Decision Support Systems 73 (2015) 15–27

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Analyzing initial public offerings' short-term performance using decision trees and SVMs

Eyup Bastı [a], Cemil Kuzey [b], Dursun Delen [c,*]

[a] Department of Banking and Finance, Faculty of Economics and Administrative Sciences, Fatih University, 34500, Buyukcekmece, Istanbul, Turkey
[b] Department of Management, Faculty of Economics and Administrative Sciences, Fatih University, 34500, Buyukcekmece, Istanbul, Turkey
[c] Management Science and Information Systems, Spears School of Business, Oklahoma State University, 700 N. Greenwood Ave., Tulsa, OK 74106, USA

A R T I C L E I N F O

Article history:
Received 19 July 2014
Received in revised form 13 February 2015
Accepted 14 February 2015
Available online 21 February 2015

Keywords:
Initial public offering
Underpricing
Short-term stock performance
Decision tree algorithms
Turkey

A B S T R A C T

In this study, we investigated underpricing of Turkish companies in the initial public offerings (IPOs) issued and traded on Borsa Istanbul between 2005 and 2013. The underpricing of stocks in IPOs, or essentially leaving money on the table, is considered as an important, challenging and worthy research topic in literature. Within the proposed framework, the IPO performance in the short run and the factors that affect this short run performance were analyzed. Popular machine learning methods – several decision tree models and support vector machines – were developed to investigate the major factors affecting the short-term performance of initial IPOs. A *k*-fold cross validation methodology was used to assess and contrast the performance of the predictive models. An information fusion-based sensitivity analysis was performed to combine the values of individual variable importance results into a common representation. The results showed that there was underpricing in the initial public offerings of Turkish companies, although it was not as high as the underpricing determined in developed markets. The market sentiment, the annual sales amounts, the total assets turnover rates, IPO stocks sales methods, the underwriting methods, the offer prices, debt ratio, and number of shares sold were among the most influential factors affecting the short term performance of initial public offerings of Turkish companies.

1. Introduction

The main purpose of this study was to investigate the short-term price performance of initial public offerings (IPO) in Turkey over the period 2005–2013, and to identify the factors affecting underpricing. This study aimed at providing several invaluable contributions to the extant literature. It demonstrated that contemporary machine learning techniques are viable (and perhaps better) data analysis tools for critical assessment of IPO valuation. Considering the fact that vast majority of the previous studies in this domain (including [30,31]; Grammenos and Papapostolou [65]) used classical statistical approaches such as regression analysis, the machine learning based approach used in this study broaden and enriched the analytics landscape. Application of these algorithmic models allowed us to obtain information that is more accurate, since they are shown to be capable of providing better predictive performance [9]. Although there were other studies that used machine-learning techniques in analysis of financial statements, they were limited in scope, solely focusing on the detection of financial fraud [67,68,69]. Taking on a more challenging problem, this study used machine-learning techniques to identify major factors affecting the short-term performance of IPOs. Another differentiation of this study is that although there are many studies that took into account the performance of IPOs in developed countries, there are very few articles investigating the IPO performance in developing countries. Therefore, this study contributes to the extant literature concerning IPOs in developing countries. A literature review on IPOs performance is given in the second section. The third section summarizes our methodology including the specification of the IPO data, description of analysis methods and presentation of the results. The fourth section discusses our findings and concludes the paper.

Machine learning, a branch of artificial intelligence, is the study of computational systems/algorithms that can learn from historical data. Based on known features learned from the training data, machine learning primarily focuses on prediction of future outcomes rather than focusing on the discovery of unknown features of the data. Decision tree (DT) learning is one of the predictive modeling techniques commonly employed in machine learning and data mining. DT learning utilizes a decision tree as a predictive model. The objective of DT learning is to produce a model that predicts the value of a dependent variable (target) based on various independent (input) variables. Decision tree algorithms are among the most popular machine learning methods because they produce accurate prediction models, have excellent

* Corresponding author at: Oklahoma State University, 700 N. Greenwood Ave., #NH341, Tulsa, OK 74106, USA. Tel.: +1 918 594 8283.
E-mail addresses: ebasti@fatih.edu.tr (E. Bastı), ckuzey@fatih.edu.tr (C. Kuzey), dursun.delen@okstate.edu (D. Delen).
URL: http://www.spears.okstate.edu/delen (D. Delen).

http://dx.doi.org/10.1016/j.dss.2015.02.011
0167-9236/

visualizations, work with both numerical and categorical data types, perform very well with large data sets, and are easy to understand and interpret.

The first sale of shares to the public by corporations who have not previously floated shares is called an initial public offering (IPO). IPO is a difficult but very important process for the issuing corporation. Therefore, corporations that wish to go public consult with investment banks in order to prepare the necessary documents, apply to the responsible governmental authority, publicize the issue, set the offer price and finally sell their shares to investors. Determining the offer price is extremely important because if the offer price is set very low, the issuing company loses the opportunity to sell the stocks at a higher price, thereby leaving too much money on the table. On the other hand, if the offer price is set too high, all of the shares will not sell, and the issuing company will end up with both a loss of funds and prestige. Because of its importance, IPO performance has been studied extensively in the finance literature by researchers.

Almost all of the previous studies reached the conclusion that there was underpricing in IPOs in the short run [3,13,14,37,40,50,59–61]. Many theories/hypotheses have been proposed in order to explain the IPO underpricing phenomenon since the 1980s. By proposing a winners' curse theory, Rock [50] argued that there are two types of investors: informed and uninformed. According to Rock, underpricing is necessary in order to convince uninformed investors to purchase stocks, so issuing corporations intentionally underprice their IPOs. Beatty and Ritter [3] developed a model that assumes investment banks are better informed than the issuing corporations are, so they force issuing corporations to set a low offer price in order to minimize their selling efforts and advertisement expenditures. Signaling hypotheses assume that the issuing firms are better informed about their companies' intrinsic value than outside investors. Based on these models, the issuing companies underprice IPOs in order to signal and differentiate the quality of their companies from unqualified companies. These models assume that a company's quality is revealed exogenously after the IPOs, allowing companies to maximize their total proceeds from IPOs and subsequent seasoned equity offers (SEO) [1,25].

Prospect theory assumes that the issuing corporations do not care about leaving money on the table. Instead, the initial owners of IPO companies pay attention to the change in their wealth through the value of the shares they hold after the IPOs [39]. Market feedback theory proposes that companies sell a small portion of their shares in IPOs; based on feedback from investors regarding their stock prices, they then sell more shares later in SEOs at their true value [28,57]. Cyclical behavior theory argues that IPO underpricing is mostly encountered in hot markets instead of cold markets [49]. After reviewing many theories, Jenkinson and Ljungqvist [29] and Ritter and Welch [48] concluded that it is impossible to explain pervasive underpricing in IPOs by way of a single theory. Therefore, these theories are not mutually exclusive and for every IPO, some theories may have more explanatory power than others may.

2. Literature review

There are many published studies analyzing the performance of IPOs in the short run as well as the ones investigating the factors that influence short-term IPO performance. The vast majority of these studies have suggested that there is underpricing in the very short run (stock prices increase after IPOs). Some of the theories or the underlying hypotheses proposed to explain underpricing in IPOs are summarized below.

One of the hypotheses that attempt an explanation of the underpricing phenomenon is asymmetric information, which has several different versions. The first version of the asymmetric information hypothesis, called "the winners' curse hypothesis", argues that there is informational asymmetry among investors. This asymmetric information among investors is believed to cause underpricing as follows: Some investors are informed about IPOs while others are uninformed. If an IPO is underpriced, the informed investors apply to buy this stock issue, meaning that uninformed investors can purchase only a small amount of these stocks, because of rationing. On the other hand, when an IPO is overpriced, the informed investors do not apply to buy that stock issue meaning that the uninformed investors are able to purchase as much stock as desired. However, in this case, they stand to lose money because the stock price could decrease when trading begins. Because of this adverse selection potential, uninformed investors do not apply for IPOs. Therefore, in order to attract uninformed investors to IPOs and guarantee the sale of all issued shares, IPOs must be underpriced [30,50].

Another version of asymmetric information is assumed to be between the investment banks and the issuing corporations. Based on this hypothesis, investment banks are better informed about IPOs than the issuing corporations, so they force the issuing corporations to underprice in order to be successful in IPOs, thereby increasing their reputation [3]. The investment banks argue that underpricing is necessary in order to convince investors to purchase stocks while keeping their advertising costs low [2].

Still another type of asymmetric information is between the issuing corporations and their investors. Based upon this model, the owners of the issuing corporations know the prospects and intrinsic value of their company better than outside investors. In order to differentiate their company from low quality companies and to signal the quality of their company to outside investors, the issuing corporations underprice their IPOs. This model of asymmetric information, which is called the "signaling model", assumes that the quality of the issuing firms is revealed exogenously after the IPO. Based on signaling models, the corporations issue only a small portion of their capital in IPO and initial owners generally do not sell their shares in IPO. Instead, these companies make seasoned equity offers and maximize the total proceeds from IPO and subsequent SEO [1,25,30,52,61].

The market feedback model of asymmetric information also assumes informational asymmetry between investors and owners; however, it is in the opposite direction. Based on market feedback theory, the investors are better informed about an IPO than the initial owners and managers. The initial owners determine the IPO percentage and price in order to maximize information production from informed investors such as financial analysts. The management of the firm learns the actual value of the company after the IPO. Based on feedback taken from the IPO, the corporations revise the expected returns of their projects upwards and make SEOs at market prices to provide funds for these projects. Therefore, the total proceeds from the IPO and subsequent SEO are maximized [28,56,57].

Another model attempting to explain underpricing in IPOs is prospect theory. According to prospect theory, the initial owners of IPO companies do not care about underpricing or leaving money on the table, because they do not take into account just the number of shares they sold in the IPO, but also the amount of shares they hold after the IPO. Instead of getting upset because of IPO underpricing, they become happy as a result of the price increase in their unsold shares [24,36,38,39].

Cyclical behavior hypothesis argues that IPOs are much more heavily underpriced during hot markets than cold markets. Ritter [49] proved that IPO underpricing is realized in specific periods and in some sectors. Loughran and Ritter [40] determined that underpricing in IPOs increased by 15% during the 1990–1998 period; the figures then jumped to 65% during the internet bubble years of 1999–2000 and fell to 12% during the 2001–2003 period. Boonchuaymetta and Chuanrommanee [4] investigated the factors affecting IPO underpricing in Thailand. They found that IPO allocation to institutional investors and the length of the lock-up period are the key determinants of IPO underpricing. Based on their results, the issue size, the industry, and the hot issue market also significantly influence initial returns. Kıymaz [31] analyzed the IPO performance of Turkish stocks in various sectors during the period 1990–1996. His results revealed that the Turkish IPOs are underpriced on the initial trading day, by an average of 13.1%. He argued that the size of the issuer, the rising prices on the stock market between the date of public offering and the first trading day, institutional ownership, and self-issued offerings were significant determinants of underpricing.

Orhan [45] investigated underpricing on the Istanbul Stock Exchange for 18 sectors for the period 1996–2005. His analysis showed that half of the sectors provided a negative first day return. He argued that this contradicting IPO performance result was due to several economic crises Turkey experienced during the analysis period. However, he reached this result by analyzing sectors separately. If Orhan [45] analyzed IPOs' average aggregate performance, it would be possible to detect a marginal underpricing along with similar to the various studies conducted on Turkish stocks [46,55,63]. Similarly, Yalçıner [63] analyzed the first day performance of IPOs on the Istanbul Stock Exchange for the period 1997–2004. His results revealed that Turkish stocks provided a 7.2% abnormal return on average on the first day, concluding that there was definite underpricing in Turkish stocks. He also tested the influence of some factors on IPO underpricing but he could not find a significant relationship.

Ünlü and Ersoy [55] also investigated the IPO performance of the Istanbul Stock Exchange listed companies for the period of 1995–2008. Their results revealed the existence of underpricing by 6.52%, based upon the first trading day's closing price. They also concluded that underpricing was more substantial in companies that are over 20 years old, as well as in companies that issue stocks at a fixed price. Relatedly, Otlu and Ölmez [46] examined the IPO performance of Turkish firms for the period of 2006–June 2011 determining that IPO stocks provided a 6.99% abnormal return on average, based upon closing prices on the first trading days. Ünlü and Ersoy [55] and Otlu and Ölmez [46] tested the factors that affect short-term cumulative stock performance. While Ünlü and Ersoy [55] determined that first day's return, standard deviation of returns in previous days and IPO method were effective on short-term cumulative performance, Otlu and Ölmez [46] concluded that the factors having the highest effect on stock prices are first day's return and standard deviation of returns in previous days. However, these analyses seem subjective since cumulative returns include the first day's return. Therefore, it is most likely to have a relationship between first day's return and cumulative returns because of this questionable analysis.

Previous studies frequently utilized regression analysis to investigate the underpricing of IPOs [30,31,65]. Machine learning methods in general and decision tree algorithms in specific are new to this application domain. In this study, we developed and compared several machine learning techniques in both predictive as well as for descriptive purposes. Some of these analytical methods were also recently used in other studies to address different problem settings in the field of finance [19,20,35].

According to the recent literature, there are significant advantages of using contemporary machine learning methods in financial studies [19,20,35]. Despite many studies focusing on IPO pricing using classical statistical techniques, the review of the extant literature showed that there have not been many studies investigating IPO pricing using ML methods, in both developed as well as developing countries. There seem to be a void in literature where classical statistical methods are compared to machine learning methods in analysis of IPO pricing. An extensive search returned only one previous research study focusing on using data mining tools for investigating IPO pricing. In that study, Chen & Cheng [12] proposed three data mining models for solving the classification problems of IPO returns in the stock market. They used various hybrid machine learning approaches such as decision trees (C4.5), experiential knowledge, and feature selection methods, minimized entropy principle approach, rough set theory, and rule filter. The proposed hybrid models outperformed the traditional methods in accuracy as well as in generated comprehensible rules applied in knowledge-based systems for investors. In order to provide a comparative perspective, in Table 1, we present the recent IPO pricing literature that studied developing countries. Also included in Table 1 are the list of variables used in each study as well as the research methods applied. Based on Table 1, it is evident that the previous studies predominantly employed some variant of simple regression analysis and statistical t-tests. Therefore, this research study distinguishes itself from these studies by employing machine learning techniques that are capable of capturing and representing complex relationships between the input and output variables hidden in large databases without being subject to constraining assumption such as linearity, normality and multicollinearity.

3. Data and the research methodology

In this study, the existence of underpricing in the IPOs of Turkish companies, issued and traded on Borsa Istanbul between 2005 and 2013, was analytically investigated. Moreover, the underlying factors affecting underpricing were also identified and critically examined. Borsa Istanbul (BIST), formerly called as Istanbul Stock Exchange, started operations with 40 listed corporations at the beginning of 1986. BIST has memberships in various international federations and associations such as the World Federation of Exchanges, Federation of Euro-Asian Stock Exchanges, Federation of European Securities Exchanges, and International Capital Market Association [7]. BIST has five markets: the equity market, the emerging companies market, the debt securities market, the futures and options market and the precious metals and diamond market. The equity market also has eight submarkets: the national market, the collective products market, the secondary national market, the watch-list companies market, the primary market, the wholesale market, the rights coupon market and the free trade platform.

BIST has been developing many aspects, such as the number of listed corporations, the daily trading volume, the total market capitalization of listed companies, the number of markets, since its inception. There were 421 companies listed on BIST by April 2014. The total market capitalization of BIST companies was $237.64 billion by the end of 2013. 62.5% of the publicly traded shares of BIST companies are owned by foreigners (CMB Monthly Statistics Bulletin, December 2013). Its daily trading volume was $1.48 billion by April 25, 2014 [6]. The BIST Equity Market is ranked 33rd in the world, based upon market capitalization by the end of 2013 [62].

3.1. Data

The within study covered all IPOs except security investment trusts during the period of 2005–2013. As a result, our sample included the data of all IPO corporations during this time period. Of all of these IPOs, 65% were underpriced and 35% were overpriced. Summary information about those companies is provided in Table 2 below.

As shown in Table 2, the total proceeds provided by the IPOs during the period of 2005–2013 were $10.58 billion. The highest proceeds with $3.29 billion were in 2007 while there were no IPOs during the global crisis year of 2009.

3.2. Methodology

To begin, the first day returns of IPO companies were calculated by utilizing Eq. (1):

$$R_{i,t} = \left(\frac{P_{i,t}}{P_{i,IPO}}\right) - 1 \tag{1}$$

where $R_{i,t}$ represents the return of stock “i” at the end of first trading day t, $P_{i,t}$ is the closing price of stock “i” at the end of first trading day t and $P_{i,IPO}$ is the offer price of the same stock.

Table 1
List of studies about IPO pricing from developing countries.

Authors	Variables	Control variables	Method	Managerial implications
Ekkachai Boonchuaymetta and Wiparat Chuanrommanee, 2013 (Thailand)	Underwriter reputation, ownership concentration, book-building, IPO allocation, length of the lock up period and investor interest	Age of the firm, issue size, the industry, hot issue market	OLS and t-statistics	As institutional investors play very limited roles in Thai IPO activity, issuer firms should select underwriters that have strong retail networks.
Jirapun Chorruk and Andrew C. Worthington, 2010 (Thailand)	The study investigated the factors that affected the long-term performance of IPO stocks. (SET Market Analysis and Reporting Tool, official Prospectus Filing Forms, SET Fact book Series)		Multivariate regression	An important implication for the prospects of the owners of firms is that they are not significantly disadvantaged in wealth term in considering an IPO. Because underpricing level is low in developing countries.
Anna P.I. Vong and Duarte Trigueiros, 2010 (Hong Kong)	Offer price, the offering size (lnsize, lnasset), underwriter reputation, subscription rate (level of informed demand), single or multi underwriter, state of the market. (Factbooks of HKEx and the IPO prospectuses)	Age, whether the IPO is timing, firms syndicating the IPO, origin of the firm going public	Cross sectional regression model	The reputation of underwriters helps to reduce excess returns since information gathering and price-setting activities are more efficient.
Manapol Ekkayokkaya and Tulaya Pengniti, 2012 (Thailand)	Subscription period, offer price, numbers of listed and offered shares, firm age, issue managers, pricing techniques, uses of proceeds. (Thomson Financial Securities Data Company (SDC) New Issues database, New Securities and Company Profile databases in SETSMART, Data stream)		Multivariate analysis	Riskier firms specify proceeds use. Therefore, there is positive relation between the specificity of proceeds use disclosure and underpricing during the post reform period.
K. Keasey and P.B. McGuinness [43] (Hong Kong)	Percentage of equity retained by pre-listing shareowners, Ratio of total liabilities to total assets, Logarithm of total assets, Market-to-book ratio of target firm, Market-to-book ratio of the Hang Seng Index. (HKEx web site secondary market trading data was drawn from DataStream)		Regression	There is a positive relationship between percentage of equity retained by pre-listing shareowners and level of underpricing. Earnings forecast disclosure dummy and leverage also positively affect IPO underpricing. Size negatively affects IPO performance.
Saikat Sovan Deb and Vijaya B. Marisetty, 2010 (India)	Method of the offer, offer price, listing price, issue amount, total subscription (Total), subscription by qualified institutional investors (QIB), subscription by retail/non-institutional investors (Ret), promoter's holding post IPO issue, total asset (TA), debt to equity ratio (DE), return on net worth (RONW), earning per share (EPS) and current ratio.		Cross-section multiple regression	Grading decreases IPO underpricing and positively influences demand of retail investors. Grading reduces secondary market risk and improves liquidity. In emerging markets, regulator's role to signal the quality of an IPO contributes towards the market welfare.
Halil Kiymaz, 2000 (Turkey)	Firm size, proceeds, age, Market trend Offer rate Privatization Institutional ownership Method of going public (all data obtained from ISE)		Cross-sectional regression	The factors influencing the initial performance of Turkish IPOs are size of the issuer, rising stock market between the time of price fixing and first trading day, and self issued offerings

Table 2
Sample of IPOs in Turkey.

Year	Aggregate proceeds	
	Million dollar	Percent (%)
2005	465	4.39
2006	919	8.68
2007	3,288	31.07
2008	1,873	17.70
2009	0	0.00
2010	2,104	19.88
2011	833	7.87
2012	346	3.27
2013	755	7.14
Total	10,583	100.00

Following this, the BIST 100 Market Index return was calculated on the same day by utilizing Eq. (2):

$$R_{m,t} = \left(\frac{P_{m,t}}{P_{m,t-1}}\right) - 1 \tag{2}$$

where $R_{m,t}$ is the return of the BIST 100 Index on day t, $P_{m,t}$ is the closing price of the BIST 100 Index on day t. $P_{m,t-1}$ is the closing price of the BIST 100 Index on the previous day.

Later, the market index return was subtracted from the IPO company stock return in order to find the excess return of the IPO company in its first trading day by utilizing Eq. (3):

$$ER_{i,t} = R_{i,t} - R_{m,t}. \tag{3}$$

Finally, the first day's excess returns of IPO companies, with some variables, are explained. The variables employed in this analysis were separated into three groups: the stock market sentiment-specific, the pre-IPO financial status and operational performance-specific, and the IPO characteristics of the issuing company specific. A history of 21 days' return of the BIST 100 Index was used to calculate the stock market sentiment. The variables expected to reflect financial and operational performance were: the firm age, the total assets, the total equity, the sales, the operating profit, the net income, the cash flows from operations, the return on assets (ROA), the total assets turnover rate and the debt ratio. The variables believed to reflect stock issue characteristics are the offer price, the number of shares sold, the issue proceeds, the percentage of insider retained shares, the IPO underwriting method and the IPO stocks sales method.

A number of studies argued that IPOs take place during hot market episodes. Those studies also show that stock market sentiment during IPOs influenced the IPO stocks' initial return [0,22,34,38,40,42,59,65]. The BIST 100 Index's 21 days return was included as a proxy for the market sentiment prior to an IPO in order to explain IPO underpricing.

The age of the firm was considered a risk factor to IPO performance studies. Generally, older companies are considered safer than younger ones. Therefore, less underpricing is expected to be found in the IPOs of older companies. However, no significant relation was detected between firm age and the level of underpricing in IPOs [22,59]. Firm age was included in this study as an explanatory variable.

Some studies used the logarithm of total assets as the size factor for the issuing company, finding a negative and significant relation between the company's total assets and the level of underpricing [40,59]. The total assets were used to measure the size of a firm. As IPOs of small companies are more speculative than IPOs of big companies, the IPOs of small companies were expected to be underpriced more than those of larger companies. We also used total assets as a size factor.

As well, annual sales were used as a size factor to explain IPO underpricing in previous studies [38,40]. Those studies detected a negative and significant relationship between annual sales amount and IPO underpricing. Authors of those studies argued that annual sales are an indication of size and uncertainty concerning the issuing firms, which suggests that companies with low sales volume underprice more because of general uncertainty about their performance, and those issues provide high positive returns on their first trading day. In other words, they argue that a negative relationship between annual sales and first-day returns can be interpreted as demonstrating the relationship between the risk of an IPO and underpricing. Annual sales were included in the explanatory variables.

ROA was used to explain IPO underpricing by Grammenos and Papapostolou [65]. They applied OLS regression, detecting a significant and negative relationship between ROA and IPO underpricing. They stated that underwriters had a tendency to set the offer price of high ROA firms closer to the intrinsic value of the firm's stocks, and therefore underpricing decreased. ROA is also among the explanatory variables. For the time being, it is impossible to estimate the direction of the relationship between ROA and underpricing. If issuing firms set a high offer price for high ROA firms' stocks, then a negative relationship must be

Table 3
Variable definitions.

One day excess return	(First trading day closing price − offer price) / offer price
Stock market sentiment	21 days' return on BIST 100 index prior to first trading date
Firm age	First trading date–inception date
Total assets	Taken from the last balance sheet prior to IPO
Total equity	Taken from the last balance sheet prior to IPO
Sales	Taken from the last annual income statement prior to IPO
Operating profit	Taken from the last annual income statement prior to IPO
Net income	Taken from the last annual income statement prior to IPO
Cash flow from operations	Taken from the last annual statement of cash flows prior to IPO
ROA1	Net income/total assets
ROA2	Operating profit/total assets
Total assets turnover rate	Sales/total assets
Debt ratio	(Short term financial liabilities + long term liabilities)/short term financial liabilities + long term liabilities + equity
Offer price	Taken from Borsa Istanbul's Website
Number of shares sold	Taken from Borsa Istanbul's Website
Issue proceeds (USD)	(Issue price × number of shares sold) / Central bank US dollar buying rate
Insider retention	1 − IPO percentage
Underwriting method	Taken from Borsa Istanbul's Website
Sales method	Taken from Borsa Istanbul's Website

expected between these variables as was detected by Grammenos and Papapostolou [66]. On the other hand, if the offer price is set independent of the ROA profitability measure, the investors should provide a higher demand for IPOs of these firms, creating a positive relationship between these two variables. The total assets turnover rate is another explanatory variable for IPO performance [65]. The total assets turnover rate is an indication of operational efficiency. Higher operational efficiency is expected to increase investor demand for the IPOs of those companies, and a higher initial return is expected.

Debt ratio was also used as an explanatory variable for IPO performance by Grammenos and Papapostolou [65]. They found a positive relationship between debt ratio and underpricing. They argued that the underwriters of indebted firms considered these companies riskier, and therefore they underprice the issue. As debt ratio is associated with higher riskiness, we expect a lower demand for the IPOs of indebted companies with a lower initial return.

The offer price is the first issue characteristic variable included in the study. Previous studies suggested that the offer price is a proxy for uncertainty about value. Thus, as it increases, the expected level of underpricing should decrease [5,27,59]. A similar relationship between offer price and IPO performance is expected. IPOs with high expected proceeds are considered to be less risky. Higher IPO proceeds with a higher number of shares issued are related to the size of the issuing company. Since big companies are considered to be less risky, less underpricing is expected in IPO companies whose expected IPO proceeds are higher [30,65]. The variable of the number of shares issued also had similar features compared to IPO proceeds.

The percentage of insider retained shares after IPO was another variable of IPO characteristics. Signaling and market feedback theories and some studies which did not mention theories argued that there was a positive relationship between the insider retention ratio and IPO underpricing [8,30,64]. Therefore, the insider retention ratio, i.e., the unsold portion of capital after IPO, was used as an explanatory variable for IPO underpricing.

The underwriting method was also included in the analysis as an explanatory variable for IPO underpricing. Three types of underwriting techniques are applied in Turkey: firm commitment, partial firm commitment and the best efforts issue. It was reported in the literature that more underpricing occurs in best efforts issues than in firm commitment issues, since relatively small firms issue their shares via the best efforts issue, and that underwriters do not stand behind the issuing firms using the best efforts issue [5]. Therefore, we also expect more underpricing in best efforts issues than in partial firm commitment and firm commitment issues. A dummy variable was employed and given a value of 0 if the offering was conducted through best efforts, 1 if the issue was conducted through partial firm commitment, and 2 if the issue was conducted through firm commitment.

The IPO stocks sales method is another variable that was expected to influence IPO short-term performance. Küçükkocaoğlu and Alagöz [34] and Otlu and Ölmez [46] found more underpricing in IPOs issued via book building with a price range method than in IPOs issued via book building with a fixed price method for Turkish IPOs. On the other hand, Loughran et al. [41], Ekkayokkaya and Pengniti [22] and Ünlü and Ersoy [55] identified the opposite. There are mainly two IPO sales methods in Turkey, book building and sales on the exchange. The book building method has two subsales methods: book building with a fixed price and book building with a price range. Sale on the exchange method has three submethods: the continuous auction method, book building and sales with a fixed price method, and book building and sales with a variable price method. Although rarely used in the literature, total equity, operating profit, net income and cash flows from operations were also included in the study as explanatory variables in order to enrich the analysis. The definitions of all the variables used in this study are provided in Table 3.

With respect to the analysis methods, we choose to use the most popular machine learning techniques. Our choice of methods and techniques were based on testaments obtained from previous comparative studies [19–21,35,44] and on our own experimentations. After a consolidation of our observations, we found that decision trees and support vector machines performed significantly better than their machine learning and statistical counterparts, namely naïve Bayes, nearest neighbor, neural networks and logistic regression. Since decision trees have significant advantages over other machine learning techniques in terms of being an easy to understand, transparent (as opposed to a black-box), visually appealing and easily deployable, we included the two most popular decision tree method (C5 and CART) into our comparative analysis. What follows is a brief description on the specific decision tree and support vector machine models that we used in this study.

3.2.1. Decision tree algorithms

Decision tree (DT) algorithms have gained increasing popularity in analytics and in the ML field. Classification tree analysis and regression tree analysis are the two main types of decision tree analysis methods. The most commonly used DT algorithms are CART, C5.0, C4.5, CHAID, and QUEST, although there are many specific DT algorithms. Among the popular ones, arguably the most commonly used ones are C5.0 and CART algorithms and were the ones used and compared in this study. C5.0 was developed by Quinlan [47]. It offers a number of improvements over its previous version C4.5: empirically speaking, C5.0 is significantly faster than C4.5; it is more memory efficient than C4.5; it creates a considerably smaller decision tree while producing similar or often better more accurate results; it boosts the trees, improving them and creating better accuracy; it makes it possible to weight different attributes and misclassification types; and finally, it automatically winnows the data to help reduce impact of noise inherent on the data. As a result, it improves the objectivity and precision of the decision tree classification algorithm.

Classification and regression trees (CART) were first introduced by Breiman et al. [10]. CART is a binary decision tree algorithm capable of processing both continuous and/or categorical predictor and/or target variables. That is, in contrast to C5.0, CART not only develop decision trees for classification type problems – where the dependent variable is a nominal valued variable – but also capable of developing decision trees for regression type prediction problems — where the dependent variable is a continues numerical variable. CART algorithm works recursively: it partitions data into two subsets to make the records in each subset more homogeneous (all of the records in the subset belong to the same class value) than the previous/alternative subsets; the two subsets are then split again until the homogeneity criterion or some other time-based stopping criteria are satisfied. The same predictor variable may be used several times in the process of growing the decision tree. The ultimate aim of splitting is to determine the right variable associated with the right threshold to maximize the homogeneity of the subgroups/branches.

A generalized depiction of the decision tree methodology employed in this study is shown in Fig. 1. As shown, from left to right; the data is pre-processed, 10-fold cross validation splits are applied, decision tree methods are developed (for each of the two decision tree algorithms – CART and C5 – 10 different prediction models are developed and tested as per the 10-fold cross validation methodology) and finally the accuracy and sensitivity analysis results are aggregated and presented.

3.2.2. Support vector machine (SVM) algorithm

Support vector machine (SVM) which was originally developed by Vapnik [58] is one of the most robust and accurate methods in machine learning algorithms. It combines the statistical methods as well as machine learning methods; therefore, its theoretical foundation is based on statistical learning theory. SVM is supervised learning technique that learns from observations by generating input–output mapping functions from a training data. The structure of SVM includes an input space, an output space and a training set, and the learning type (i.e. binary or multiple classification problems) is being decided by

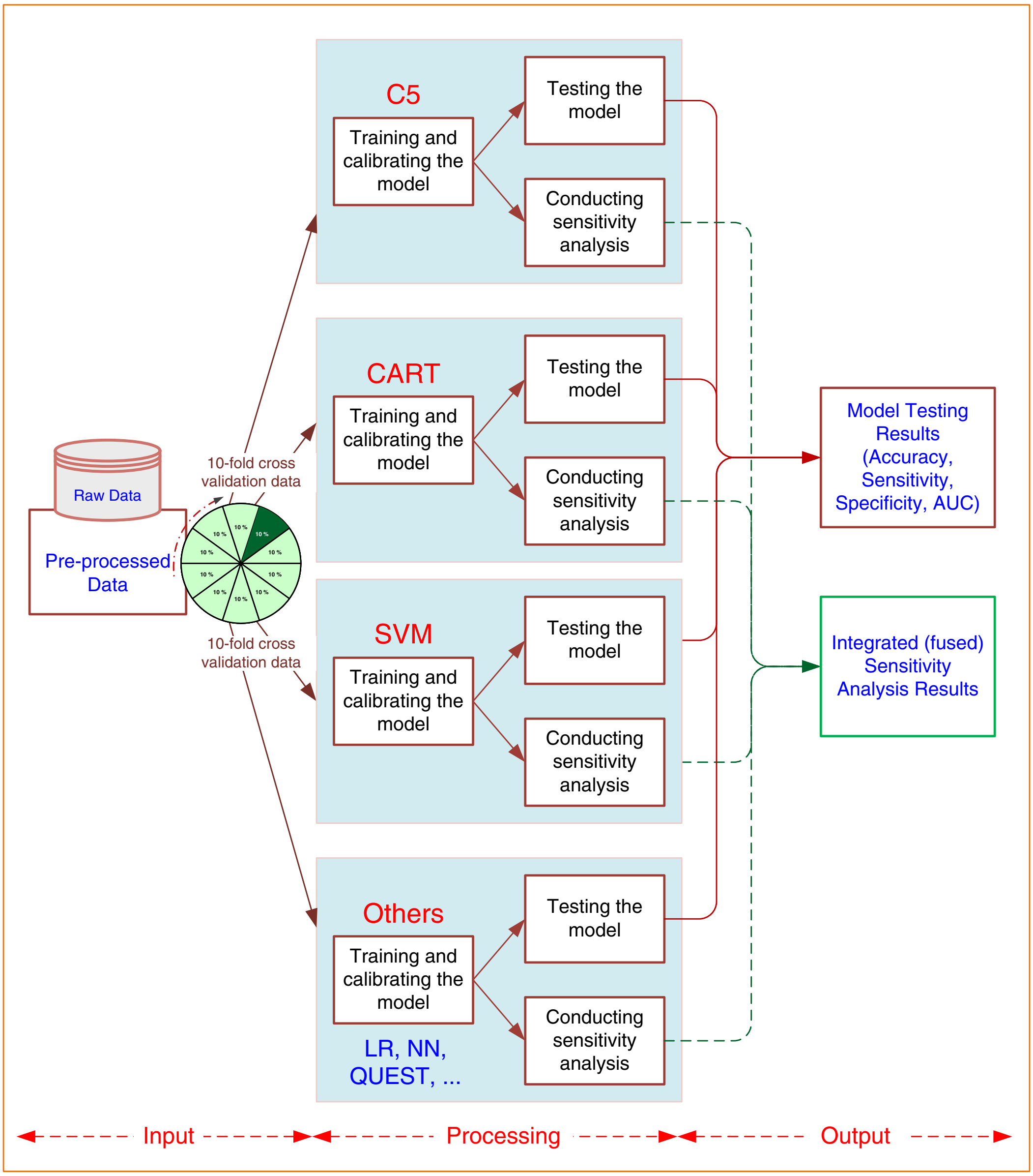

Fig. 1. The research methodology used in this study.

output space. It uses mapping functions that can be either classification or regression function in order to map the data to a high dimensional feature space. SVM is considered a maximal margin classifier. In the possibility of not easily separable input data, it uses four kernel functions such as linear, polynomial, radial based and sigmoid functions for classification problems by transforming the input data to high dimensional feature space in order to make the data easily separable.

3.2.3. Cross validation methodology

Cross validation is a popularized technique to estimate the unbiased accuracy of a predictive model's performance in practice. It is sometimes called rotation estimation and the aim of the technique is to assess how the result of a predictive analysis technique will generalize to an independent data set. 10-fold cross validation is widely used in data mining research since the empirical studies demonstrated that *10* was an "optimal" number of folds, creating a fine balance between sampling bias (i.e., diversification of training and testing subsamples) and timing (time it takes to complete the model building and testing activities) [33]. Essentially, in 10-fold cross validation, the data set is randomly split into 10 mutually exclusive subsets of approximately equal sizes. The models are trained/developed first and then tested, and the process is repeated for 10 times. Each time, the model is trained on nine folds (as a combined training data that includes 90% of the total dataset) and tested on the remaining 1 fold (10% of the total dataset). The cross validation estimate of the overall accuracy of a model is calculated by averaging the 10 individual accuracy measures coming from each fold as shown in Eq. (4):

$$CVA = \frac{1}{k}\sum_{i=1}^{k} A_i \tag{4}$$

where, "*CVA*" stands for cross validation accuracy, k is the number of folds (here $k = 10$), and A is the accuracy measure.

3.2.4. Performance measurements of prediction models

A confusion matrix, also known as coincidence matrix, is used in order to determine the performance of models used in predicting binary (two-group) outcomes. It contains valuable information about the actual and predicted classifications created by the prediction model [32]. According to Caruana et al. [11], evaluation of the performance of learning methods is crucial. Therefore, well-known performance measures such as overall accuracy, AUC (Area under the ROC Curve), Recall and F-measure were employed. Overall accuracy (AC) is defined as the percentage of records that are correctly predicted by the model. It is also defined as being the ratio of correctly predicted cases to the total number of cases. Precision is defined as the ratio of the number of True Positive (correctly predicted cases) to the sum of the True Positive and the False Positive. Recall is also known as the Sensitivity or True Positive rate which is defined as the ratio of the True Positive (the number of correctly predicted cases) to the sum of the True Positive and the False Negative. F-measures take the harmonic mean of the Precision and Recall Performance measures. Therefore, it takes into consideration both the Precision and the Recall Performance as being important measurement tools for these calculations. Specificity is also known as the True Negative Rate (TN), which is defined as the ratio of the number of the True Negative to the sum of the True Negative and the False Positive.

3.2.5. Sensitivity analysis (assessing predictors' importance)

The objective of sensitivity analysis is to measure the importance of predictor variables. Davis [15] stated that the “Cause and effect” relationship between the dependent (output) and independent (input) variables of a prediction model is determined by “sensitivity analysis” in machine learning algorithms. It is commonly used to identify and focus on the more important variables and to ignore or drop the least important ones. They are related to the importance of each variable in making a prediction, not necessarily whether the prediction itself is accurate. The variance of predictive error is arrived at by dropping one predictor variable at a time, and observing the performance of the remainder. A variable is considered more important than another if it increases the variance, compared to the complete model containing all the variables [69]. Predictor importance is determined by evaluating the variance reduction of the target attributable to each predictor (see Eq. (5)). Predictors are ranked according to the sensitivity measure defined as [53]:

$$S_i = \frac{V_i}{V(Y)} = \frac{V(E(Y|X_i))}{V(Y)} \tag{5}$$

where Y is the target (dependent variable), X_j ($j = 1, \dots, k$) are predictors (independent variables). $V(Y)$ is the unconditional output variance. Predictor importance of ith variable is then computed as the normalized sensitivity (see Eq. (6)).

$$PI_i = \frac{S_i}{\sum_{j=1}^{k} S_j}. \tag{6}$$

It is shown that S_i is the proper measure of sensitivity to rank the predictors in order of importance in the existence of any combination of complex interaction and non-orthogonality among predictors [51].

Table 4
Descriptive statistic results.

Variable	Mean	Std. dev.	Min	Max
1st day excess return (%)	6.09	9.85	−17.49	31.55
10 days excess returns (%)	10.36	29.09	−52.76	160.55
ROA	0.06	0.10	−0.18	0.49
Total assets turnover rate	2.71	8.89	0.00	62.47
Net income (Million TL)	55.5	260	−5.83	2550
Debt ratio	0.36	0.26	0.00	1.00
Number of issued shares (millions)	29	82.9	0.29	625

Table 5
Correlation analysis.

	Variables	V1	V2	V3	V4	V5	V6	V7
V1	1st day excess return	1						
V2	10 days excess returns	.67**	1					
V3	ROA	.21*	.06	1				
V4	Total assets turnover rate	.19*	.24**	−.11	1			
V5	Net income	−.03	−.04	.19*	−.05	1		
V6	Debt ratio	−.06	−.12	−.27**	.01	.10	1	
V7	Number of issued shares	−.04	−.07	.09	−.06	.74**	.10	1

** $p < 0.01$.
* $p < 0.05$.

3.2.6. Information fusion-based sensitivity analysis

Data fusion is a process that combines data and knowledge from different sources with the aim of maximizing the useful information content, for improved reliability or discriminant capability, while minimizing the quantity of data ultimately retained [54]. In this study, obtained predictions are the data or information, “prediction models” are the sources, and combining the predictions is the process of fusion. Fuller et al. [23] and Delen [18] showed that combining predictions (fusion) reveals more accurate and more robust results. Accordingly, each decision tree model (C5.0 and CART) created variable importance scores for each independent variable. The combination of these prediction models is called information fusion-based sensitivity analysis. Each of the prediction models produced different predictor important values. An information fusion-based sensitivity analysis was performed to combine these values into a common representation. The relative variable importance score produced by each decision tree model was normalized by using Eq. (7) below. They were then aggregated into a single set of importance numbers and were represented in a tabular form. Finally, the normalized variable importance scores were combined using Eq. (8) to find a single combined (fused) relative importance value for each variable.

$$PI_{new} = \frac{PI - PI_{min}}{PI_{max} - PI_{min}} \tag{7}$$

$$PI_{n(fused)} = w_1 PI_{1n} + w_2 PI_{2n} + \dots + w_m PI_{mn} \tag{8}$$

where

- PI represents the relative predictor importance score that was initially produced by the individual model.
- w_i normalized weight values for each model. This represents the importance of models and is proportional to their predictive powers.
- m represents the number of prediction models.
- n represents the number of variables.

These fused sensitivity scores were presented as bar-charts to visually illustrate the relative importance of the independent variables from the highest (most important) to the lowest (least important) for predicting (contributing to the prediction of) the dependent variable.

4. Results

The data screening process was very crucial during the statistical analysis. Therefore, the missing data analysis was initially provided. Firms with many missing values were eliminated from the analysis; as well, multiple imputations were applied in order to replace the missing values. Following the missing data analysis, influential multivariate outliers were removed by calculating the Mahalanobis d-squared values.

Table 6
Prediction results, performances of the models.

Algorithms	AC	TP	TN	FP	FN	P	F-measure	AUC
C5.0	.965	.965	.964	.036	.035	.965	.965	.976
C&R Tree	.805	.719	.893	.107	.281	.872	.788	.840
SVM	.717	.772	.661	.339	.228	.698	.733	.827
QUEST	.558	.140	.982	.018	.860	.889	.242	.561
CHAID	.575	.982	.161	.839	.018	.544	.700	.572
Neural network	.478	.298	.661	.339	.702	.472	.366	.573

Nomenclature: AC: accuracy; TP: sensitivity/true positive rate/recall; TN: specificity/true negative rate; FP: false positive rate; FN: false negative rate; P: precision; AUC: Area under curve; and SVM: support vector machines.
Model parameter specifications — neural networks: input layer: 29 neurons; hidden layer 1: 3 neurons; output layer: 1 neuron; Persistence: 200; Alpha: 0.9; Initial Eta: 0.3; High Eta: 0.1; Eta decay: 30; Low Eta: 0.01; Number of records: 1017; Analysis Accuracy: 47.788%. Support vector machine (SVM): Number of records: 1017; analysis accuracy: 71.681%; Stopping criteria: 1.0E-3; Kernel type: RBF; Regularization parameter (C): 10; Regression precision (epsilon): 0.1; RBF gamma: 0.1; Gamma: 1.0; Bias: 0.0; Degree: 3, C5 Decision Tree: Tree depth: 6; Pruning severity: 75; Minimum records per child branch: 2; Winnow attributes: false; Use global pruning: true. C&R decision tree: Tree depth: 5; Levels below root: 5; Maximum surrogates: 5; Minimum change in impurity: 0.0; Impurity measure for categorical targets: Gini; Stopping criteria: Use percentage; Minimum records in parent branch (%): 2; Minimum records in child branch (%): 1; Prune tree: true. CHAID decision tree: Levels below root: 5; Alpha for splitting: 0.05; Alpha for Merging: 0.05; Epsilon For Convergence: 0.001; Maximum iterations for convergence: 100; Use Bonferroni adjustment: true; Allow splitting of merged categories: false; Chi-square method: Pearson; Stopping criteria: Use percentage; Minimum records in parent branch (%): 2; Minimum records in child branch (%): 1.
QUEST decision tree: Levels below root: 5; Maximum surrogates: 5; Alpha for Splitting: 0.05; Stopping criteria: Use percentage; Minimum records in parent branch (%): 2; Minimum records in child branch (%): 1; Prune tree: true.

4.1. Sample and descriptive statistics

The descriptive statistics results are presented in Table 4. Borsa Istanbul provided the data for IPO companies on its website. Offer prices, number of shares sold, issue proceeds, IPO percentages, underwriting methods and sales methods were taken directly from Borsa Istanbul's website. The percentage of the unsold equity was calculated by subtracting the IPO percentage from 1. The inception dates of the IPO firms as well as their total assets, total equity, sales, earnings before interest and taxes, net income, and cash flows from operations were taken from the prospectuses of the IPO companies. The age of the firms was calculated by subtracting the inception date of the issuing company from the IPO date. The return on assets (ROA), total assets turnover rate and debt ratio were calculated by utilizing the financial data extracted from the IPO prospectuses. According to the results, the average excess return on the first trading day was 6.09% with a standard deviation of 9.85%, while the excess return for 10 days was 10.36% with a standard deviation of 29.09%. Additionally, the average return on assets was 6%, the total assets turnover rate was 2.71, and the debt ratio was 36%. Finally, the average net income was 55,500,000 Turkish Liras (TL) and the average number of issued shares was 29,000,000.

Table 7
Confusion matrices of the models based on 10-fold cross validation test data.

Model type		0	1			Overall accuracy	Per-class accuracy
C5.0	0	486	18	Correct	981	96.46%	96.43%
	1	18	495	Wrong	36	3.54%	96.49%
	Sum	504	513		1017		
C&R tree	0	450	54	Correct	819	80.53%	75.76%
	1	144	369	Wrong	198	19.47%	87.23%
	Sum	594	423		1017		
SVM RBF	0	333	171	Correct	729	71.68%	74.00%
	1	117	396	Wrong	288	28.32%	69.84%
	Sum	450	567		1017		

Table 8
Raw and normalized variable importance scores.

Variables	Raw variable importance score			Normalized variable importance score		
	SVM	C5	CART	N_SVM	N_C5	N_CART
Cash flow from Operations	.040	.000	.005	.115	.000	.031
Debt ratio	.137	.000	.045	.611	.000	.276
Equity	.034	.000	.045	.084	.000	.276
Firm age	.037	.000	.045	.095	.000	.276
Insider retention	.024	.000	.045	.029	.000	.276
Offer price	.035	.000	.149	.089	.000	.915
Issue proceeds (USD)	.022	.000	.012	.019	.000	.076
Market sentiment	.047	.219	.162	.151	.661	1.000
Net profit	.039	.000	.045	.108	.000	.276
Number of shares sold	.018	.000	.113	.000	.000	.694
Operating profit	.036	.000	.045	.090	.000	.276
ROA1	.033	.000	.045	.075	.000	.276
ROA2	.048	.000	.045	.152	.000	.276
Sales	.031	.332	.045	.068	1.000	.276
Sales method	.213	.000	.045	1.000	.000	.276
Total assets	.030	.000	.045	.063	.000	.276
Total assets turnover rate	.054	.266	.066	.182	.800	.408
Underwriting method	.124	.183	.000	.541	.553	.000

4.2. Correlation analysis

Table 5 provides the Pearson correlation coefficient results. There was a positive and significant relationship between the first day excess returns and the 10 days' excess returns ($r = 67\%$; $p < .01$), there were also positive and significant correlations between the first day excess return and ROA ($r = 21\%$; $p < .05$) as well as the total assets turnover rate ($r = 19\%$; $p < .05$). It was also clear that there was a significant association between the excess returns for 10 days and the total assets turnover rate ($r = 24\%$; $p < .01$). Additionally, the ROA had a positive and significant relationship with net income ($r = 19\%$; $p < .05$) while it had a negative and significant association with debt ratio ($r = -27\%$; $p < .01$). Finally, net income and the number of shares issued showed a strong, positive and significant association ($r = 74\%$; $p < .01$).

4.3. Decision tree analysis, SVM and sensitivity analysis results

In order to formulate this study, one output (dependent variable) and eighteen inputs (independent variables) were used. The output variable was the one-day excess return, while the input variables were cash flow from operations, debt ratio, equity, firm age, insider

Table 9
Aggregated sensitivity analysis results.

Rank	Variables	Fused score
1	Market sentiment	1.551
2	Sales	1.236
3	Total assets turnover rate	1.232
4	Sales method	.939
5	Underwriting method	.922
6	Offer price	.800
7	Debt ratio	.660
8	Number of shares sold	.559
9	ROA2	.331
10	Net profit	.299
11	Firm age	.290
12	Operating profit	.287
13	Equity	.282
14	ROA1	.276
15	Total assets	.267
16	Insider retention	.243
17	Cash flows from operations	.108
18	Issue proceeds (USD)	.075

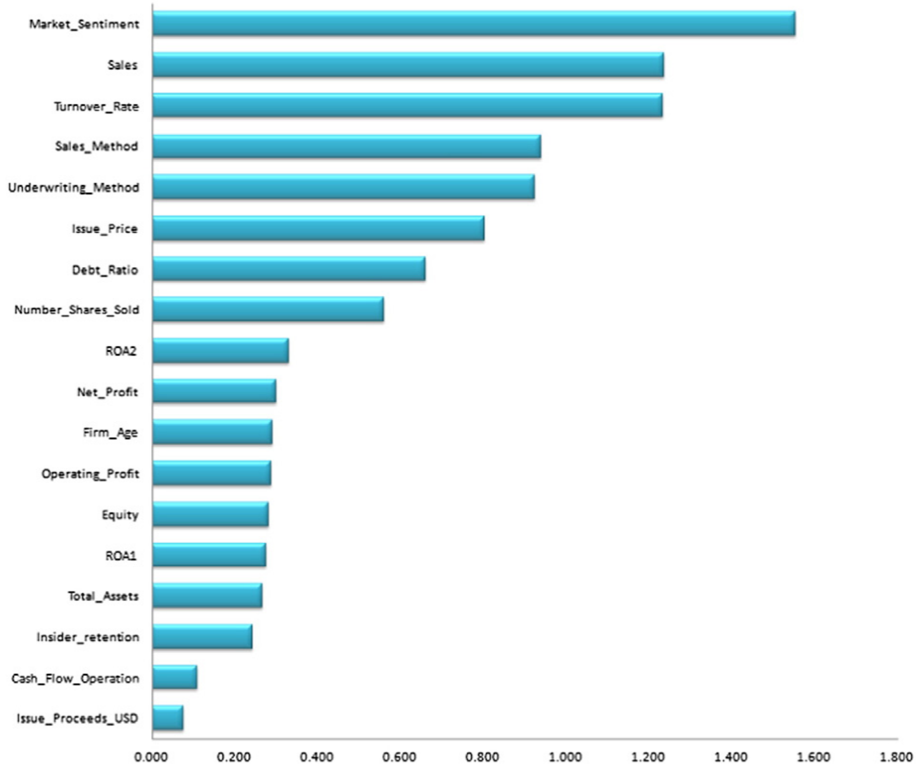

Fig. 2. Graphical representation of the sensitivity analysis result.

retention, offer price, issue proceeds (USD), market sentiment, net profit, number of shares sold, operating profit, ROA1, ROA2, sales, sales method, total assets, total assets turnover rate, and the underwriting method. The output variable was entered into the model as a binary variable by employing the central tendency measure (median) value as a split criterion: the class with a one day excess return score above the median value was rated as 1 (successful) and the class with a one day excess return score below the median value was rated as 0 (unsuccessful).

4.4. Prediction results

Various classification algorithms were used including C5, CART, SVM, QUEST, CHAID, Logistic Regression and Neural Networks. Out of these models, C5, CART and SVM algorithms performed significantly better than those of the others in terms of prediction accuracy. Therefore, three classification models – two from decision tree algorithms along with support vector machines – were included (C5.0, CART, and SVM) in the final analysis. For each model, the 10-fold cross validation methodology was employed to obtain the most representative prediction results. In this cross validation method, 10 different models were trained and tested, each time using a different, mutually exclusive 10% of the total dataset as the hold-out/test sample. The testing results were combined and used for comparison of the prediction models. The comparison of the prediction models are shown in Table 6. The results indicated that the C5.0 DT model outperformed the CART and SVM models: the overall accuracy of C5.0 was nearly 97% and the overall accuracy of CART was 81% while that of SVM was 72%. In addition to overall accuracy, the other performance measures such as sensitivity, specificity, precision, F-measure and AUC also showed that the C5.0 decision tree model performed best. In order to compare the performance of these contemporary machine learning techniques to a similar classical approach, logistic regression (LR), we applied the same 10-fold cross validation methodology to train and test logistic regression models. The results showed that decision tree and SVM models outperformed logistic regression.

The confusion matrices and overall accuracy rates, as well as per-class accuracy rates for each model constructed from the test data samples are shown in Table 7. According to the obtained results, prediction accuracy for the successful class was higher than the prediction rate for the unsuccessful class in both models. The prediction rate for successful cases was 96.49% for the C5.0 model, while it was 87.23% for the CART model. Accordingly, the employed DT models predicted a successful one-day excess return for the selected firms, with at least 87% and 96% prediction rates. Similarly, C5.0 predicted an unsuccessful one-day excess return for firms with a 96.43% accuracy rate, while CART predictions had a 75.76% accuracy rate.

4.5. Sensitivity analysis results

Model-specific sensitivity analysis and information fusion based multi-model sensitivity analysis were used for determining the relative predictor importance of the inputs, since the individual DT models generated different predictor importance scores. First, the relative predictor importance values created by each DT model were normalized using Eq. (7). The raw variable importance scores as well as the normalized variable importance scores are shown in Table 8.

In the next step, the normalized scores of each model were multiplied by the weight values of each model; these multiplied values were then added together using Eq. (8), in order to find a single fused predictor importance score for each input variable. The rankings of the fused scores of each input are represented in Table 9. To illustrate the visual representation of the fused predictor importance values of independent variables in the order of importance, a bar-chart was created using the aggregated sensitivity values (see Fig. 2). The y-axis shows input variables while the x-axis shows the predictor importance score for each indicator. According to Fig. 1, market sentiment was the single most important predictor in determining the one-day excess return, while sales was the second most important predictor. Accordingly, the total assets turnover rate, IPO stocks sales method, the underwriting method, the offer price, debt ratio and the number of shares sold were followed as the leading variables in the one-day excess return.

5. Summary, implications and conclusions

In this study, the existence of underpricing in IPOs of Borsa Istanbul listed companies and determinants of initial performance were investigated. All of the IPOs except for securities investment trusts were included in the study for the period of 2005–2013. Results show that, although not as high as the underpricing detected in most of the previous studies, there was underpricing in the Turkish IPO market. The average first day underpricing in IPOs for the analysis period was 6.09%. This result is lower than the results of the previous studies, which detected underpricing in the range of 6.52% to 13.1%.

This research study provides several managerial implications. Underpricing level is relatively low in Turkey, somewhat similar to the results of previous researches executed in developing countries [14,22,59]. The provided results indicate that market sentiment is the crucial factor that affects IPO performance. This result is in accordance with the evidences reached in Kiymaz [31] and Boonchuaymetta and Chuanrommanee [4]. Thus, firms that are planning to go public should try to time the market and sell their stocks during the period when the market sentiments are at a positive trajectory. In addition, results indicated that sales and total assets turnover ratios influence IPO performance. It suggests that firms that do not have problems in increasing their absolute sales and sales as the ratio of total assets may sell their stocks at relatively higher prices without encountering demand problems. This implication shows that investors overvalue the efficiency of the IPO firms. Moreover, the sales method was found to be an important factor on IPO performance. Firms that plan to offer their stocks via IPO should sell their stocks using variable price methods rather than using fixed price methods, which lead to lower underpricing in IPOs. All in all, Table 1 depicted the fact that all results from the developing countries yielded different but important implications depending on the specific characteristics of the country. This might be because of the legal, economic and financial infrastructures of the developing countries. Because of the fact that the financial data is becoming readily available in large quantities, the decision makers can use contemporary machine learning techniques such as DT, SVM, and NN to investigate the most important market variables, and hence, make the most optimal decisions for their firms.

Contemporary ML methods such as decision tree algorithms and SVM were successfully employed in this study. As recommended by the previous studies [18,35], in order to combine the scores of more than one algorithm, the data fusion technique was applied to determine the factors affecting underpricing, rather than focusing on single method scores. Information-based sensitivity analysis enabled the reliability as well as the discriminant capability to be improved while minimizing the amount of obtained data, as recommended by Starr and Desforges [54], in order to obtain useful information by combining knowledge from the two different DT algorithm results.

Based on the employed DT and SVM methods, the initial performances of IPO companies were affected by the market sentiment, the annual sales amount, the total assets turnover rate, the sales method, the underwriting method, the offer price, debt ratio and the number of shares sold. The influence of the sentiment of the market on IPO underpricing demonstrated that the cyclical behavior theory was true for Turkish IPOs. This result was in accordance with the findings of many previous studies, such as Boonchuaymetta and Chuanrommanee [4], Loughran and Ritter [40], Kiymaz [31] and Ritter [49]. The cyclical behavior theory argues that stock issues during bull markets are more in demand, and therefore provide a higher initial return.

The effect of financial measures such as annual sales amount, the total assets turnover rate, and debt ratio on underpricing reflects the fact that the winner's curse theory was not supported by our results. The winners' curse theory classifies investors as being either informed or uninformed. Since publicly available data influence IPO performances, the informed and uninformed classification of investors was not true in the Turkish IPO market. In other words, the effect of publicly available data on IPO underpricing proved that there was no informational asymmetry among investors.

The IPO stocks sales method is the first significant variable (out of all IPO issue characteristic variables) that has a significant effect on IPO performance. There are basically two different IPO stocks sales methods, which are sale by book building and sale on the exchange. Both methods have sale with fixed price and sale with a price range alternatives. Therefore, affects of fixed price and variable price sales methods on IPO performance are an expected outcome. This finding is in accordance with the results of Küçükkocaoğlu and Alagöz [34], Otlu and Ölmez [46], Loughran et al. [41], Ekkayokkaya and Pengniti [22] and Ünlü and Ersoy [55].

There was also a relationship between the underwriting method and the IPO performance. According to the literature, there was more underpricing in the best efforts issues than in the firm commitment issues, since relatively small firms offered their shares via the best efforts issue and the underwriters did not stand behind the issuing firms for their best efforts issues. Therefore, the relationship between the underwriting method and the IPO short-term performance was the expected outcome.

The offer price was also determined to be effective in short-term IPO performance. The offer price of an IPO was used as an ex-ante risk proxy, since IPOs with higher offer prices lead to lower levels of underpricing. Therefore, this result must stem from the investors' perceptions that low priced IPOs are less risky and thus provide higher demand to those stock issues. This finding was consistent with the evidence of Ibbotson et al. [27], Booth and Chua [5] and Vong and Trigueiros [59], all of whom found a significant relationship between the offer price and the IPO underpricing level.

The number of shares sold was associated with IPO riskiness. Since IPO companies with more shares to be issued were regarded as safer, lower underpricing was expected in the IPOs of those firms. This study also indicated that there was a relationship between the number of shares sold and the level of IPO underpricing. This result may be regarded to be in keeping with the results of Kennedy et al. [30] and Grammenos and Papapostolou [65], both of which detected a negative relationship between IPO proceeds and IPO underpricing.

Some studies had included underwriter reputation as an explanatory variable, which produced mixed results in explaining short-term IPO performance [4,59]. They took differing measures as proxies for underwriter reputation, such as the market share of an underwriter being a percentage of the number of companies that were declared publicly, the natural logarithm of the capital volume of the IPOs, or the market share of the lead underwriter. Therefore, determination of the underwriter's reputation is somehow subjective. In addition, in Turkey, IPOs are performed by underwriting syndicates, that is, many investment banks handle the issues jointly. As it is difficult to determine which underwriters' reputation is more effective in IPOs performance, it is not included in our study as an explanatory variable. The issue of not including underwriter reputation as an explanatory variable may be viewed as a limitation of our study.

Detection of the underpricing level is very low in our study, which complies with many other studies on developing economies as well as Turkey [14,22,46,55,59]. Low levels of underpricing are good for issuing corporations, but they are not beneficial for investors when combined with inadequate investor protection in developing countries. The causes and remedies of low underpricing could be a future research subject because low IPO performance may diminish investor interest in IPOs, causing unsuccessful IPOs in the future. For example, Indian and Chinese authorities have been taking action to resolve low IPO performance in order not to encounter future problems in the IPO market. India introduced a unique certification mechanism for IPOs in 2007, whereby all

IPOs have to undergo mandatory quality grading by independent rating agencies. This positively influenced investor demand for IPOs and decreased underpricing [16]. Since underpricing or overpricing may adversely affect the long-term development of the IPO market, China began requiring the disclosure of factors behind pricing decisions after April 2012, in situations where the price-to-earnings ratio of an IPO is expected to be 25% higher than that of publicly traded companies in the same industry [26].

In this study, after considering a wide variety of machine learning techniques, we settled on using decision trees and SVM as our prediction methods. It is common knowledge that most machine learning methods (including the ones used in this study) have a number of modeling parameters that need to be "optimized." While there are techniques to improve the predictive power by systematically changing/adjusting these modeling parameters (such as the ones that we used in this study), there is no guaranty to reach the ultimate best (the optimal) model — hence, they are often called as heuristic methods [17]. Future research would include additional prediction models and meta-heuristic optimization techniques to achieve even better prediction accuracy and more robust variable importance measures.

References

[1] F. Allen, G. Faulhaber, Signaling by underpricing in the IPO market, Journal of Financial Economics 23 (1989) 303–323.
[2] D.P. Baron, A model of the demand for investment banking advising and distribution services for new issues, The Journal of Finance 37 (4) (1982) 955–976.
[3] R.P. Beatty, J.R. Ritter, Investment banking, reputation, and the underpricing of initial public offerings, Journal of Financial Economics 15 (1986) 213–232.
[4] E. Boonchuaymetta, W. Chuanrommanee, Management of the IPO performance in Thailand, Journal of Multinational Financial Management 23 (2013) 272–284.
[5] J.R. Booth, L. Chua, Ownership dispersion, costly information, and IPO, Journal of Financial Economics 41 (1996) 291–310.
[6] Borsa Istanbul Daily Bulletin, http://borsaistanbul.com/en/data/data/equity-market-data/bulletin-data April 25, 2014.
[7] Borsa Istanbul Website, http://borsaistanbul.com/en/data/data/ipo-data.
[8] D.J. Bradley, B.D. Jordan, Partial adjustment to public information and IPO underpricing, Journal of Financial and Quantitative Analysis 37 (4) (2002) 595–616.
[9] L. Breiman, Statistical modeling: the two cultures, Statistical Science 16 (3) (2001) 199–231.
[10] L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone, Classification and Regression Trees, Chapman & Hall/CRC, New York, 1984.
[11] R. Caruana, N. Karampatziakis, A. Yessenalina, Empirical evaluation of supervised learning in high dimensions, ICML, 2008.
[12] Y.-S. Chen, C.-H. Cheng, A soft-computing based rough sets classifier for classifying IPO returns in the financial markets, Appl, Soft Computing 12 (1) (2012) 462–475.
[13] W.Y. Cheng, Y.L. Cheung, K.K. Po, A note on the intraday patterns of initial public offerings: evidence from Hong Kong, Journal of Business Finance & Accounting 31 (2004) 837–860.
[14] J. Chorruk, A.C. Worthington, New evidence on the pricing and performance of initial public offerings in Thailand, 1997–2008, Emerging Markets Review 11 (2010) 285–299.
[15] G. Davis, Sensitivity analysis in neural net solutions, IEEE Transactions on Systems, Man, and Cybernetics 19 (1989) 1078–1082.
[16] S.S. Deb, V.B. Marisetty, Information content of IPO grading, Journal of Banking & Finance 34 (9) (2010) 2294–2305.
[17] D. Delen, Real-World Data Mining: Applied Business Intelligence and Decision Making, Financial Times Press (a Pearson Company), Upper Saddle River, New Jersey, 2015.
[18] D. Delen, A comparative analysis of machine learning techniques for student retention management, Decision Support Systems 49 (2010) 498–506.
[19] D. Delen, H. Zaim, C. Kuzey, S. Zaim, A comparative analysis of machine learning systems for measuring the impact of knowledge management practices, Decision Support Systems 54 (2) (2013) 1150–1160.
[20] D. Delen, C. Kuzey, A. Uyar, Measuring firm performance using financial ratios: a decision tree approach, Expert Systems with Applications 40 (10) (2013) 3970–3983.
[21] D. Delen, N. Emanet, H.R. Oz, N. Bayram, A comparative analysis of machine learning methods for classification type decision problems in healthcare, Decision Analytics 1 (1) (2014) 6–15.
[22] M. Ekkayokkaya, T. Pengniti, Governance reform and IPO underpricing, Journal of Corporate Finance 18 (2012) 238–253.
[23] C.M. Fuller, D.P. Biros, D. Delen, An investigation of data and text mining methods for real world deception detection, Expert Systems with Applications 38 (2011) 8392–8398.
[24] C. Ghosh, M. Petrova, Z. Feng, M. Pattanapanchai, Does IPO pricing reflect public information? New insights from equity carve-outs, Financial Management 41 (1) (2012) 1–33.
[25] M. Grinblatt, C.Y. Hwang, Signalling and the pricing of new issues, Journal of Finance 44 (1989) 393–420.
[26] H. Guo, T. Wang, Y. Li, H.G. Fung, Challenges to China's new stock market for small and medium-size enterprises: trading price falls below the IPO price, Technological and Economic Development of Economy 19 (Suppl. 1) (2013) S409–S424.
[27] R.G. Ibbotson, J. Sindelar, J. Ritter, The market's problem with the pricing of initial public offerings, Journal of Applied Corporate Finance 6 (1994) 66–74.
[28] N. Jegadeesh, M. Weinstein, I. Welch, An empirical investigation of IPO returns and subsequent equity offerings, Journal of Financial Economics 34 (1993) 153–175.
[29] T. Jenkinson, A. Ljungqvist, Going Public: The Theory and Evidence on How Companies Raise Equity Finance, Clarendon Press, Oxford, 2001.
[30] D.B. Kennedy, R. Sivakumar, K.R. Vetzal, The implications of IPO underpricing for the firm and insiders: tests of asymmetric information theories, Journal of Empirical Finance 13 (2006) 49–78.
[31] H. Kiymaz, The initial and aftermarket performance of IPOs in an emerging market: evidence from Istanbul stock exchange, Journal of Multinational Financial Management 10 (2) (2000) 213–227.
[32] R. Kohavi, F. Provost, Glossary of terms. Editorial for the special issue on applications of machine learning and the knowledge discovery process, Machine Learning 30 (2–3) (1998) 271–274.
[33] R. Kohavi, A study of cross-validation and bootstrap for accuracy estimation and model selection, Proceedings of the 14th International Conference on AI(IJCAI), Morgan Kaufmann, San Mateo, CA, 1995, pp. 1137–1145.
[34] G. Küçükkocaoğlu, A. Alagöz, İMKB'de uygulanan halka arz yöntemlerinin karşılaştırmalı analizi, Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi 24 (2) (2009) 65–86.
[35] C. Kuzey, A. Uyar, D. Delen, The impact of multinationality on firm value: a comparative analysis of machine learning techniques, Decision Support Systems 59 (1) (2014) 127–142.
[36] M. Larraza-Kintana, R.M. Wiseman, L.R. Gomez-Mejia, T.M. Welbourne, Disentangling compensation and employment risks using the behavioral agency model, Strategic Management Journal 28 (2007) 1001–1019.
[37] X. Liu, J. Ritter, Local underwriter oligopolies and IPO underpricing, Journal of Financial Economics 102 (3) (2011) 579–601.
[38] T. Loughran, B. McDonald, IPO first-day returns, offer price revisions, volatility, and form S-1 language, Journal of Financial Economics 109 (2013) 307–326.
[39] T. Loughran, J. Ritter, Why don't issuers get upset about leaving money on the table in IPOs? Review of Financial Studies 15 (2002) 413–444.
[40] T. Loughran, J. Ritter, Why has IPO underpricing changed over time? Financial Management 33 (3) (2004) 5–37.
[41] T. Loughran, J.R. Ritter, K. Rydqvist, Initial public offerings: international insights, Pacific-Basin Finance Journal 2 (1994) 165–199.
[42] M. Lowry, G.W. Schwert, Is the IPO pricing process efficient? Journal of Financial Economics 71 (2004) 3–26.
[43] K. Keasey, P.B. McGuinness, Firm value and its relation to equity retention levels, forecast earnings disclosures and underpricing in initial public offerings in Hong Kong, International Business Review 17 (6) (2008) 642–662.
[44] D.L. Olson, D. Delen, Y. Meng, Comparative analysis of data mining models for bankruptcy prediction, Decision Support Systems 52 (2) (2012) 464–473.
[45] M. Orhan, Short and long-run performance of IPOs traded on the Istanbul stock exchange, in: G.N. Gregoriou (Ed.), Initial public offerings: An international perspective, Elsevier, U.S.A., 2006, pp. 45–55.
[46] F. Otlu, S. Ölmez, Halka ilk kez arz edilen hissesenetlerinin kısa dönem fiyat performansları ile fiyat performansını etkileyen faktörlerin incelenmesi, İMKB'debiruygulama, Akademik Yaklaşımlar Dergisi 2 (2011) 14–43.
[47] J. Quinlan, C4.5: Programs for Machine Learning, Morgan Kaufmann, Morgan Kaufmann, San Mateo, CA, 1993. (MA: MIT Press).
[48] J.R. Ritter, I. Welch, A review of IPO activity, pricing and allocations, Journal of Finance 57 (2002) 1795–1828.
[49] J.R. Ritter, The "hot issue" market of 1980, Journal of Business 57 (1984) 215–240.
[50] K. Rock, Why new issues are underpriced, Journal of Financial Economics 15 (1986) 187–212.
[51] A. Saltelli, S. Tarantola, F. Campolongo, M. Ratto, Sensitivity Analysis in Practice — A Guide to Assessing Scientific Models, JohnWiley, 2004.
[52] D.K. Spiess, R.H. Pettway, The IPO and first seasoned equity sale: issue proceeds, owner/managers' wealth, and the underpricing signal, Journal of Banking and Finance 21 (1997) 967–988.
[53] SPSS, IBM SPSS Modeler User Manual, 2012. (Chicago, IL).
[54] A. Starr, M. Desforges, Strategies in data fusion — sorting through the tool box, Proceedings of European Conference on Data Fusion, 1998.
[55] U. Ünlü, E. Ersoy, İlk halka arzlarda düşük fiyatlama v ekısa dönem performansın belirleyicileri: 1995–2008 İMKB örneği, Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi 23 (2) (2008) 243–258.
[56] J. vanBommel, T. Vermaelen, Post-IPO capital expenditures and market feedback, Journal of Banking and Finance 27 (2003) 275–305.
[57] J. vanBommel, Messages from market to management: the case of IPOs, Journal of Corporate Finance 8 (2002) 123–138.
[58] L. Vapnik, The Nature of Statistical Learning Theory, Springer-Verlag, New York, 1995.
[59] P.I. Vong, D. Trigueiros, The short-run price performance of initial public offerings in Hong Kong: new evidence, Global Finance Journal 21 (2010) 253–261.
[60] P.I. Vong, Rate of subscription and after-market volatility in Hong Kong IPO, Applied Financial Economics 16 (2006) 1217–1224.
[61] I. Welch, Seasoned offerings, imitation costs, and the underpricing of initial public offerings, Journal of Finance 44 (1989) 421–449.
[62] World Federation of Exchanges Website, http://www.world-exchanges.org/statistics/monthly-query-tool.

[63] K. Yalciner, Düşük fiyatlama olgusu ile halka arz şekilleri ve halka arz fiyatı arasındaki ilişkininanalizi: 1997–2004 dönemine ait bir inceleme, Gazi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi 7 (2) (2006) 145–158.
[64] S.X. Zheng, J.P. Odgen, F.C. Jen, Pursuing value through liquidity in IPOs: underpricing, share retention, lockup, and trading volume relationships, Review of Quantitative Finance and Accounting 25 (2005) 293–312.
[65] C.T. Grammenos, N.C. Papapostolou, US shipping initial public offerings: Do prospectus and market information matter? Transportation Research Part E: Logistics and Transportation Review 48 (1) (2012) 276–295.
[66] E.W.T. Ngai, Yong Hu, Y.H. Wong, YijunChen, Xin Sun, The application of data mining techniques infinancial fraud detection: a classification framework and an academic review of literature, Decision Support Systems 50 (2011) 559–569.
[67] M.E. Edge, P.R.F. Sampaio, The design of FFML: A rule-based policy modelling language for proactive fraud management in financial data streams, Expert Systems with Applications 39 (11) (2012) 9966–9985.
[68] F. Louzada, A. Ara, Bagging k-dependence probabilistic networks: An alternative powerful fraud detection tool, Expert Systems with Applications 39 (14) (2012) 11583–11592.
[69] SPSS, Clementine12 User Manual, 2007. Chicago, IL.

Dr. Eyup Bastı is an Associate Professor and the head of the Banking and Finance Department of Faculty of Economics and Administrative Sciences at Fatih University, Turkey. He received his BA degree on Management from Middle East Technical University in 1996 and his MBA from Fatih University in 1998. He obtained his Ph.D. degree from Istanbul University in Finance in 2004 with a thesis titled as "2001 Financial Crisis of Turkey in the Light of Financial Crises Theories: The Effects of Financial Crisis on the Efficiency of Turkish Financial Sector". His PhD thesis is published by the Capital Market Boards of Turkey. He wrote numerous articles published in Turkish and foreign scientific journals. His current research interests are financial crises, corporate valuation, financial performance of firms, initial public offerings, capital structure theories and asset pricing.

Dr. Cemil Kuzey is an Assistant Professor at the Department of Management at Fatih University in Istanbul, Turkey, teaching Operation Research and Statistics for Social Sciences. He acquired his Ph.D. degree in Business Administration through the Department of Quantitative Analysis, Istanbul University, Turkey. Among his academic pursuits, he took several graduate courses at the Ontario Institute for Studies in Education, University of Toronto. His research interests are related to Operation Research, Data Mining, and Business Intelligence.

Dr. Dursun Delen is the William S. Spears Endowed Chair in Business Administration, Neal Patterson Chair in Business Analytics, Research Director for the Center for Health Systems Innovation, and Professor of Management Science and Information Systems in the Spears School of Business at Oklahoma State University (OSU). He received his Ph.D. in Industrial Engineering and Management from OSU in 1997. Prior to his appointment as an Assistant Professor at OSU in 2001, he worked for a privately-owned research and consultancy company, Knowledge Based Systems Inc., in College Station, Texas, as a research scientist for five years, during which he led a number of decision support and other information systems related research projects funded by federal agencies, including DoD, NASA, NIST and DOE. His research has appeared in major journals including Decision Support Systems, Decision Sciences, Communications of the ACM, Computers and Operations Research, Computers in Industry, Journal of Production Operations Management, Artificial Intelligence in Medicine, Expert Systems with Applications, among others. He recently published four books: Advanced Data Mining Techniques with Springer, 2008; Decision Support and Business Intelligence Systems with Prentice Hall, 2010; Business Intelligence: A Managerial Approach, with Prentice Hall, 2010; and Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications, with Elsevier, 2012. He is often invited to national and international conferences for keynote addresses on topics related to Data/Text Mining, Business Intelligence, Decision Support Systems, and Knowledge Management. He served as the general co-chair for the 4th International Conference on Network Computing and Advanced Information Management (September 2–4, 2008 in Soul, South Korea), and regularly chairs tracks and mini-tracks at various information systems conferences. He is the associate editor-in-chief for International Journal of Experimental Algorithms, associate editor for International Journal of RF Technologies, and is on editorial boards of five other technical journals. His research and teaching interests are in data and text mining, decision support systems, knowledge management, business intelligence and enterprise modeling.