Comparative Study of Outlier Detection Algorithms via Fundamental Analysis Variables: An Application on Firms Listed in Borsa Istanbul

Senol Emir

Corresponding Author: Asst. Prof., Faculty of Economics, Istanbul University, 34126 Beyazit, Istanbul, Turkey

Hasan Dincer

Assoc.Prof. of Finance, Istanbul Medipol University, School of Business and Management, Beykoz, 34810, Istanbul, Turkey

Umit Hacıoglu

Assoc.Prof. of Finance, Istanbul Medipol University, School of Business and Management, Beykoz, 34810, Istanbul, Turkey

Serhat Yuksel

Asst.Prof. of Economics & Finance, Konya Food & Agriculture University, Faculty of Social Sciences and Humanities, Konya, Turkey

Abstract

In a data set, an outlier refers to a data point that is considerably different from the others. Detecting outliers provides useful application-specific insights and leads to choosing right prediction models. Outlier detection (also known as anomaly detection or novelty detection) has been studied in statistics and machine learning for a long time. It is an essential preprocessing step of data mining process. In this study, outlier detection step in the data mining process is applied for identifying the top 20 outlier firms. Three outlier detection algorithms are utilized using fundamental analysis variables of firms listed in Borsa Istanbul for the 2011-2014 period. The results of each algorithm are presented and compared. Findings show that 15 different firms are identified by three different outlier detection methods. KCHOL and SAHOL have the greatest number of appearances with 12 observations among these firms. By investigating the results, it is concluded that each of three algorithms makes different outlier firm lists due to differences in their approaches for outlier detection.

Key Words: *Outlier Detection, Fundamental Analysis, Stock Exchange, k-Nearest Neighbor (k-NN) Global Outlier Score, Histogram Based Outlier Score (HBOS), Robust Principal Component Analysis (rPCA) Outlier Score.*

JEL classification: G2

Introduction

Financial Analysis is the process of evaluating financial reports of the companies (Cooper and Kaplan, 1991). In this process, financial experts compare some important accounts over the years in order to make comment about financial performance of them. With the help of financial analysis, it can be possible to define future performance of these companies. Therefore, financial reports of the companies are so significant that they affect the investment decisions for these companies.

Ratio analysis is the main part of the financial analysis. In this process, some ratios of the company, created by using financial accounts, are evaluated (Nissim and Penman, 2001). Hence, it is used to determine extraordinary changes for some accounts over the years. Another benefit of ratio analysis is that it defines the relationship between some important accounts. As a result, ratio analysis helps to make comment about financial position of that company.

Because of the advantages emphasized above, ratio analysis is very helpful in order to make investment decision. Many investors use financial ratios of the company to learn the financial situation. In other words, these ratios support investors to evaluate financial performance of the company. Therefore, it can be said that ratio analysis helps investors to make reasonable decision and to minimize the risk in this process (Johnson, 1970).

However, there are some criticisms about the quality of ratio analysis. According to efficient market hypothesis, necessary information in order to gain profit from the stocks can be reached by everybody (Fama, 1998). Therefore, it is impossible to get profit by using ratio analysis related to the company. The main reason behind this situation is that financial reports of the companies may not reflect the real condition. Hence, ratios created from these reports may give misleading results.

The paper is organized as follows: second part explains fundamental analysis method. The third part gives information about outlier detection. The fourth part includes empirical analysis. Finally, the analyze results were given at conclusion.

Literature Review

There are many studies in the literature related to fundamental analysis. Most of them analyze the performance of fundamental analysis. Some of these studies are explained in the table 1.

Chen and others developed a technique for stock market forecasting by using fundamental analysis in their study. They aimed to create a model in order for the investors to be helpful in investment decision. Industrial indicators are provided from Taiwan Stock Exchange Corporation. Moreover, 16 financial ratios were used in this study to achieve this objective (Chen, et. al., 2016). Maharaja and Saravanakumar made a study related to fundamental analysis of five major Indian banks in order to give investment decision. With respect to the fundamental analysis, 10 financial ratios were used for the period between 2009 and 2013. As a result, of the analysis, it was determined that the performance of these banks is successful. Another result of this study is that fundamental analysis is very helpful in making investment decision (Maharaja and Saravanakumar, 2016). Shen and Tzeng tried to create a soft computing model for stock selection by using fundamental analysis. This model included 20 different rules in order to classify the value of the stocks. In addition to them, stocks in Taiwan were used in this study to achieve this objective. As a result, it was defined that fundamental analysis is very helpful in order to predict stock price (Shen and Tzeng, 2015). Bistрова and Lace tested the relevance of fundamental analysis on Baltic equity markets. Within this scope, the data of 45 companies for the period between 2000 and 2008 was used. As a result, of the analysis, it was determined that fundamental analysis is not helpful in order to get profit from the stock investment in Baltic market (Bistрова and Lace, 2015). Yan and Zheng made a study about the relationship between fundamental analysis and stock returns. Within this context, monthly data for the period between 1963 and 2013 was used in this study. Furthermore, they defined 217 different ratios in this analysis. Finally, they concluded that fundamental signals are significant predictors of stock returns (Yan and Zheng, 2015). Shukla and Nerlekar tried to determine which tools of fundamental analysis are successful in determining the stock price. Within this scope, sugar sector in India was analyzed in this study. Moreover, monthly data between 2008 and 2012 and 7 different ratios related to fundamental analysis was used. It was concluded that inventory turnover ratio is the key indicator for sugar sector of India (Shukla and Nerlekar, 2015).

Table 1: Studies Related to Fundamental Analysis

Author	Scope	Result
(Chen, et. al., 2016)	Taiwan	They created a model related to investment decision.
(Maharaja and Saravanakumar, 2016)	India	It was defined that Indian banks are very successful according to fundamental analysis.
(Shen and Tzeng, 2015)	Taiwan	It was defined that fundamental analysis is very helpful in order to predict stock price.
(Bistrova and Lace, 2015)	Baltic countries	It was determined that fundamental analysis is not helpful in order to get profit from the stock investment in Baltic market.
(Yan and Zheng, 2015)	NYSE, AMEX, and NASDAQ common stocks	It was concluded that fundamental signals are significant predictors of stock returns.
(Shukla and Nerlekar, 2015)	India	It was concluded that inventory turnover ratio is the key indicator for sugar sector of India.
(Fan, 2015)	Taiwan	It was determined that fundamental analysis give directive information.
(Chapman, 2015)	Dow Jones Index	It was concluded that intangibles of the company, such as competitive advantage, should be considered in addition to fundamental analysis.
(Wafi, et. al., 2015)	Egypt	It was defined that technical analysis gives better results than fundamental analysis.
(Waworuntu and Suryanto, 2015)	Indonesia	They concluded that investors can get higher profit by integrating fundamental and technical approaches.
(Megharaja, 2015)	India	It was determined that ICICI Bank has the greatest point.
(Goodman, et. al., 2013)	S&P 100 index call option	It was determined that fundamental analysis is very successful in order to predict option price.
(Amsaveni and Gomathi, 2013)	India	They concluded that Colgate Palmolive is the best FMCG company in India according to the results of the analysis.
(Iqbal, et. al., 2013)	Karachi Stock Exchange	It was concluded that there is insignificant relationship between fundamental analysis and future stock price.
(Horobet and Belascu, 2012)	Romania	It was defined that profit margin is the most significant indicator of fundamental analysis.

Source: Authors

Fan made a study related to fundamental analysis of electronic corporation in Taiwan. Within this context, 20 financial indicators were analyzed for the period between 2012 and 2014. As a result of the study, it was determined that fundamental analysis give directive information (Fan, 2015). Chapman tested fundamental analysis by using information of 30 different companies in Dow Jones Index. Within this scope, firstly he calculated the prices of the stocks by using fundamental analysis. After that, he compared these results with the market price of these stocks. Finally, it was concluded that intangibles of the company, such as competitive advantage, should be considered in addition to fundamental analysis (Chapman, 2015). Wafi and others compared the performance of technical analysis and fundamental analysis. For this purpose, he analyzed Egyptian stock exchange for the years between 1998 and 2009. Furthermore, within this scope, 37 nonfinancial companies were included in this study. As a result of this analysis, it was defined that technical analysis gives better results than fundamental analysis (Wafi, et. al., 2015). Waworuntu and Suryanto also made a study about the performance of technical and fundamental analysis. Within this context, the data of Indonesian stock exchange for the periods between 2004 and 2009 was analyzed in this study. In conclusion, it was defined that both technical and fundamental analysis are successful in making investment decision. Another result of this study is that investors can get higher profit by integrating these two approaches (Waworuntu and Suryanto, 2015).

Megharaja made a study related to fundamental analysis of the financial institutions in India. Within this scope, he compared 3 banks in India in this study. In addition to this aspect, 7 different ratios were used in this analysis. According to fundamental analysis result, it was determined that ICICI Bank has the greatest point (Megharaja, 2015). Goodman and others tried to analyze whether fundamental analysis can predict absolute stock price movements or not in option market. To achieve this purpose, the data between the years 1996 and 2001 was used in this study. As a result, it was determined that fundamental analysis is very successful in order to predict option price (Goodman, et. al., 2013). Amsaveni and Gomathi made a study about the fundamental analysis of fast moving consumer goods companies in India. For this purpose, the data of 6 Indian companies for the years between 2006 and 2012 was used in this study. They concluded that Colgate Palmolive is the best FMCG company in India according to the results of the analysis (Amsaveni and Gomathi, 2013). Iqbal and others tried to identify whether fundamental analysis can predict future stock prices or not. Within this scope, all non-financial companies listed on Karachi Stock Exchange were analyzed for the years between 2000 and 2009. As a result of ordinary least square analysis, it was determined that there is insignificant relationship between fundamental analysis and future stock price (Iqbal, et. al., 2013). Horobet and Belascu made a study about the performance of fundamental analysis in order to make investment decision. For this purpose, the data of non-financial companies in Romania was used for the period between 2002 and 2009. According to the results of panel data analysis, it was defined that profit margin is the most significant indicator of fundamental analysis (Horobet and Belascu, 2012).

Research and Methods

Fundamental Analysis and its concept

Financial reports refer to the summary of the financial performance of the companies. Because they give information about financial activities, they are used by the investors in order to make investment decision for this company (Gniewosz, 1990). In addition to the investors, financial reports are also helpful for top management to make strategic decision related to this company.

Balance Sheet gives detailed information about assets, debts and capital amount of the company (Damodaran, 1996). Moreover, it is also possible to classify short and long-term debts and liquid and illiquid assets. In addition to them, receivables and stock can also be seen. Income Statement gives details all incomes and expenses of a company for a given period (Penman and Penman, 2002). Therefore, it includes the amount of sales, cost of these sales, fixed and variables costs of the company. At the end of this report, net profit of the company is also explained. Statement of Changes in Equity explains increases and decreases in capital amount of the company (Costuleanu and Codreanu, 2010). Thus, it is possible to learn the details of the capital amount for this company. Cash Flow Statement gives information about all cash flows of a company for a given period (Carslaw and Mills, 1991). In other words, all cash inflows and outflows of this company are explained in this report. Therefore, liquidity condition of a company can be followed by using cash flow table. Fund Flow Statement explains the sources of a company provided for a given period and the usage of them. Therefore, it gives information about the investment and finance of this company (Siddiqua and Hossan, 2012). The Statement of Profit Appropriation provides information about the profit distribution of the company. In other words, it explains whether the company distributes the profit or not and how much it is distributed (Riccardi, 2016). The Statement of Cost of Goods Sold presents detailed information about the costs of the company related to the goods sold for a given period. Therefore, stock movements of a company can be analyzed by looking this report (Wagner, 1922).

Fundamental analysis is an approach in order to define the real price of the stocks. By making this analysis, investors have a chance to compare the actual price of the stock and the prices calculated by using fundamental analysis (Thomsett, 2006). Therefore, this approach is helpful for investors in order to make buy or sell decision. If the market price is greater than the calculated price, then this stock should be sold. On the other hand, lower market price than the calculated price also gives a signal to buy this stock. Many issues are considered during the process of fundamental analysis. The most important factors that affect fundamental analysis are the financial reports of the company. In addition to them, macroeconomic factors, such as inflation and growth rate are also taken into the consideration in this analysis. Moreover, important situations related to the sector of the company are also included in the fundamental analysis.

Fundamental analysis consists of three different stages, which are economic analysis, sector analysis and company analysis (Kramer and Pushner, 1997). With respect to economic analysis, the macroeconomic variables, which are expected to affect the company, are analyzed (Chu, et. al., 1996). In other words, in order to make an investment to a company, investors firstly evaluate the condition of the country in which this company operates. The main reason behind this situation is that if there is an economic problem in that country, there is high probability that this situation also affects the company negatively. Within the scope of economic analysis, GDP growth rate is a significant indicator. For example, when there is a recession in the country, the stock price of the company will probably be affected. In addition to GDP growth rate, unemployment rate should also be taken into the consideration. In case of high unemployment, there can be economic recession in the country. Moreover, high inflation rates decrease stability in an economy. That is to say, when there is low inflation rate in the country, because of stable economic environment, investors become more willing to make investment in that country. Budget deficit and current account deficit are also other important criteria used in fundamental analysis. High budget deficit leads to high inflation rates and this situation affects the price of stock exchange negatively. Similar to this issue, high rates of current account deficit causes unstable economic environment.

Sector analysis is the second step of fundamental analysis. The main reason of this analysis is that there can be problems for some specific sectors although there is no problem regarding the economy of the country. Therefore, the sector of the company, which we aim to invest, should be analyzed as well (Kevin, 2015). The results of the sector analysis are important determinants for the investment. With respect to the sector analysis, sales and profit amount for this sector should be evaluated. These numbers should also be compared with previous years to determine whether there is an extraordinary difference. Government politics and international relations for this sector should also be analyzed.

Company analysis is the last step of fundamental analysis. Within this context, financial reports of the company are evaluated. By using the ratios calculated from these reports, many important aspects, such as liquidity, profitability of the firm can be analyzed. By using these results, strengths, weaknesses, opportunities and threats of the company are determined. As a result, investors have an idea in order to give their investment decisions as for this company (Ranganatham, 2006).

Key Ratios in Fundamental Analysis

Ratio analysis is the most significant part of the fundamental analysis. In this process, some ratios, calculated by using accounts in financial reports, are used. These ratios can be classified as liquidity ratios, financial ratios, operating ratios and profitability ratios. This classification is depicted on the following table.

Table 2: Key Ratios Used in Fundamental Analysis

Group of the Ratio	Name of the Ratio	Formula
Liquidity Ratios	Current Ratio	Current Assets/Short Term Liabilities
	Liquidity Ratio	(Current Assets-Stocks) / Short Term Liabilities
	Cash Ratio	Cash and Cash Equivalents / Short Term Liabilities
Financial Ratios	Financial Leverage Ratio	Total Debt / Total Assets
	Capital Ratio	Total Capital / Total Assets
	Debt to Equity Ratio	Total Debt / Total Equity
	Self-Financing Ratio	(Profit Reserves-Accumulated Losses) / Capital Paid In
	Fixed Asset to Capital Ratio	Fixed Assets / Capital
Operating Ratios	Receivable Turnover Ratio	Net Sales / Average Receivables
	Inventory Turnover Ratio	Cost of Goods Sold / Average Stock
	Asset Turnover Ratio	Net Sales / Average Assets
Profitability Ratios	Net Profit Margin	Net Profit / Total Sales
	Return on Equity	Net Profit / Total Capital
	Return on Asset	Net Profit / Total Assets
	Interest Coverage Ratio	(Net Income Before Tax + Interest Expense) / Interest Expense

Liquidity ratios show how liquid the company is for a given period. In other words, they give information about the solvency of the company for short-term debt (Saleem and Rehman, 2011). Some ratios related to the liquidity are emphasized below.

Current Ratio is the ratio of current assets to short-term liabilities. As it can be understood from this definition, this ratio shows the capacity of the company to pay short-term debts. This ratio is expected to be more than two, but it is also recommended to evaluate this ratio according to the sector of the company (Edmister, 1972). Liquidity Ratio gives information about the capacity of the company to pay its short-term debt without using its stock. It is accepted that if this ratio is greater than "1", it means that this company can pay its short-term debt easily (Howton and Perfect, 1998). Cash Ratio shows the capacity of the company to pay its debt in an emergency condition. It is accepted for a company to have cash ratio higher than "0.2" in order not to have any problem (Callao, et. al., 2007).

In addition to them, financial ratios explain how the assets of the company are financed. That is to say, the main purpose of these ratios is to understand the assets are financed with the capital or debt (Chen and Shimerda, 1981). Some of the financial ratios are explained below.

Financial Leverage Ratio is the ratio of total debt to total assets. Having high leverage ratio decreases the credibility of the company. The main reason is that if this ratio is high, then there is a high possibility for this company to face burden of the debt problem (Welch, 2011). Capital Ratio is the ratio of total capital to total assets. As it can be understood from the definition this ratio explains what percentage of assets are financed by the owner of the company. Therefore, unlike financial leverage ratio, capital ratio is preferred to be high (Peek and Rosengreen, 1995). Debt to Equity Ratio is also another financial ratio that gives information about the way of financing assets. In order to have a lower financial risk, it is preferred for a company to have less debt than the equity. Thus, this ratio is supposed to be less than "1" (Koutmos and Saidi, 1995). Self-Financing Ratio explains how much the company finances its assets from its own resources. Hence, high self-financing ratio is preferred in order to have better financial condition (Aizenman, et. al., 1995). Fixed Asset to Capital Ratio gives information about what percentage of fixed assets is financed by using capital. Therefore, this ratio is preferred to be low (Wirawan, 2013).

Moreover, operational ratios give information about whether the assets are used efficiently or not (Yepes and Dianderas, 1996). Receivable Turnover Ratio explains how efficiently the assets are used. Because of this issue, it is measured as the ratio of net sales to average accounts receivables. If this ratio is high, it demonstrates that this firm can collect its receivables effectively (Witkowska, 2006). Inventory Turnover Ratio gives information about how long the goods are waiting as a stock before they are sold. Stocks should not be waited too much because they cause extra costs, such as rent. Therefore, inventory turnover ratio is preferred to be high (Koliass, et. al., 2011). Asset Turnover Ratio shows how efficiently assets of the company are used for a given period. Therefore, it is calculated as a ratio of net sales to average assets. Therefore, higher asset turnover ratio refers that this company uses assets efficiently (Brown and Bukovinsky, 2001).

Furthermore, profitability ratios are used in order to evaluate how this company is successful with respect to its earnings. These ratios are also compared with competitors to see the financial condition of the company (Saleem and Rehman, 2011). Net Profit Margin is the ratio of net profit to net sales. In other words, this ratio demonstrates how the sales are converted to the profit. Because of this issue, high profit margin is always preferred (Waldman, et. al., 2011). Return on Equity is the ratio of net profit to total capital amount. Hence, it can be said that this ratio explains how effectively the capital amount is used. Because of this aspect, this ratio should be high (Hellman, 1993). Return on Assets is the ratio of net profit to total assets. In other words, it gives information how effectively the company uses its assets. Therefore, high ratio of return on asset is preferred (Azhar Rosly and Afandi Abu Bakar, 2003). Interest Coverage Ratio gives information about the capacity of the company in order to pay its interest expense. Therefore, high interest coverage ratio is preferred (Mills and Yamamura, 1998).

Outlier Detection Methods

Generally, an outlier is defined as a data point (observation) that has significant differences, based on a predetermined measure, compared to other data points. Outlier detection is an important preprocessing step of data mining trying to identify observations that do not fit into the general structure of data set (Agrawal & Agrawal, 2015). Detecting outliers is one of the core steps towards building successful predictive models, especially on data sets containing a large number of attributes. Because outliers may have a harmful effect on leading wrong model specifications. Due to

biased model parameters, predictive models can produce results that are not sufficiently successful (Ben-Gal, 2005). Outliers may be the observations that are erroneously recorded during data collection phase or different ones from the other observations. In both cases, they may impose excessive influence on the methods that are used for data analysis. Thus, identifying them by using reliable outlier detection techniques before applying any predictive method is important (Vijendra & Shivani, 2014). As outliers help in choosing the right predictive models and their parameters, they contribute to the data analysis (Kamath, 2009)

Some of the data mining techniques are not strongly influenced by outliers and are called robust methods. However, in the existence of outliers, some of the methods give inconsistent and unreasonable results (Berthold et al., 2010). Thus, using predictive methods and sampling techniques that are robust to outliers affects the quality of results considerably.

There is a wide variety of outlier detection approaches. Details of methods are investigated in surveys (Agrawal & Agrawal, 2015; Chandola et al., 2009; Gupta et al., 2014; Hodge & Austin, 2004; Pimentel et al., 2014; Markou & Singh, 2003).

Since unsupervised algorithms do not need a supervisor/expert to label the training data, the majority of outlier detection algorithms rely on unsupervised learning (Amer & Goldstein, 2012). One of the most commonly used types of unsupervised outlier detection techniques is based on nearest neighbor approach. These techniques presume that outliers occur in sparse neighborhoods so they lay on positions far from their nearest neighbors. Outlier scores of observations are determined by taking into account their neighborhood. In this study, first outlier detection algorithm we experiment is *k Nearest Neighbor (k-NN) global outlier score*. Outlier score is calculated as the average distance of the k - Nearest Neighbors (Angiulli & Pizzuti, 2002) or as the distance to the k^{th} neighbor (Ramaswamy et al., 2000).

The other type of outlier detection algorithms use statistical techniques in which firstly, a statistical model is built on the given data set and then a statistical inference test is utilized to conclude if a new observation fits this statistical model or not. Statistics-based outlier detection methods suppose that outliers lay on the regions of the statistical distribution, which have low probability contrary to normal observations laying on the regions having a high probability (Chandola et al., 2009). In parametric statistical techniques, for determining model parameters from data, a prespecified underlying distribution is assumed whereas nonparametric techniques do not need to assume an underlying distribution. The second algorithm we experiment in this study is a nonparametric statistical outlier detection method called *Histogram-based Outlier Score (HBOS)*. This method calculates a separate univariate histogram for every attribute in the data set. Method has two modes (one with a static and one with a dynamic binwidth). In the static mode, every bin has the same binwidth equally distributed over the value range. In the dynamic mode, the binwidth can vary and minimum number of examples contained in a bin can be specified. The binwidth / minimum number values per bin is then calculated automatically. Usually, the square root of the number of observations is used for determining the default value for the number of bins. For computing the outlier scores of observations, the histograms are normalized to one in height first. Then, the score is inverted, so that outliers have a high score and normal observations have a low score (RapidMiner Extension: Anomaly Detection, 2014).

Spectral-based outlier detection techniques use a combination of features that capture the most of the variability in the dataset for attaining an approximation of data set. In these techniques, it is assumed that data can be mapped into a lower dimensional space in which normal observations and outliers occur importantly different (Chandola et al., 2009). The third outlier detection algorithm that is experimented in this study is *Robust Principal Component Analysis Anomaly Score (rPCA)* algorithm that is a one of the spectral technique. *rPCA* computes an anomaly score based on a robust PCA estimation. For robustness, trimming of the original data set based on the Mahalanobis distance is performed first. Then, PCA is computed and a score is determined based on the top upper and/or lower principal components (Shyu et al., 2003).

Empirical Analysis

The analysis is constructed using the data set from 2011 to 2014. The end of year values are considered to analyze the fundamental financial parameters. Total number of observations is 400 for initial raw data set. Then, observations that have missing values are excluded and final size of data set is reduced to 349.

In the literature, there are several kinds of fundamental analysis parameters to evaluate firm values. However, the limitation of this study is to consider common parameters that fit to all firms and Table 3 gives information on the selected variables for creating outlier detection models. Accordingly, nine fundamental variables are employed to evaluate the outliers.

Table 3: Selected Variables for Outlier Detection

Variable	Symbol
Current Ratio	V1
Cash Ratio	V2
Net Sales	V3
Net Profit	V4
Total Assets	V5
Short Term Liabilities	V6
Net Profit / Net Sales	V7
Net Profit / Total Assets	V8
Short Term Liabilities / Total Assets	V9

Descriptive of variables is given in Table 4. Minimum, maximum and mean values of variables are presented. These values provide useful information for evaluating the results of outlier detection models.

Table 4: Descriptive Statistics for model variables

Variable	N	Minimum	Maximum	Mean
V1	349	0,07	237,26	4,34
V2	349	0,01	232,81	2,97
V3	349	51.31	68.969.387.000	3.846.838.395
V4	349	-753.735.000	2.710.145.000	254.031.810
V5	349	47.493.761	230.526.555.000	6.541.022.123
V6	349	543.191	169.096.825.000	2.968.036.354
V7	349	-58,80	1.172,59	3,44
V8	349	-1,37	0,59	0,04
V9	349	0,01	3,03	0,32

Table 5 illustrates top 20 outlier results of k-NN Global Outlier Detection algorithm. Nine different firms take place in the outlier list. The top outlier observation (SAHOL-31.12.2014) has the maximum value of V5 (230.526.555.000) and V6 (169.096.825.000). It has greater values of V3, V4 and V9 than means of these variables. SAHOL is in first four place, KCHOL and TUPRS have the next four places consecutively. THYAO follows these firms with two observations. EKGYO, YAZIC, BIMAS, TCELL and AEFES are the other outliers in the list. K-NN global outlier detection algorithm commonly identifies as outlier the holdings and companies with large sales volume, short-term liabilities and net profit.

Table 6 figures out the top 20 outlier results of Histogram - Based Outlier Detection algorithm. The top outlier observation (SAHOL-31.12.2013) in this algorithm is also the first outlier in k-NN. The top eight seats are shared by SAHOL and KCHOL with four observations each. Histogram Based method does not produce a consecutive outlier order structure as k-NN as expected. Eight different firms take place in the outlier list. VKGYO, KOZAL, ECZYT are firms in the list that do not appear in the k-NN results.

Histogram – Based method scores the firm (SAHOL-31.12.2013) with lower the current and cash ratio, net profit/net sales, net profit/total asset, short-term liabilities/total assets than the mean values as the most prominent outlier

Table 5: Top 20 k-NN Global Outlier Scores

Date	Firm	V1	V2	V3	V4	V5	V6	V7	V8	V9	Outlier Score
31.12.2014	SAHOL	0,65	0,09	10.517.510.000	2.079.114.000	230.526.555.000	169.096.825.000	0,20	0,01	0,73	187192670852
31.12.2013	SAHOL	0,70	0,15	8.457.484.000	1.731.396.000	206.570.819.000	150.872.625.000	0,21	0,01	0,73	160903550467
31.12.2012	SAHOL	0,67	0,10	7.088.379.000	1.858.491.000	171.826.030.000	125.832.866.000	0,26	0,01	0,73	132447550645
30.12.2011	SAHOL	0,60	0,08	10.595.650.000	1.877.987.000	150.855.400.000	113.432.029.000	0,18	0,01	0,75	120918135403
30.12.2011	KCHOL	0,80	0,13	68.969.387.000	2.124.469.000	98.621.087.000	62.031.471.000	0,03	0,02	0,63	87719342492
31.12.2014	KCHOL	1,33	0,52	68.336.365.000	2.710.145.000	63.941.008.000	19.016.744.000	0,04	0,04	0,30	48288295044
31.12.2013	KCHOL	1,35	0,47	65.942.213.000	2.679.713.000	58.789.960.000	19.182.420.000	0,04	0,05	0,33	44471062510
31.12.2012	KCHOL	1,37	0,45	65.449.383.000	2.324.150.000	48.687.778.000	15.816.621.000	0,04	0,05	0,33	40247168308
31.12.2012	TUPRS	1,13	0,40	42.436.908.000	1.464.119.000	16.647.907.000	8.068.100.000	0,04	0,09	0,49	20978190635
30.12.2011	TUPRS	1,08	0,15	40.747.047.000	1.241.738.000	14.757.986.000	8.386.151.000	0,03	0,08	0,57	20451634731
31.12.2013	TUPRS	0,94	0,35	41.078.427.000	1.197.223.000	21.139.387.000	10.396.466.000	0,03	0,06	0,49	20017502238
31.12.2014	TUPRS	0,82	0,46	39.722.712.000	1.458.963.000	21.932.560.000	8.561.001.000	0,04	0,07	0,39	19017782943
31.12.2014	THYAO	0,77	0,20	24.157.801.405	1.819.259.536	31.875.607.062	8.505.344.748	0,08	0,06	0,27	16665988650
31.12.2013	THYAO	0,68	0,21	18.776.784.325	682.707.427	25.402.077.818	6.652.755.831	0,04	0,03	0,26	9237248344
31.12.2014	EKGYO	0,95	0,50	1.804.523.000	954.397.000	14.953.485.000	5.711.879.000	0,53	0,06	0,38	6142296058
31.12.2012	YAZIC	0,83	0,18	1.423.523.000	909.396.000	11.827.706.000	7.495.033.000	0,64	0,08	0,63	5672939212
31.12.2014	BIMAS	0,90	0,16	14.463.059.000	395.299.000	3.238.131.000	2.021.398.000	0,03	0,12	0,62	5317388998
31.12.2014	TCELL	2,67	1,81	12.043.587.000	1.866.924.000	23.668.317.000	4.991.169.000	0,16	0,08	0,21	5084878629
31.12.2013	AEFES	1,58	0,73	9.195.773.000	2.608.920.000	22.366.984.000	3.147.302.000	0,28	0,12	0,14	4881726690
31.12.2013	EKGYO	1,60	1,21	2.331.138.000	1.060.537.000	13.470.982.000	4.512.022.000	0,46	0,08	0,34	4867679029

Table 6: Top 20 Histogram Based Outlier Scores

Date	Firm	V1	V2	V3	V4	V5	V6	V7	V8	V9	Outlier Score
31.12.2013	SAHOL	0,70	0,15	8.457.484.000	1.731.396.000	206.570.819.000	150.872.625.000	0,21	0,01	0,73	9,25
30.12.2011	KCHOL	0,80	0,13	68.969.387.000	2.124.469.000	98.621.087.000	62.031.471.000	0,03	0,02	0,63	8,96
30.12.2011	SAHOL	0,60	0,08	10.595.650.000	1.877.987.000	150.855.400.000	113.432.029.000	0,18	0,01	0,75	8,65
31.12.2014	SAHOL	0,65	0,09	10.517.510.000	2.079.114.000	230.526.555.000	169.096.825.000	0,20	0,01	0,73	8,55
31.12.2012	SAHOL	0,67	0,10	7.088.379.000	1.858.491.000	171.826.030.000	125.832.866.000	0,26	0,01	0,73	8,51
31.12.2012	KCHOL	1,37	0,45	65.449.383.000	2.324.150.000	48.687.778.000	15.816.621.000	0,04	0,05	0,33	8,40
31.12.2014	KCHOL	1,33	0,52	68.336.365.000	2.710.145.000	63.941.008.000	19.016.744.000	0,04	0,04	0,30	8,22
31.12.2013	KCHOL	1,35	0,47	65.942.213.000	2.679.713.000	58.789.960.000	19.182.420.000	0,04	0,05	0,33	8,10
31.12.2014	VKGYO	237,26	232,81	2.603.345	21.854.652	749.969.806	1.344.933	8,40	0,03	0,00	7,46
31.12.2013	TUPRS	0,94	0,35	41.078.427.000	1.197.223.000	21.139.387.000	10.396.466.000	0,03	0,06	0,49	7,19
31.12.2014	THYAO	0,77	0,20	24.157.801.405	1.819.259.536	31.875.607.062	8.505.344.748	0,08	0,06	0,27	6,29
31.12.2013	ALGYO	120,77	100,79	32.208.298	84.385.039	388.760.710	1.671.142	2,62	0,22	0,00	6,18
31.12.2014	KOZAL	17,41	14,34	885.888.000	494.890.000	2.019.552.000	74.667.000	0,56	0,25	0,04	5,77
31.12.2013	THYAO	0,68	0,21	18.776.784.325	682.707.427	25.402.077.818	6.652.755.831	0,04	0,03	0,26	5,71
30.12.2011	VKGYO	89,45	88,78	29.464.403	25.790.717	189.197.017	543.191	0,88	0,14	0,00	5,51
31.12.2012	TUPRS	1,13	0,40	42.436.908.000	1.464.119.000	16.647.907.000	8.068.100.000	0,04	0,09	0,49	5,49
31.12.2014	TUPRS	0,82	0,46	39.722.712.000	1.458.963.000	21.932.560.000	8.561.001.000	0,04	0,07	0,39	5,33
30.12.2011	TUPRS	1,08	0,15	40.747.047.000	1.241.738.000	14.757.986.000	8.386.151.000	0,03	0,08	0,57	5,25
31.12.2014	ECZYT	38,60	36,39	1.268.808.655	25.458.248	1.276.624.569	6.277.694	0,02	0,02	0,01	5,22
31.12.2014	ALGYO	75,00	63,56	14.919.333	78.151.728	463.942.210	2.994.025	5,24	0,17	0,01	5,21

Table 7: Top 20 Robust PCA Outlier Scores

Date	Firm	V1	V2	V3	V4	V5	V6	V7	V8	V9	Outlier Score
31.12.2014	VKGYO	237,26	232,81	2.603.345	21.854.652	749.969.806	1.344.933	8,40	0,03	0,00	42,20
31.12.2013	ALGYO	120,77	100,79	32.208.298	84.385.039	388.760.710	1.671.142	2,62	0,22	0,00	18,58
31.12.2014	SAHOL	0,65	0,09	10.517.510.000	2.079.114.000	230.526.555.000	169.096.825.000	0,20	0,01	0,73	17,86
31.12.2013	SAHOL	0,70	0,15	8.457.484.000	1.731.396.000	206.570.819.000	150.872.625.000	0,21	0,01	0,73	14,39
31.12.2014	GOZDE	3,27	1,19	51.315	60.171.733	1.596.993.791	159.960.907	1172,60	0,04	0,10	10,70
31.12.2012	SAHOL	0,67	0,10	7.088.379.000	1.858.491.000	171.826.030.000	125.832.866.000	0,26	0,01	0,73	9,67
31.12.2013	BJKAS	0,08	0,01	142.106.681	-143.902.222	104.646.652	317.904.163	-1,01	-1,38	3,04	9,47
30.12.2011	SAHOL	0,60	0,08	10.595.650.000	1.877.987.000	150.855.400.000	113.432.029.000	0,18	0,01	0,75	7,85
30.12.2011	BJKAS	0,08	0,01	153.475.240	-150.801.385	126.947.414	345.134.942	-0,98	-1,19	2,72	7,30
30.12.2011	KCHOL	0,80	0,13	68.969.387.000	2.124.469.000	98.621.087.000	62.031.471.000	0,03	0,02	0,63	6,65
30.12.2011	VKGYO	89,45	88,78	29.464.403	25.790.717	189.197.017	543.191	0,88	0,14	0,00	6,21
31.12.2014	ALGYO	75,00	63,56	14.919.333	78.151.728	463.942.210	2.994.025	5,24	0,17	0,01	5,67
31.12.2014	KCHOL	1,33	0,52	68.336.365.000	2.710.145.000	63.941.008.000	19.016.744.000	0,04	0,04	0,30	5,66
31.12.2013	KCHOL	1,35	0,47	65.942.213.000	2.679.713.000	58.789.960.000	19.182.420.000	0,04	0,05	0,33	4,42
31.12.2012	KCHOL	1,37	0,45	65.449.383.000	2.324.150.000	48.687.778.000	15.816.621.000	0,04	0,05	0,33	4,08
31.12.2013	VKGYO	70,87	70,51	2.338.085	4.358.389	198.991.299	785.622	1,86	0,02	0,00	3,99
31.12.2012	BJKAS	0,15	0,05	147.426.786	-68.299.282	100.698.378	211.934.015	-0,46	-0,68	2,11	3,97
31.12.2014	AEFES	1,78	0,62	10.079.137.000	-512.233.000	20.113.805.000	2.533.723.000	-0,05	-0,03	0,13	3,16
31.12.2014	BJKAS	0,21	0,00	222.818.633	-140.478.649	179.621.502	338.397.664	-0,63	-0,78	1,88	3,01
30.12.2011	TUPRS	1,08	0,15	40.747.047.000	1.241.738.000	14.757.986.000	8.386.151.000	0,03	0,08	0,57	2,86

The top 20 outlier results of Robust PCA Outlier Detection algorithm are given in Table 7. The top outlier observation is (VKGYO - 31.12.2014) while it is the ninth in histogram-based outlier list. Outliers do not have consecutive orders as histogram-based approach. In the list, there are eight different firms. The first outlier is the firm having the highest current and cash ratios among all observations. The second outlier (ALGYO-31.12.2013) has values of current and cash ratios far greater than the mean. GOZDE and BJKAS join as outliers firstly in this list. (GOZDE-31.12.2014) is at forefront of net profit/net sales while (BJKAS-31.12.2013) has the highest value of short-term liabilities / total assets.

Table 8: Firm based summary of outlier methods

Firm	k-NN Global	Histogram Based	Robust PCA	Total
KCHOL	4	4	4	12
SAHOL	4	4	4	12
TUPRS	4	4	1	9
VKGYO	-	2	3	5
ALGYO	-	2	2	4
BJKAS	-	-	4	4
THYAO	2	2	-	4
AEFES	1	-	1	2
EKGYO	2	-	-	2
BIMAS	1	-	-	1
ECZYT	-	1	-	1
GOZDE	-	-	1	1
KOZAL	-	1	-	1
TCELL	1	-	-	1
YAZIC	1	-	-	1

Table 8 demonstrates the firm based summary of outlier methods. There are 15 different firms in the three lists produced by three outlier detection methods. KCHOL and SAHOL have the great number of appearances with 12 observations. KCHOL, SAHOL and TUPRS are firms that appears on all lists. EKGYO, BIMAS, TCELL, YAZIC for k-NN global; ECZYT, KOZAL for histogram-based; BJKAS, GOZDE for robust PCA are placed in its own list only.

Empirical findings show that each outlier detection approach uses variables in different weights. Thus, methods give different outlier firm lists to explore the inner structure of data set.

Conclusion

In this study, it is aimed to identify abnormal observations with respect to the fundamental analysis. Within this scope, three outlier detection algorithms namely k-NN Global Outlier Score , Histogram - Based Outlier Score and Robust PCA Outlier Score are utilized using end year values of nine significant fundamental analysis variables of firms listed in Borsa Istanbul for the period between 2011 and 2014.

According to the results of k-NN Global Outlier Score algorithm, nine different firms took place in the outlier list. (SAHOL-31.12.2014) has the maximum values of the variables “total assets” and “short term liabilities”. Additionally, KCHOL and TUPRS have the next four places consecutively. In addition, EKGYO, YAZIC, BIMAS, TCELL and AEFES are the other outliers in the list.

(SAHOL-31.12.2013) is also the first outlier of Histogram - Based Outlier Score algorithm. It has lower current and cash ratios, net profit/net sales, net profit/total asset, short-term liabilities/total assets comparing with others. However, Histogram Based method does not produce a consecutive outlier order structure as in k-NN Global algorithm. KCHOL, VKGYO, KOZAL, ECZYT are also in the outlier list.

(VKGYO - 31.12-2014) is the top outlier in Robust PCA Outlier Score algorithm whereas it is the ninth outlier in Histogram-Based outlier list. Similar to this situation, other outliers do not also have consecutive orders as histogram-based approach. The first outlier in Robust PCA Outlier Score algorithm is the firm having the highest current and cash ratios among all observations. In addition, there are eight different firms in the list.

In conclusion, 15 different firms were identified in this study by three different outlier detection methods. Out of these firms, KCHOL and SAHOL have the greatest number of appearances with 12 observations. However, it was also defined that each of three algorithms creates different outlier firm lists. The main reason behind this situation is that each outlier detection approach uses a different approach for identifying outliers.

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