friendly” or “hostile”. A hostile bid occurs when an unsolicited or uniformed occurs from the part of the bidder to the target company’s Board of Directors. A friendly deal, is when a deal is pre-approved by the Board of Directors and each other's' interests are met and both agree to the proposed deal (Datta, Pinches, & Narayanan, 1992).

Two other important papers provided further support for relevant explanatory variables in M&A. The first paper is from KPMG's Advisory team (Tiemann & Kelly, 2010) which summarizes the key variables that are able to generate both higher and lower abnormal returns through corporate M&A: (1) cash-only deals had higher returns than both stock-and-cash and stock-only deals; (2) acquirers with lower P/E ratios completed more successful deals; (3) the number of past deals pursued by an acquirer was relevant, or as commonly mentioned the M&A experience was a significant factor; (4) the reason to pursue a deal did matter, that those transactions that were motivated by increase financial strength were most successful, more than those motivated by a desire to acquire IP or technology and the motivation to increase revenue was the least successful; (5) the size of the acquirer, as measured by its market capitalization, was not a statically significant element. The second paper is from McKinsey (Cyriac, Koller, & Thomsen, 2012) were they analyze the world's top 1000 nonbanking companies' M&A practices and find that (1) the size of the target acquired matters (market capitalization); (2) number of deals per year each organization pursues. From these papers, which have in their selves comprise great literature reviews and the experience of two important advisory teams, we are able to later understand the kind of variables to capture from our dataset later.

3. Methodology

3.1 Event-study dataset

Having the right methodology was key to acquire and organize the dataset and, to be able to achieve the present results. From the structure defined in the *Introduction* the *Methodology* is broken down into (A) the preparation of the dataset so it can be prepared for a statistical study, (B) detail of the value creation metric, timeframe and explanatory variables and ultimately, (C) processes and methods for the FA and CA.

The selected sample comprises 5’966 transactions and was collected from Bloomberg’s M&A database, with all filters based on information level and disclosure (*Figure 1*). The research process starts with collecting and formatting data into to Excel, calculating and integrating same relevant variables from there and later on preparing the dataset to be transposed IBM SPSS 21.

“Factors Influencing Wealth Creation from Mergers and Acquisitions: A Meta-Analysis” (Datta, Pinches, & Narayanan, 1992) was a great entry point to help organize the Bloomberg M&A database. Not only did the authors review and summarize 41 studies on M&A wealth effects, they described the select few factors that better explain wealth gains for bidding and target shareholders involved and, that M&A studies were mainly driven by ‘targets’ and `bidders’. Bidding firms are those that initiate the transaction and a target firm or asset is the object of interest. Logically, this point defined that our sample and the variables to be analyzed were transaction-based. Rather than organizing our date into a set of aggregate bidders’ transactions, a transaction-based sample was more meaningful and easier to measure. The transactions listed in the Bloomberg M&A database was then ordered by announcement date. In the dataset, an acquirer listed was already known to be the winning bidder in case of competing bid process, since only completed transactions were listed. Information on competition was limited as Bloomberg only listed whether or not a transaction was had a competing bid, a mandatory offer or neither. Although mentioned as important by several authors in our literature review, the mode of payment was not fully disclosed by Bloomberg. We knew if a public transaction was financed solely with cash as it was mentioned. If any exchange terms were disclosed we could only conclude that the specific transaction was not fully financed with cash.

As described in the paper reviews both the results by the McKinsey & Co. paper (Cyriac, Koller, & Thomsen, 2012) as well as the fit provided by Bruner (2002) with the event-study research on M&A, Excess Total Return to Shareholders (TRS) is the metric used to gauge value creation. For the purposes of the thesis the designation followed is Cumulative Abnormal Return (CAR).

Equation 1 - Cumulative Abnormal Return (CAR)

$$\text{Cumulative Abnormal Return (CAR)} = \sum_{d=1}^{365} \text{Acquirer Daily Total Return} - \sum_{d=1}^{365} \text{Benchmark Index Daily Total Return}$$

Notes: Total Return to Shareholders captures capital appreciation from stock price changes, regular and special cash dividends as well as stock buybacks. Since different stocks have different levels of political and country risks, a formula was created with the Bloomberg Microsoft Excel plug-in to select the corresponding country index according to Bloomberg – e.g. if General Electric as an acquirer completed transaction, Bloomberg would select S&P 500 as the index to measure total return from.

The timeframe for measuring CAR for each transaction is one year, the reason being to minimize calendar distortions, seasonal effects and provide enough time for investors to act on these corporate events. One year is the balance between an enough time for investors to perceive value creation, while reducing seasonality effects by not having over one year, reducing the number and effect of other corporate or strategic events. As explained before with the CAR, this hypothesis is treated with care as it is not consistent with the EMH. Still, reflecting carefully, if the EMH were to be in place, it would not make much sense to analyze further than the one day period do it the immediate market reaction and yet authors (Ikenberry, Lakoniskok, & Vermaelen, 1995) found that there is a slow investor reaction to share repurchases (the simplest of the corporate events), implying average abnormal returns to be made over time, evidence that is aligned with the paper and inconsistent with the EMH.

From the research papers the relevant explanatory M&A transaction variables we were not able include in our analysis neither regulatory changes nor motives for a transaction. These were not always disclosed or captured in the Bloomberg M&A database. The included variables for the later FA are: (1) Number of Bidders (competing factor), whether there were any other bidding offers competing for the deal before the deal was closed by the acquirer; (2) Tender Offer, a yes or no variable that considers if there was any tender offer in place; (3) PE/VC involvement, a binary variable that picks-up the records from Bloomberg both from Buy and Sell side and records if there were any Private Equity or Venture capital firms involved; (4) Deal Experience, from 1994 to the year-end of 2011, counts the number deals pursued from acquirers; (5) Announced Total Value Adjusted to 2011 dollars is the announced transaction amounts where each transaction is made comparable by the CPI[1] providing a relative comparable between transaction; (6) Total Assets Multiple; (7) Market Capitalization of the Acquirer, also adjusted by the CPI; (8) Relative Size, the percentage of the deal amount to the acquirer's market capitalization at the announcement date, providing a measure of relative importance; (9) Nature of the Bid, identified by Bloomberg from a range of Friendly to Hostile; (10) Cash Terms, which if either the deal was fully financed with Cash or not; (11) if the transaction is considered either In border or Cross border; (12) if it is considered Intrasector, within the same sector, or Extrasector; (13) Ansoff's Growth Strategies, where each transaction is classified from one to four according to the type of transaction underdone.

[1] Consumer Price Index (CPI) – due to the economic importance and relevant stake of the Unites States economy in global M&A and widely used measure, the CPI is a good way to make comparable M&A transactions over time as it is a "measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services." (Bureau of Labor Statistics, 2010)

3.2 Factor Analysis (FA)

In the case of large sets of data, there tends to be are a large number of possible variables for selection. If already disregarding meaningless variables, many others tend to be correlated and must be reduced to a manageable level, allowing for a balanced and more sensible analysis later on. Therefore, the method of FA is used primarily for data purposes. The objective of the FA is to determine the level of information being explained amongst variables, later allowing us to assess the number of variables to be included in the CA (Malhotra, 2009). Variables should be ideally measured on a ratio or interval scale, although not always possible, especially in a M&A transaction dataset. Therefore, the analysis was conducted with variables considered great in the interest of explaining value creation as well as were situated in some sort on interval or fluctuation band (i.e. EBITDA multiple – although continuous, it is standardized and comparable across transactions). Dedicated literature (Malhotra, 2009) also indicates that one should, on reasonable terms, have as a sample 4 to 5 times the number of variables to be included. It should not be a problem, since there are limited variables (13) for evaluating a database of 5’966 cases. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, as the name suggests, by testing whether the partial correlations among variables are small validating a sample’s adequacy. If KMO statistic is large enough (>0.5) one may proceed with the analysis without having concerns with the sample. In this case 0.571 was obtained, a large enough figure to comply with the analysis, understandable due to the large dataset and the fact that some of the variables are continuous (e.g. Market Capitalization Adj. CPI) rather than bounded or measured between an interval. Please refer below to *Table 1*.

Table 1 - KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,571
Bartlett's Test of Sphericity	Approx. Chi-Square	3606,044
	Df	78
	Sig.	,000

The next step of the FA is to obtain a correlation matrix and identify variables which may provide the same level of information and are not suited to be added together to the CA – please refer to *Table 2* in the Appendix. Before obtaining the from correlation matrix an obvious fact that all valuation multiples were strongly correlated, did provide the same information level and in some industries (e.g. Financials) some valuation multiples, namely EBITDA multiple, was not available. For that reason the valuation metric of choice is the Total Asset Multiple, the most complete in the database. Furthermore, the correlation matrix was very useful to understand that, the variables (Intra)Extrasector and (In)Cross border provided a limited degree of information and a better variable good be reached, the Ansoff Matrix 1-4. Now one could use the two variables to achieve both the level of product and market growth strategy from each transaction (Ansoff, 1957). The Ansoff Matrix presented and assigned points according to the degree of growth and risk for every one of four growth strategies: Market Penetration (1 point; same market, same product line); Market Development (2 points; new/different market, same product line); Product Development (3 points; same market, new/different product line); and finally, Diversification (4 points; different market, different product line). Despite the insight of the new variable, all the three variables were included in the FA for review purposes.

Provided the above literature review and dataset, the pre-selected variables for the CA were the following: Ansoff Matrix Growth Strategies, PE/VC Involvement, Nature of the Bid, Total Assets Multiple, Market Capitalization of Acquirer Adjusted to CPI, Target Announced Amount Adjusted to CPI, Relative Size (% Market Cap.), Cash Terms, Deal Experience, Tender Offer, Competing Factor, (In)Cross border, (Intra)Extrasector – please refer to *Table 2*.

Proceeding with the selection of variables for FA, the Bartlett's test for sphericity is conducted, which tests the hypothesis that the correlation matrix is an identity matrix. If its null hypothesis was verified it would indicate that the variables are unrelated and therefore unsuitable for structure detection. Inability to form a structure would mean that we would not be able to build a factor out of any two or more variables, therefore eliminating the possibility of FA. Bartlett's test performed reached a significance of .000 (*Table 1*) which means that for any level of significance we have enough evidence to reject the null hypothesis of being in presence of an identity matrix. When performing and interpreting the FA, the number of factors can be determined (1) à priori or (2) by interpretation, usually a result of the eigenvalues, total variance explained per factor and interpretation of the scree plot (*Figure 2*) (Malhotra, 2009). À priori would mean the factors are already known beforehand and that, factoring would only help understand which of the presented variables fit which factor and how well - i.e. a consumer's rationale to buy toothpaste, the health benefit factor and aesthetic factor - which is not the case. In this situation, the percentage of explained variance in each factor helps one to understand the contribution of each variable to the total variance explained and get to the ideal number of components to be later on included in the CA. The analysis turned out to be very balanced by both interpreting the scree plot (*Figure 2*) and table of total variance explained (*Table 4*). Total variance explained, indicated by initial eigenvalues, accumulated and individual variances were different between all variables and percentage of variance ranging between 4.116-14.165% (*Table 4*). Additionally, from the scree plot there is an indication that the number of components should be between 5 and 6, close to the recommended 1.0 threshold level by literature (Malhotra, 2009). From the sixth component onwards the eigenvalue levels starts to marginally decrease for each component added to the scree plot. This part although based in the fundamental research (Malhotra, 2009) is as much an art as it is a science. For this case, there is the tendency to be close to the maximum bound of components possible for the CA, as it provides for richer analysis later on. However, including too many components has the risk of not being research supported and being difficult to define causality later on in the CA. Therefore, the line not to be crossed was determined at the marginal decrease of eigenvalues, which determines 7 to be the maximum components to be included, fairly close to the 1.0 threshold suggested in the literature, with 0.974 eigenvalue and 7.489% of individual variance for the seventh and final component (*Figure* 2). Since factors might take the economical meaning out of variable one could indeed select surrogate variables - variables that best substitute each factor - those with the higher loadings that help explain the most (percentage of variance) and those that à priori do make sense to be included. (Malhotra, 2009). After having identified from the *Literature Review* that these variables are adequate in explaining CAR, the use of surrogate variables provided for better economic interpretation instead of the factors and, knowing that each of these variables together leaves very little room for unexplained variation, the next step was to perform a CA with the present variables (*Table 2*). We selected a Principal Component Analysis (PCA) extraction method and Varimax with Kaiser Normalization for the rotation method for the FA as suggested by the main literature (Malhotra, 2009). PCA is a non-parametric method for extracting relevant information from "confusing" data sets (Shlens, 2009). Varimax seeks that "for each factor, high loadings (correlations) will result for a few variables; the rest will be near zero" (Kaiser, 1958).

Out of the 13 rotated variables, the 7 components selected for CA and segmentation from the FA are: Ansoff Matrix Growth Strategies, PE/VC Involvement, Nature of the Bid, Total Assets Multiple, Market Capitalization of Acquirer Adjusted to CPI, Relative Size (% Market Cap.) and Cash Terms.

3.3 Cluster Analysis (CA)

Cluster analysis is a "class of techniques used to classify objects or cases in relatively homogenous groups called clusters" (Malhotra, 2009). Also designated as classification analysis or numerical taxonomy, it allows the researcher to classify or segment data. It is of particular importance to this research to let data "speak for itself" making possible, with the right methodology, to segment Global M&A transactions and help understand which segments are formed. Additionally it fits perfectly to the problem in hands, as a CA with the right methodology is able to handle both continuous and categorical variables/attributes while. In this case it suits perfectly, since the balance and judgment of the research can only help one reach so far, especially the ultimate purpose is to determine how many clusters it will "naturally" form. However, if we fixed the number of clusters, without any paramount reason we might be damaging the balance between the ideal number of clusters and the model's balance.

The first step to conducting CA is to select the variables. In our case, having done the CA and *literature review* the variables are already pre-selected. Secondly, one should define the method of clustering. A distance measure will help determine how similar or dissimilar the objects being clustered, as explained later on. Thirdly, one should determine the appropriate number of clusters. After the validity of the clustering process is assessed the economic interpretation from the CA is drawn. When selecting the variables these should be "variables that best explain the distribution into the groups we have found" (Berrendero, Justel, & Svarc, 2011). Since both the *Literature Review* and the FA validate the variables selected, "non-informative" variables that are innocuous, redundant or strongly correlated information are excluded. It has two steps: 1) pre-cluster the cases (or records) into as many pairs according to their similarity; 2) group these sub-clusters into the desired number of clusters or as a result of an optimization process that a process that automatically decides the number of clusters. In the present case the method chosen was a two-step CA. The method is a scalable algorithm designed to handle very large sets of data and be setup to either segment into a prefixed number of clusters or to instead allow it, through a clustering criterion, to automatically determine the number of cluster (IBM, 2012).

Three important metrics define the success and quality of the clustering process: (1) how many and which variables are selected and of these, which are categorical, continuous and of the continuous, which are assumed to be and which need to be standardized; (2) the distance measure applied to define the clusters, the actual algorithm of the two-step method; (3) and finally, the clustering criterion. The first step has been largely facilitated by the CA, having only to identify which of the variables are categorical, standardized continuous and to be standardized continuous variables. In the second step one assigns the log-likelihood measure. The log-likelihood was selected as it is a distance measure that can handle both continuous and categorical variables. It is a probability based distance. In calculating log-likelihood, normal distributions for continuous variables and multinomial distributions for categorical variables are assumed. One main assumption is that the variables are independent of each other, and so are the cases, reason for the correlation analysis undertaken with the FA. IBM SPSS User Guide provides the steps for the actual the distance between a given cluster is as being defined by:

Equation 2 - Distance between to clusters related to the decrease in log-likelihood as they are combined into one cluster

$$d(j,s) = \xi_j + \xi_s - \xi_{<j,s>}$$

where, $\xi_v = -N_v\left(\sum_{k=1}^{K^A}\frac{1}{2}\log(\hat{\sigma}_k^2 + \hat{\sigma}_{vk}^2) + \sum_{k=1}^{K^B}\hat{E}_{vk}\right)$ and $\hat{E}_{vk} = -\sum_{l=}^{L_k}\frac{N_{vkl}}{N_v}\log\frac{N_{vkl}}{N_v}$.

N	Number of data records in total.
$\mathbf{N_k}$	Number of data records in cluster k.
$\widehat{\boldsymbol{\mu}_k}$	The estimated mean of the kth continuous variable across the entire dataset.
$\widehat{\boldsymbol{\sigma}_k^2}$	The estimated variance of the kth continuous variable across the entire dataset.
$\widehat{\boldsymbol{\sigma}_{vk}^2}$	The estimated variance of the kth continuous variable across the entire dataset.
$\mathbf{N_{vkl}}$	Number of data records in cluster j whose kth categorical variable takes the lth category.
$\mathbf{N_{kl}}$	Number of data records in the kth categorical variable that take the lth category.
d(j, s)	Distance between clusters j and s.
(j,s)	Index that represents the cluster formed by combining clusters j and s.

If $\hat{\sigma}_k^2$ is ignored in *Equation 2*, the distance between clusters j and s would be exactly the decrease in log-likelihood when the two clusters are combined. The $\hat{\sigma}_k^2$ term is added to solve the problem caused by $\hat{\sigma}_{vk}^2 = 0$, which would result in the natural logarithm being undefined (this would occur, for example, when a cluster only has one case) (Ming-Yi, Jheng, & Lien-Fu, 2010). IBM SPSS provides the user with the option to consider the dataset to have outliers. In the present case, due to the large dataset a higher interest in having more sound "averages" rather than understanding ranges, minimum or maximum bounds, the outlier-handling helps to offset exaggerations or erroneous inputs from Bloomberg. The log-likelihood distance assumes outliers or noises to follow a uniform distribution. The method goes about calculating log-likelihood to assigning a record to a noise-cluster and that resulting from assigning it to the closest non-noise cluster. Subsequently, the record is assigned to the cluster with the cluster which leads to the largest log-likelihood.

Equation 3 - Log-likelihood distance

$C = \log(V)$, where $V = \prod_k R_K \prod_m L_m$.

Otherwise, it is designated as an outlier defined by IBM SPSS under the cluster (-1).

The clustering criterion assigned was the Bayesian Information Criterion (BIC) which has the advantage to determine the number of components in a model and deciding between which two or more groups most closely matches the data for a given model (Fraley & Raftery, 1998). IBM SPSS allowed for all major methods of clustering. Fraley and Raftery (1998) found that after clinically assigning each case to the known *à priori* best cluster for each, they measured error rates for Model-based Classification (BIC), Single Link (Nearest Neighbor) and K-Means, and found out, with corresponding 12%, 47% and 36%, being that a Model-based produced less error in assignment, in addition to being able to treat categorical and continuous variables. Missing values are treated on a Listwise basis by SPP. However, the dataset presented no missing values.

Overall clustering success can be measured by the silhouette coefficient, which is a measure of both cohesion and separation (Norušis, 2011). In our model the average silhouette is of 0.7, with a very good result being above the 0.5 mark, above 0.2 considered moderate-to-fair and below 0.2 a bad result, according to IBM IPSS (*Model Summary – Figure 3*)

4. Conclusion

Having performed a two-step cluster analysis, the process yielded 6 segments from 7 variables. The 7 variables were selected out of 13 from the CA. The input with higher predictor importance was the Ansoff Matrix Growth Strategy and the Cash Terms variables (*Figure 4*). Out of all clusters there is a strong grouping affect in regards toward growth strategy. Market Penetration is the dominant strategy in Global M&A *(Figure 4)*. Valuations are more favorable for a market penetration growth strategy (Cluster 1, 6) and do not depend on the acquirer's size, the Relative Size of the target (percentage of the acquirer's market capitalization), the Nature of the Bid or the Terms of Deal (cash/stock/cash and stock/other) (*Table 9*). PE/VC involvement is inversely related to the dimension of growth strategy pursued amongst the clusters, although worth mentioning PE/VC involvement is generally low across all six clusters, bounded between 1-4%. The extremes are Cluster 5 (Diversification) with only 0.8% of its transactions with PE/VC involvement compared to Cluster 1 (Market Penetration) that 3.7%, more than four times Cluster 5 (*Table 7*). The same happens with the nature of transactions. Market Penetration (Cluster 1, 6) has relatively more friendly deals (99.2%) when compared to Geographic Expansion (97.2%) and Market Expansion (98.6%) and even more when compared against Diversification strategies (97.3%) (*Table 9*). The clusters seem to suggest that as companies initiate M&A transactions with geographic and new market growth strategies, they tend to face relatively more non-friendly bidding processes before completing the transactions (friendly-to-unsolicited, unsolicited, unsolicited-to-hostile and hostile). The Materials sector, which comprises Chemicals, Construction Materials, Metals & Mining and Paper & Forest Products, although a generally dominant sector across all clusters, in the case of Geographic or Market Expansion (Cluster 2, 3 and 5) rank either first and second in absolute and relative terms across all 10 industry groups. Clusters with cash financing strategies in 100% of the cases are associated with relatively smaller acquirers/dominant counterparties. These small acquirers

(Cluster 1, 2) have an average of $7.20 and $6.26 billion (market capitalization at the announcement date) compared to the other clusters ranging from $13.74 - $19.38 billion (Cluster 3, 4, 5, 6); Clusters formed by small size companies seem to point to fully-financed cash transactions, being the inverse equally true, larger firms tend to have equity financing in completed bids. With the effect of outliers exempt in the CA, Clusters 3, 5, 6 present higher median Cumulative Abnormal Returns (CAR) with -1.98%, -3.16% and -3.52%, respectively (*Table 10*). From a growth strategy point-of-view it does not seem possible to establish a linear relation between the Ansoff Matrix point system and corresponding levels of return (CAR). Across all clusters, CAR is on average +0.11%, a small figure to argue for value M&A creation excluding outliers and a lower +0.9% with the effect of outliers. Although, overall skewness is positive (mean>median) which leads us to conclude that there are few very positive transactions that outweigh a larger number of less negative transactions, 50% of the cases (median) have CARs of no more than -4.5% over the period of one year for acquiring shareholders (*Table 10*)

More importantly and touching on the methodology and innovative side of the paper, even though other variables could have been different as could the overall study been done differently, the main proposed objectives were achieved. The implementation of having surrogate variables and an automatic clustering criterion ended up being the best methodological framework for the thesis, as both increase economical interpretation of the rotated set of components and the clusters are “natural” groupings, not conducted or forced in anyway.

References

[1] Ansoff, I. H. (Sep-Oct de 1957). Strategies for Diversification. Harvard Business Review, pp. 113-124.

[2] Asquith, P. (1983). Merger bids, uncertainty, and stockholder returns. Journal of Financial Economics, 51-83.

[3] Berrendero, J. R., Justel, A., & Svarc, M. (1 de September de 2011). Principal components for multivariate functional data. Computational Statistics & Data Analysis, pp. 2619–2634.

[4] Bruner, R. J. (2002). Does M&A pay? A survey of evidence for the decision-maker. Journal of Applied Finance, 2-15.

[5] Bureau of Labor Statistics. (September de 2010). Frequently Asked Questions (FAQ) - "What is the CPI?". Obtido de Consumer Price Index - U.S. Bureau of Labor Statistics: http://www.bls.gov/cpi/cpifaq.htm

[6] Chen, C., & Findlay, C. (2003). A Review of Cross-border Mergers and Acquisitions in APEC.

[7] Cyriac, J., Koller, T., & Thomsen, J. (February de 2012). McKinsey on Finance, pp. 8-15.

[8] Datta, D. K., Pinches, G. E., & Narayanan, V. K. (1992). Factors Influencig Wealth Creation from Mergers and Acquisitions: A Meta-Analysis. Strategic Management Journal, 13, pp. 67-84.

[9] Fraley, C., & Raftery, A. E. (1998). How Many Clusters? Which Clustering Method? Answers via Model-Based Cluster Analysis. The Computer Journal, Vol.41, No.8, pp. 578-588.

[10] Hoang, T. V., & Lapumnuaypon, K. (2007). Critical Success Factors in Merger & Acquisition Projects: A Study from the Perspective of Advisory Firms.

[11] IBM. (2012). IBM SPSS Statistics 21 Documentation. IBM Corporation: ftp://public.dhe.ibm.com/software/analytics/spss/documentation/statistics/21.0/en/client/Manuals/IBM_SPSS_Statistics_Core_System_Users_Guide.pdf

[12] Ikenberry, D., Lakoniskok, J., & Vermaelen, T. (1995). Market underreaction to open market share repurchases. Journal of Financial Economics, 181-208.

[13] Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. Psycometrika, Vol. 23, 187-200.

[14] Malhotra, N. K. (2009). Marketing Research: An Applied Orientation. Prentice Hall; 6th edition .

[15] Megginson, W. L., Morgan, A., & Nail, L. (2004). The determinantes of positve long-term performance in strategic mergers: corporate focus and cash. Journal of Banking & Finance, 523-552.

[16] Ming-Yi, S., Jheng, J.-W., & Lien-Fu, L. (2010). A Two-Step Method for Clustering Mixed Categroical.

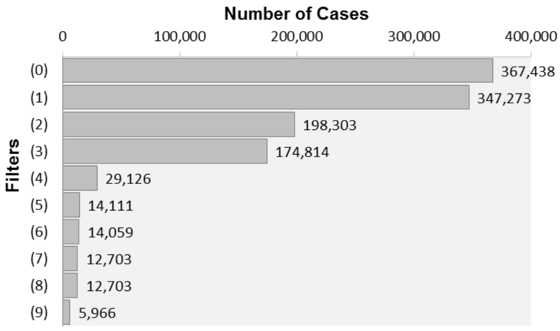
[17] Norušis, M. (2011). Chapter 17 - Cluster Analysis. In IBM SPSS Statistics Guides (pp. 375-404). Addison Wesley.

[18] Shlens, J. (2009). A Tutorial on Principal Component Analysis. NY, USA: Central for Neural Science, New York University.

[19] Tiemann, D. D., & Kelly, J. (2010). The Determinants of M&A Sucess: What Factors Contribute to Deal Success? KPMG Advisory, pp. 5-13.

Appendices

Figure 1 – Sample evolution: number of filters, description and cases reached after each filter.



Filters	
(0) Unfiltered, from 01/Jan/1900 to 31/Dec/2012: 367’438 results;	(1) Deal Status = {Completed}: 347’273 results;
(2) Deal Size = Min=$ 0.0001mn; Max= ∞ -. Requires that each deal has its size disclosed: 198’303;	(3) Payment Type = {Cash, Stock, Cash AND Stock, Cash OR Stock, Cash AND Debt, Cash AND Stock AND Debt, Stock AND Debt, Debt} OR {NOT Undisclosed} – deal terms are known: 174’814 results;
(4) Announced Premium = {Min = -100%; Max = ∞ } - premium is known, which in turn means the acquired firm is publicly listed: 29’126 results;	(5) Acquirer = {Public}, acquirer is publicly listed, essential to later measure abnormal returns: 14’111 results;
(6) Elimination of duplicated deals: 14’059 results; Errors of Bloomberg’s database.	(7) Elimination of deals with Multiple Acquirers, not being able to measure Acquirer 1 year Total Return : 12’703 results;
(8) Modification of the related index of 64 deals for the S&P 500 Index. Each deal had associated its local country index (i.e. Portugal – PSI20 Index) allowing for a better and more comparable measure of Cumulative Abnormal Return (CAR). Exceptionally, and in the case of these 64 deals, S&P 500 Index was the used index of replacement since it is the most representative within the sample – most acquirers are US based: 12’703 results;	(9) Omission of missing cases with missing values: 5’966

Table 2 – Factor Analysis: Input Variables

Variable	**Input**
Number of Bidders (Competition Factor)	1 = At least one competing bid; 0 = No competing bid
Tender Offer	1 = Yes; 0 = No, tender offer
PE/VC Involvement	1 = PE and VC, VC or PE involved; 0 = No PE or VC involved
Number of Deals (Since 1994-to-date)	Count of the number of deals per bidder
Announced Total Value Adjusted to 2011 dollars	Announced Value adjusted to present value (2011) by the rate of inflation (CPI)
Market Capitalization of Acquirer	Market Capitalization of the Acquirer at the announcement of the completion adjusted by the same CPI rate
Relative Size (% Market Cap)	Announced Total Value Adj. 2011 / Market Capitalization of Acquirer
Nature of Bid	0 = Friendly; 1 = Friendly to Unsolicited; Unsolicited; Unsolicited to Hostile; Hostile
Cash Terms	0 = Cash (only); 1 = Stock; Stock and Cash; Other
In border/Cross border	0 = In border; 1 = Cross border
Intrasector/Extrasector	0 = Intrasector; 1 = Extrasector
Ansoff Growth Strategies 1-4	1 = Market Penetration; 2 = Geographic Expansion; 3 = Market Expansion; 4 = Diversification

Table 3 – Factor Analysis: Correlation Matrix and Communalities

		Product/ Ansoff Matrix 1-4	Number of Bidders	Tender Offer	PE/VC Involvement	Number of Deals Acquirer Since 1994 to Date	Announced Total Valued (mil) Adj. 2011 CPI	Total Assets Multiple	Market Cap Adj. CPI	Relative Size (% of Market Cap)	Nature of Bid	Cash Terms	In / Cross-boarder	Intra/Cross-sector Transaction
Correlation	Product/Ansoff Matrix 1-4	1,000	-,012	,047	-,029	,071	-,019	,029	,041	-,036	,016	-,119	,204	,223
	Number of Bidders	-,012	1,000	,074	-,011	,019	-,003	,001	,008	-,012	,058	-,034	,043	-,010
	Tender Offer	,047	,074	1,000	-,068	,050	-,018	-,009	,019	-,018	,043	-,124	,062	,008
	PE/VC Involvement	-,029	-,011	-,068	1,000	-,061	,076	-,004	-,024	,042	-,019	,068	-,051	-,017
	Number of Deals Acquirer Since 1994 to Date	,071	,019	,050	-,061	1,000	,034	,005	,412	-,096	,009	-,104	,098	,108
	Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	-,019	-,003	-,018	,076	,034	1,000	,003	,198	,084	,093	,062	,013	-,062
	Total Assets Multiple	,029	,001	-,009	-,004	,005	,003	1,000	,006	-,004	-,001	-,011	,032	,012
	Market Cap Adj. CPI	,041	,008	,019	-,024	,412	,198	,006	1,000	-,084	,014	-,126	,174	,087
	Relative Size (% Market Cap)	-,036	-,012	-,018	,042	-,096	,084	-,004	-,084	1,000	,024	,139	-,076	-,065
	Nature of Bid	,016	,058	,043	-,019	,009	,093	-,001	,014	,024	1,000	-,049	,053	-,008
	Cash Terms	-,119	-,034	-,124	,068	-,104	,062	-,011	-,126	,139	-,049	1,000	-,291	-,123
	In / Cross-boarder	,204	,043	,062	-,051	,098	,013	,032	,174	-,076	,053	-,291	1,000	-,021
	Intra/Cross-sector Transaction	,223	-,010	,008	-,017	,108	-,062	,012	,087	-,065	-,008	-,123	-,021	1,000

a. Determinant = .546

Communalities

	Initial	Extraction
Product/Ansoff Matrix 1-4	1,000	,616
Number of Bidders	1,000	,321

Tender Offer	1,000	,393
PE/VC Involvement	1,000	,269
Number of Deals Acquirer Since 1994 to Date	1,000	,632
Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	1,000	,583
Total Assets Multiple	1,000	,266
Market Cap Adj. CPI	1,000	,708
Relative Size (% of Market Cap)	1,000	,384
Nature of Bid	1,000	,429
Cash Terms	1,000	,494
In-border / Cross-boarder	1,000	,636
Intra-sector/Cross-sector Transaction	1,000	,714

Extraction Method: Principal Component Analysis.

Table 4 - Factor Analysis: Total Variance Explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,842	14,165	14,165	1,842	14,165	14,165	1,506	11,588	11,588
2	1,314	10,110	24,275	1,314	10,110	24,275	1,329	10,222	21,810
3	1,175	9,039	33,315	1,175	9,039	33,315	1,237	9,516	31,326
4	1,094	8,415	41,730	1,094	8,415	41,730	1,204	9,261	40,587
5	1,020	7,844	49,574	1,020	7,844	49,574	1,168	8,988	49,574
6	,990	7,618	57,192						
7	,974	7,489	64,681						
8	,935	7,194	71,876						
9	,899	6,918	78,793						
10	,824	6,342	85,135						
11	,783	6,022	91,157						
12	,614	4,727	95,884						
13	,535	4,116	100,000						

Extraction Method: Principal Component Analysis.

Figure 2 – Factor Analysis: Scree Plot

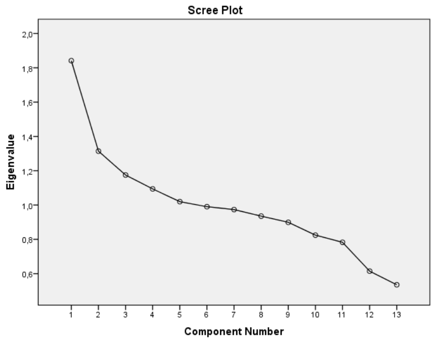


Table 5 - Factor Analysis: Component Matrix, Rotated Component Matrix and Transformation Matrix

Component Matrix

	Component 1	2	3	4	5
Product/Ansoff Matrix 1-4	,418	-,305	-,155	,554	,133
Number of Bidders	,095	-,034	,457	-,142	,285
Tender Offer	,235	-,186	,423	-,166	,311
PE/VC Involvement	-,194	,234	-,115	,379	-,142
Number of Deals Acquirer Since 1994 to Date	,578	,383	-,236	-,273	,146
Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	,052	,674	,181	,305	,001
Total Assets Multiple	,056	-,037	-,022	,237	-,453
Market Cap Adj. CPI	,598	,557	-,146	-,137	-,008
Relative Size (% of Market Cap)	-,322	,209	,177	,395	,220
Nature of Bid	,109	,130	,515	,279	,240
Cash Terms	-,572	,297	-,191	-,001	,203
In-border / Cross-boarder	,554	-,113	,300	,180	-,440
Intra-sector/Cross-sector Transaction	,343	-,236	-,466	,296	,486

Extraction Method: Principal Component Analysis.
a. 5 components extracted.

Rotated Component Matrix

	Component 1	2	3	4	5
Product/Ansoff Matrix 1-4	-,039	,322	,709	,088	-,021
Number of Bidders	-,006	-,003	-,077	,064	,557
Tender Offer	,004	,076	,049	-,075	,616
PE/VC Involvement	-,071	-,005	,021	,374	-,352
Number of Deals Acquirer Since 1994 to Date	,776	-,008	,106	-,119	,063
Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	,335	,029	-,139	,669	-,055
Total Assets Multiple	-,094	,393	-,047	,064	-,311
Market Cap Adj. CPI	,826	,135	,009	,087	-,020
Relative Size (% of Market Cap)	-,215	-,201	,044	,542	,029
Nature of Bid	-,034	,136	,050	,464	,439
Cash Terms	-,113	-,593	-,159	,234	-,222
In-border / Cross-boarder	,119	,784	,020	,009	,084
Intra-sector/Cross-sector Transaction	,142	-,147	,814	-,099	-,011

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 6 iterations.

Component Transformation Matrix

Component	1	2	3	4	5
1	,650	,573	,394	-,170	,255
2	,648	-,221	-,373	,601	-,176
3	-,249	,350	-,413	,353	,722
4	-,296	,280	,545	,685	-,261
5	,091	-,649	,488	,131	,561

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 6 - Factor Analysis: Component Score Coefficient Matrix

Component Score Coefficient Matrix

	Component				
	1	2	3	4	5
Product/Ansoff Matrix 1-4	-,108	,193	,570	,139	-,055
Number of Bidders	-,016	-,047	-,065	,060	,489
Tender Offer	-,026	-,010	,020	-,044	,528
PE/VC Involvement	-,044	,053	,053	,309	-,297
Number of Deals Acquirer Since 1994 to Date	,529	-,118	,032	-,101	,029
Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	,230	,034	-,091	,548	-,045
Total Assets Multiple	-,098	,366	-,068	,062	-,307
Market Cap Adj. CPI	,553	,019	-,051	,069	-,053
Relative Size (% of Market Cap)	-,135	-,122	,111	,454	,063
Nature of Bid	-,061	,083	,059	,409	,380
Cash Terms	,004	-,415	-,043	,157	-,124
In-border / Cross-boarder	-,012	,607	-,075	,043	-,009
Intra-sector/Cross-sector Transaction	,066	-,226	,684	-,032	-,009

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 7 - Cluster Analysis: Variables and Cluster Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Two-step Cluster Number	5966	-1	6	3,71	1,869
Total Assets Multiple	5966	,00	2984,91	2,29	39,28
Relative Size (% of Market Cap)	5966	0,00%	66,54%	0,3391%	1,29475%
Market Cap Adj. CPI	5966	$2.24	$536,405.70	$16,973.53	$43,627.58
Announced Total Valued (mil) Adjusted to 2011 dollars by the Con	5966	$0.00	$96,450.25	$1,024.73	$4,349.96
Number of Deals Acquirer Since 1994 to Date	5966	1	23	2,15	2,161
Cumulative Abnormal Return (CAR)	5966	-2,10	6,42	-,0009	,47417
Tender Offer	5966	0	1	,28	,450
Cash Terms	5966	0	1	,28	,450
Nature of Bid	5966	0	1	,02	,145
Valid N (listwise)	5966	-	-	-	-

Table 8 - Cluster Analysis: Schwarz's Bayesian Criterion (BIC)

Auto-Clustering

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Ratio of BIC Changes[b]	Ratio of Distance Measures[c]
1	21114,837			
2	15414,105	-5700,732	1,000	1,210
3	10719,186	-4694,919	,824	1,707
4	8011,732	-2707,453	,475	1,579
5	6334,611	-1677,121	,294	1,160
6	4902,791	-1431,820	,251	1,965

a. The changes are from the previous number of clusters in the table.
b. The ratios of changes are relative to the change for the two cluster solution.
c. The ratios of distance measures are based on the current number of clusters against the previous number of clusters.

Table 9 - Cluster Analysis: Cluster Distribution, Centroids and Clusters v. Variables

Cluster Distribution

		N	% of Combined	% of Total
Cluster	1	921	15,4%	15,4%
	2	739	12,4%	12,4%
	3	1027	17,2%	17,2%
	4	1005	16,8%	16,8%
	5	511	8,6%	8,6%
	6	1691	28,3%	28,3%
	Outlier (-1)	72	1,2%	1,2%
	Combined	5966	100,0%	100,0%
Total		5966		100,0%

Centroids

		Total Assets Multiple		Market Cap Adj. CPI		Relative Size (% of Market Cap)	
		Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Cluster	1	1,4765	4,44	$7,202.82	$20,454.15	0,5284%	0,8772%
	2	1,7390	7,50	$6,256.66	$18,174.18	0,4924%	0,8163%
	3	1,8814	3,33	$22,282.53	$41,059.87	0,1702%	0,3898%
	4	1,6369	4,02	$13,737.79	$29,789.26	0,2224%	0,5629%
	5	2,0861	9,49	$19,379.40	$36,368.72	0,1562%	0,4480%
	6	1,6080	3,37	$16,145.23	$34,871.24	0,2305%	0,5225%
	Outlier (-1)	50,6589	353,67	$223,771.11	$171,123.75	4,2314%	9,5981%
	Combined	2,2888	39,28	$16,973.53	$43,627.58	0,3391%	1,2947%

Product/Ansoff Matrix 1-4

		Market Penetration		Geographic Expansion		Market Expansion		Diversification	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Cluster	1	921	34,9%	0	0,0%	0	0,0%	0	0,0%
	2	0	0,0%	235	18,5%	406	28,4%	98	15,7%
	3	0	0,0%	1027	80,7%	0	0,0%	0	0,0%
	4	0	0,0%	0	0,0%	1005	70,3%	0	0,0%
	5	0	0,0%	0	0,0%	0	0,0%	511	81,8%
	6	1691	64,1%	0	0,0%	0	0,0%	0	0,0%
	Outlier (-1)	26	1,0%	11	0,9%	19	1,3%	16	2,6%
	Combined	2638	100,0%	1273	100,0%	1430	100,0%	625	100,0%

PE/VC Involvement

		No PE/VC Involvement		PE/VC Involvement	
		Frequency	Percent	Frequency	Percent
Cluster	1	887	15,1%	34	33,7%
	2	725	12,4%	14	13,9%
	3	1021	17,4%	6	5,9%
	4	990	16,9%	15	14,9%
	5	507	8,6%	4	4,0%
	6	1668	28,4%	23	22,8%
	Outlier (-1)	67	1,1%	5	5,0%
	Combined	5865	100,0%	101	100,0%

Nature of Bid

		Friendly		Friendly to Unsolicited; Unsolicited; Unsolicited to Hostile; Hostile	
		Frequency	Percent	Frequency	Percent
Cluster	1	914	15,7%	7	5,5%
	2	729	12,5%	10	7,8%
	3	998	17,1%	29	22,7%
	4	981	16,8%	24	18,8%
	5	497	8,5%	14	10,9%
	6	1651	28,3%	40	31,3%
	Outlier (-1)	68	1,2%	4	3,1%
	Combined	5838	100,0%	128	100,0%

Descriptive Statistics
Statistics * Cluster

Acquirer Sector S&P GICS

		Consumer Discretionary		Consumer Staples		Energy		Financials		Healthcare		Industrials		Information Technology		Materials		Telecommunications		Utilities	
		Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %	Count	Row N %
Cluster	1	188	20,4%	31	3,4%	1	0,1%	269	29,2%	56	6,1%	90	9,8%	74	8,0%	128	13,9%	58	6,3%	26	2,8%
	2	142	19,2%	34	4,6%	2	0,3%	128	17,3%	41	5,5%	89	12,0%	61	8,3%	168	22,7%	39	5,3%	35	4,7%
	3	196	19,1%	60	5,8%	1	0,1%	205	20,0%	93	9,1%	122	11,9%	65	6,3%	214	20,8%	44	4,3%	27	2,6%
	4	217	21,6%	44	4,4%	2	0,2%	197	19,6%	53	5,3%	134	13,3%	76	7,6%	187	18,6%	47	4,7%	48	4,8%
	5	110	21,5%	23	4,5%	3	0,6%	77	15,1%	21	4,1%	87	17,0%	30	5,9%	95	18,6%	43	8,4%	22	4,3%
	6	368	21,8%	42	2,5%	3	0,2%	435	25,7%	116	6,9%	207	12,2%	143	8,5%	266	15,7%	60	3,5%	51	3,0%

Total Assets Multiple * Cluster

Cluster	Mean	Median	Std Dev	Kurtosis	N
1	1,4765	,6500	4,44	196,9	921
2	1,7390	,7400	7,50	498,51	739
3	1,8814	1,0600	3,33	87,44	1027
4	1,6369	,9000	4,02	247,32	1005
5	2,0861	1,1300	9,49	469,44	511
6	1,6080	,9100	3,37	203,51	1691
Total	1,6979	,8800	5,09	832,46	5894

Market Cap Adj. CPI * Cluster

Cluster	Mean	Median	Std. Dev	Kurtosis	N
1	$7,202.82	$949.92	$20,454.15	26,324	921
2	$6,256.66	$1,043.22	$18,174.18	49,211	739
3	$22,282.53	$4,798.68	$41,059.87	8,600	1027
4	$13,737.79	$2,773.55	$29,789.26	16,759	1005
5	$19,379.40	$4,039.88	$36,368.72	11,092	511
6	$16,145.23	$2,360.56	$34,871.24	11,499	1691
Total	$14,447.33	$2,249.25	$32,325.31	14,847	5894

Relative Size (% of Market Cap) * Cluster

Cluster	Mean	Median	Std. Dev	Kurtosis	N
1	0,5284%	0,1997%	0,8772%	15,318	921
2	0,4924%	0,1708%	0,8163%	16,123	739
3	0,1702%	0,0353%	0,3898%	60,021	1027
4	0,2224%	0,0341%	0,5629%	41,312	1005
5	0,1562%	0,0263%	0,4480%	78,809	511
6	0,2305%	0,0508%	0,5225%	38,937	1691
Total	0,2916%	0,0613%	0,6321%	30,590	5894

Product/Ansoff Matrix 1-4 * Cluster
Product/Ansoff Matrix 1-4

Cluster	Mean	Median	Std. Dev	Kurtosis	N
1	1,00	1,00	,000	.	921
2	2,81	3,00	,646	-,673	739
3	2,00	2,00	,000	.	1027
4	3,00	3,00	,000	.	1005
5	4,00	4,00	,000	.	511
6	1,00	1,00	,000	.	1691
Total	2,00	2,00	1,047	-1,061	5894

Cash Terms * Cluster
Cash Terms

Cluster	Mean	Median	Std. Dev	Kurtosis	N
1	1,00	1,00	,000	.	921
2	1,00	1,00	,000	.	739
3	,00	,00	,000	.	1027
4	,00	,00	,000	.	1005
5	,00	,00	,000	.	511
6	,00	,00	,000	.	1691
Total	,28	,00	,450	-1,057	5894

Nature of Bid * Cluster
Nature of Bid

Cluster	Mean	Median	Std. Dev	Kurtosis	N
1	,01	,00	,087	127,276	921
2	,01	,00	,116	69,390	739
3	,03	,00	,166	30,597	1027
4	,02	,00	,153	37,090	1005
5	,03	,00	,163	31,851	511
6	,02	,00	,152	37,413	1691
Total	,02	,00	,144	42,591	5894

Cash Terms

		Stock; Stock and Cash; Other		Cash Only	
		Frequency	Percent	Frequency	Percent
Cluster	1	0	0,0%	921	54,8%
	2	0	0,0%	739	44,0%
	3	1027	24,0%	0	0,0%
	4	1005	23,4%	0	0,0%
	5	511	11,9%	0	0,0%
	6	1691	39,5%	0	0,0%
	Outlier (-1)	52	1,2%	20	1,2%
	Combined	4286	100,0%	1680	100,0%

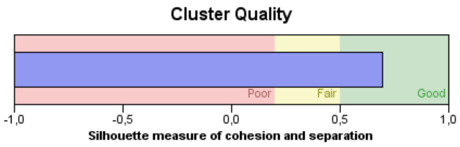
Number of Deals Acquirer Since 1994 to Date * Cluster
Number of Deals Acquirer Since 1994 to Date

Cluster	Mean	Median	Std. Deviation	Kurtosis	N
1	1,74	1,00	1,483	18,810	921
2	1,82	1,00	1,724	28,856	739
3	2,37	2,00	2,204	10,270	1027
4	2,28	1,00	2,343	12,312	1005
5	2,41	1,00	2,469	15,594	511
6	2,09	1,00	2,027	14,404	1691
Total	2,11	1,00	2,064	15,579	5894

Figure 3 – Cluster Analysis: Model Summary and Clusters

Model Summary

Algorithm	TwoStep
Inputs	7
Clusters	6



Clusters

Input (Predictor) Importance: 1,0 / 0,8 / 0,6 / 0,4 / 0,2 / 0,0

Cluster	1	2	3	4	5	6
Label						
Description						
Size	15,6% (921)	12,5% (739)	17,4% (1027)	17,1% (1005)	8,7% (511)	28,7% (1691)
Inputs	Cash Terms Cash Only (100,0%)	Cash Terms Cash Only (100,0%)	Cash Terms Stock; Stock and Cash; Other (100,0%)	Cash Terms Stock; Stock and Cash; Other (100,0%)	Cash Terms Stock; Stock and Cash; Other (100,0%)	Cash Terms Stock; Stock and Cash; Other (100,0%)
	Product/Ansoff Matrix 1-4 Market Penetration (100,0%)	Product/Ansoff Matrix 1-4 Market Expansion (54,9%)	Product/Ansoff Matrix 1-4 Geographic Expansion (100,0%)	Product/Ansoff Matrix 1-4 Market Expansion (100,0%)	Product/Ansoff Matrix 1-4 Diversification (100,0%)	Product/Ansoff Matrix 1-4 Market Penetration (100,0%)
	Relative Size (% of Market Cap) 0,53%	Relative Size (% of Market Cap) 0,49%	Relative Size (% of Market Cap) 0,17%	Relative Size (% of Market Cap) 0,22%	Relative Size (% of Market Cap) 0,16%	Relative Size (% of Market Cap) 0,23%
	Market Cap Adj# CPI $7,202.82	Market Cap Adj# CPI $6,256.67	Market Cap Adj# CPI $22,282.53	Market Cap Adj# CPI $13,737.80	Market Cap Adj# CPI $19,379.41	Market Cap Adj# CPI $16,145.24
	PE/VC Involvement No PE/VC Involvement (96,3%)	PE/VC Involvement No PE/VC Involvement (98,1%)	PE/VC Involvement No PE/VC Involvement (99,4%)	PE/VC Involvement No PE/VC Involvement (98,5%)	PE/VC Involvement No PE/VC Involvement (99,2%)	PE/VC Involvement No PE/VC Involvement (98,6%)
	Nature of Bid Friendly (99,2%)	Nature of Bid Friendly (98,6%)	Nature of Bid Friendly (97,2%)	Nature of Bid Friendly (97,6%)	Nature of Bid Friendly (97,3%)	Nature of Bid Friendly (97,6%)
	Total Assets Multiple 1,48	Total Assets Multiple 1,74	Total Assets Multiple 1,88	Total Assets Multiple 1,64	Total Assets Multiple 2,09	Total Assets Multiple 1,61

Table 10 - Cumulative Abnormal Return (CAR) v. Cluster

Cumulative Abnormal Return (CAR) * Cluster

Cumulative Abnormal Return (CAR)

Cluster	Mean	Median	Std. Deviation	Kurtosis	N
1	-,0263	-,0682	,5403	32,108	921
2	-,0094	-,0743	,5759	26,492	739
3	,0202	-,0198	,4013	13,851	1027
4	-,0171	-,0477	,4153	20,339	1005
5	-,0073	-,0316	,3727	9,546	511
6	,0223	-,0352	,4898	34,393	1691
Total	,0011	-,0431	,4751	30,288	5894

No outliers included.

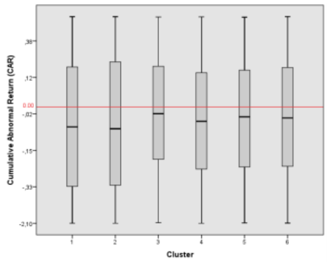
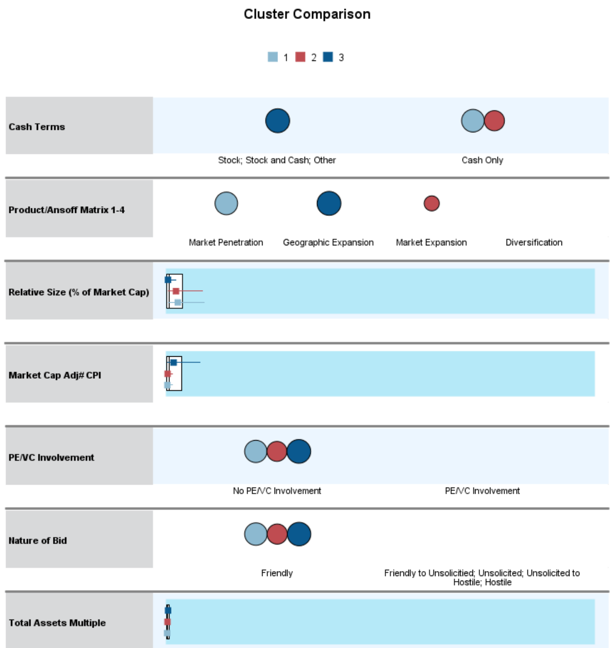
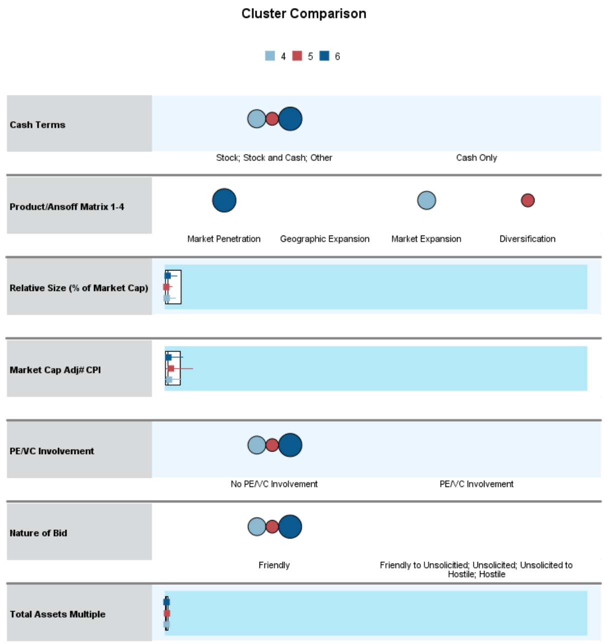


Figure 4 - Cluster Analysis: Cluster Comparison - 1 to 4





Bubbles represent cluster size (number of cases).