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ORIGINAL ARTICLE

Comparison of Management and Financial Performance in the Turkish Insurance Sector: An Example of Clustering Analysis

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Abstract

Every individual living in the world, institutions and private sectors continuing their activities, may experience losses due to financial risks related to their jobs and activities. Insurance is the most common way to compensate for any financial loss. In other words, insurance com panies compensate the basic financial losses of individuals and institutions with the different services and products they offer. For this reason, insurance companies, which are a dynamic player in the financial sector, must be managed well in order to continue their activities. In the insurance industry, the board of directors of the company is an important factor for the success of insurance companies. In this study, the relationship between the management variables of the companies operating in the Turkish Insurance Sector and the financial indicators of these companies was analyzed by clustering analysis. Also, it was investigated how managerial variables affect each other and the financial variables. In the study, 3 categorical variables and 10 financial variables were used, and 4 main clustering models were created. Under each model, different subclustering models were obtained. In addition, the study used the annual data of insurance companies between 2015- 2019. As a result of the analysis conducted on insurance companies, the study provides an idea about which variables are important in the considered scenarios.

Keywords

Corporate Governance, Board of Directors, Insurance, Cluster Analysis

JEL Classification

G30, G34, G22, C46.

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1. INTRODUCTION

There are always uncertainties and risks in people's lives. As a consequence of each risk that occurs, a material cost arises directly or indirectly. To minimize the costs, the risks are managed in different ways or separately. . Due to lack of knowledge and experience in many cases, the risks cannot be properly managed and controlled. Therefore, insurance companies step in to manage these risks.

Insurance is a tool that comes into play to distribute the losses to a number of policyholders. This means that when any person and entity under insurance protection suffers a loss resulting from a particular risk, it shares the loss through the payment of the collected premiums. On the other hand, it helps to provide mechanisms for risk management, to gather resources, to transfer resources in time and space, to deal with information and incentive problems, to expand protection, to increase economic efficiency and to maintain economic progress (Hasan, Islam and Wahid, 1995, p.370).

The insurance industry is a key component of the economy due to the amount of premiums it collects, the scale of its investments and, more fundamentally, the basic social and economic role it plays by dealing with personal and commercial risks (Corfora et al., 2019, p. 2863).

Multiple roles of insurance companies in the financial market are reflected in the transfer and allocation of money savings and their internal insurance function. An insurance company collects funds and invests them in different financial instruments by selling insurance policies and providing other financial and other services. The main function of insurance companies is insurance against different types of risk. In addition, insurance companies in developed and developing financial systems are institutional investors and important participants in the financial market due to the amount of their funds (Kramarić et al., 2018, p. 783).

It is the management style and financial indicators which emphasize the success of insurance companies that are fundamental in the financial structure like other financial companies. These two factors affect profitability, which is the most important element of the company in general. The profit variable is both a performance indicator and a material source of investments planned for the future.

In this study, the relationship between the variables of the companies operating in the Turkish Insurance Sector and the financial variables obtained from the balance sheet and income statements of the selected management was examined by clustering analysis. When cluster groups were created with these variables, it was calculated which ones were important forecasters.

2. LITERATURE RESEARCH

In this part of the study, the literature on the subject is included. A previous study examining the relationship between the management style and financial indicators (balance sheet and income statements) affecting the profit variable in the insurance sector and using cluster analysis could not be reached. Moreover, studies analyzing the management style or financial variables of insurance companies directly in the literature are limited. In the literature section, clustering analysis and other statistical studies related to insurance and insurance branches are included.

Akgül (2021) in his study, examined the effects of demographic factors related to insurance education and other education fields, which are thought to be effective in employment policies in insurance companies. In the study, it was also investigated whether the education given at universities is effective in employment. The employment data of insurance companies in Turkey between 2014-2020 were used and analyzed through logistic regression method. According to the results of the study, it has been seen that the graduates of the insurance and actuarial departments of the universities are employed in non-life insurance companies. However, it has been observed that many people employed in insurance companies are women and work as direct sales personnel. Last but not least, it has been determined that the education given in the field of insurance is not sufficient to find a job in the insurance sector.

Işık (2021), in his study, analyzed insurance-related, sector-related and macroeconomic factors that affect the profitability of foreign and domestic capital of the non-life insurance companies operating in the Turkish insurance sector in the period of 2014-2019. He used a balanced panel dataset that included 27 non-life insurance companies in his study. The results obtained according to the random effects determined that the debt ratio, premium holding ratio, the status of being traded in the stock market and the growth of total assets are the important factors that determine the profitability of domestic capital companies. However, it has been shown that the factors affecting the profitability of foreign-owned insurance companies are company size, debt ratio, underwriting risk, premium holding rate, stock market trading status and company age. On the other hand, he stated that variables such as GDP growth, inflation rate and market concentration do not have a significant effect on the profitability of foreign and domestic non-life insurance companies.

Özcan and Uzpeder (2020) grouped the insurance companies in their studies with clustering analysis according to the total premium and transportation premium mutual relationship. 5-year data of insurance companies were used. It has been observed that the insurance companies that are at the forefront of total premium production and premium production in the transportation branch have retained their positions. As a result of the clustering analysis, it has stated that if they develop the products and services in the relevant branch for the companies that are at the bottom of the premium production in the transportation branch, it will contribute to total premium production.

Dogan et al. (2018) says technological advances have affected company customer relations, sales and marketing system and every corporate formation. With a customer-oriented approach, similar qualified customer characteristics can be defined and grouped. Data mining is a way to do this grouping. In their study, customer data belonging to insurance companies operating in Turkey were analyzed by k-means clustering method. As a result of the analysis, it has stated that companies can identify the characteristics of similar customers and develop new marketing strategies suitable for them.

Lin et al. (2013) says the life insurance industry has a mechanism to modulate and stabilize the entire financial sector. The performance of the life insurance industry often affects overall economic development. The maturation of investment concepts and the liberalization of investments of state policies in the insurance sector, in recent years, have created a profitable environment for investment. Insured performances and operational capability are important evaluation indices to assess whether life insurance companies are stable and profitable. In their study, they evaluated the profitability of 28 Taiwanese life insurance companies between 2003 and 2005. They divided life insurance companies into three groups according to seven profitability indexes and found significant differences in capital allocation and operational capacity. At the end of the study, the differences between these three groups were analyzed and compared and the outputs were interpreted in the resulting section.

According to Carfora et al. (2019), several innovative car insurance concepts are proposed to achieve benefits for both insurance companies and drivers, as discussed in recent literature studies. In this context, the “pay how you use” paradigm arises, but it is not fully discussed and is much less applied. In their study, they proposed an approach to determine the driver behavior that investigates the use of unsupervised machine learning techniques. Real-world case study was carried out to assess the effectiveness of the proposed solution. In addition, it has discussed how the proposed model can be adopted as a risk indicator for car insurance companies.

Kramarić et al. (2018) focused on the analysis of the business practices of insurance companies in European countries after the selected transition. The analysis covers the Croatian, Slovenian, Hungarian and Polish insurance markets, comprising a total of 119 insurance companies in 2014. Insurance companies that use non-hierarchical clustering analysis by applying the K-average approach are divided into seven groups using various variables. These groups are ROE, the share of premium transferred to reinsurance, the number of years operating in the insurance market, leverage, written gross premium and the share of life insurance premium on the total premium. In addition, these seven clusters are grouped by country of origin, ownership and type of insurance companies. The results showed that certain groups of insurance companies in these countries share common characteristics that are not dependent solely on the country of origin and type of insurance.

In his study, Grize (2015) specifically aimed to convince us that today’s non-life insurance is not only an exciting basis for implementing existing modern statistical tools, but also an efficient environment for new and challenging statistical developments. The activities of an insurance company can be seen as an industrial process in which data management and data analysis play an important role. Therefore, this is why a basic understanding of data-related problems (such as data quality, variability, analysis and accurate interpretation) is very important for the insurance business. The selected examples are used to cover the basic aspects of general insurance, and they are all based on the author’s experience. The article ended with some explanations on the role of statisticians working in general insurance.

According to Khalili-Damghani et al. (2018), the insurance coverage proposal problem (ICRP), in which the most suitable coverage is offered for customers, is an indispensable issue for an insurance company. ICRP helps insurance companies to provide appropriate services to their customers. At ICRP, the insurance company tries to investigate the characteristics and records of data associated with customers to recommend the most economical and optimal insurance plan to customers. Insurance companies have large databases that are considered a suitable infrastructure for analyzing, modeling and predicting customer behavior. In this study, he proposed a two-stage clustering classification model to recommend appropriate insurance coverage for customers. The first stage addresses a data pre-scan phase and the clustering of customers based on their insurance coverage record. Well-known clustering algorithms were used. The superior clustering algorithm is selected according to the Davies-Bouldin metric. In the second stage, the authors chose the appropriate features.

In their study Yeo et al. (2017) provided evidence of the benefits of an approach that combines data mining and mathematical programming to determine the premium for charging car insurance policyholders to achieve an optimal portfolio. A nonlinear integer programming formulation was proposed to determine optimum premiums based on the insurer's need to find a balance between profitability and market share. To solve this problem, the nonlinear integer programming approach is used within the framework of data mining consisting of three components: separating policyholders into homogeneous risk groups and estimating the demand cost of each group using k-average clustering, determining the price sensitivity (payment trend) of each group using neural networks, and defining the optimum premium to be filled by combining the results of the first two components. The results of the first two components have been previously presented.

According to Jaimungal and Chong (2014), the role of clustering in event and/or seriousness in disaster modeling and derivative valuation is a key consideration overlooked in recent literature. Here, they proposed two marked point processes to take these characteristics into account. The first approach stated that the points were guided by a stochastic hazard ratio modulated by a Markov chain, while the signs assumed that they were taken from a regime-specific distribution. In the second approach, points were taken from an independent distribution, while points were guided by a self-stimulating process. In this context, they provided a single approach to effectively valuing disaster options, such as those embedded in disaster bonds, and showed that the results were in the 95% confidence range calculated using Monte Carlo simulations. According to their approach, the evaluation is based on deriving the PITA and uses transformations to provide semi-analytical closed form solutions.

In their study Kašćelan et al. (2016) used non-parametric data mining techniques such as clustering, support vector regulation (SVR) and kernel logistics regression (KLR) for risk estimation in car insurance. The purpose of these techniques is to classify risk and estimate the extent of damage based on data, thereby helping the insurer to assess the risk and calculate the actual premiums. They have proven that the used data mining techniques, based on case study data, can predict claims dimensions and their occurrence with better accuracy than standard methods. This represents the basis for calculating the net risk premium. In addition, the article argued that data mining methods discuss the advantages of car insurance compared to standard methods for risk assessment, as well as the characteristics of results obtained due to the small insurance market, such as Montenegro.

According to Smith et al. (2017), the insurance industry is dealing with many issues concerning the operational research community. In their study, they presented a case study involving two types of problems and solved them using various techniques within the data mining methodology. The first of these problems is related to understanding the models of retaining the customer by classifying policyholders as the possibility of renewing or terminating their policies. The second is about understanding the claims models and identifying the types of policyholders who are more at risk. Each of these issues affects the decisions regarding premium pricing, which directly influence profitability. A data mining methodology is used that displays the information discovery process in a holistic framework using hypothesis testing, statistics, clustering, decision trees and neural networks at various stages. The effects of the case study on the insurance company have been discussed.

In their study, Kiermayer and Weiß (2020) presented a grouping framework and a new method for optimizing model points in life insurance. A less complex portfolio has proposed a controlled clustering algorithm that uses neural networks to create pseudonym grouping. In a two-step approach, they first approximately calculated the selected properties of a portfolio. Subsequently, they placed this forecaster in a neural network, as cluster representatives and alias model points were calibrated according to their impact on the characteristics of the portfolio. Numerical experiments for term life insurance and defined contribution retirement plans have shown significant improvements in the neural network approach to capture the characteristics of a portfolio according to the K-means cluster, a common basic algorithm for grouping. These studies also demonstrated the flexibility of the model to include common industry practices.

3. TURKISH INSURANCE INDUSTRY OVERVIEW

Towards the end of 2019, 59 of the 63 insurance companies, reinsurance companies and pension companies operating in the Turkish insurance sector, operate as joint stock companies, two of them operate as cooperative companies, and two companies continue their activities as branches of companies with headquarters abroad. The number of insurance companies, which was 62 at the end of 2018, increased to 63 as of the end of 2019, as a result of the merger of two non-life companies and the initiation of one non-life and one reinsurance company in the insurance sector. In 2019 S.S. All Motor Carriers Mutual Insurance Cooperative and Türk Reasürans AŞ started their activities in the insurance sector, Ergo Sigorta AŞ disappeared from the market after HDI Sigorta AŞ took over Ergo Sigorta AŞ completely. Of the 63 insurance companies operating in the sector in 2019, 38 hold licenses in non-life insurance, 5 in life insurance, 17 in life and retirement, and 3 in reinsurance. However, there are one non-life, one life, and one reinsurance company that are not operating despite their license. Together with these, the total number of licensed companies reaches 66. In the Table 1 below, the number of companies in the last three years according to whether they produce premiums and contributions (active and inactive) is given by the operating group.

Table 1
Number of Licenced and Active Companies

	2017		2018		2019	
Company Type	**Active**	**Not Active**	**Active**	**Not Active**	**Active**	**Not Active**
Non -Life Ins. Companies	38	2	38	1	38	1
Life Ins. Companies	4	1	5	1	5	1
Pension Companies	18	-	17	-	17	-
Reinsurance Companies	2	1	2	1	3	1
Total	62	4	62	3	63	3

Source: *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.12*

As of 31.12.2019, the reasons for the non-operation of companies, that have licenses but do not produce premiums, are explained in the Table 2 below.

Table 2
Information About Run-off Business Companies

Company Name	Date (*)	The Reason of Suspending Operations
MERKEZ	03.04.2003	Authority of Selling New Contracts Has Been Removed
NEW LIFE	19.06.2010	Authority of Selling New Contracts Has Been Removed
ARTI RE (**)	01.11.2011	Authority of Selling New Contracts Has Been Removed

(*) Dates are shown with Turkish form (dd/mm/yyyy). Source: T.C. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.13

When the insurance companies, which are operating in the Turkish insurance sector, are classified according to the invested capital, it is stated that 22 companies have domestic capital and continue their activities, while 41 are foreign-owned companies. In addition, when the share ratios of common foreigners in foreign-owned insurance companies exceed the 50% limit, they are called foreign-owned insurance companies.

As a result of the activities compared to the last month of 2019, the gross premium total produced in the sector increased by approximately 26 % if compared to the gross premium total for the previous year, while financially the total realized premium was 68,8 billion TL. The total premium production in the field of life insurance was approximately 20,06 % of the total premium production and the monetary amount was 13,80 billion TL. Total premium production in non-life insurance approximately represents 79.94% of total premium production. Premium production in the field of non-life insurance was 55 billion TL in monetary value.

When Table 3 is examined, towards the end of 2019, a total of 68.8 billion TL premium production was realized in the insurance sector. Compared to the previous year, premium production in the insurance sector increased by 26%. During this period, premium production in non-life companies increased by 20%, while premium production in life / pension companies increased by 59%.

Table 3
Distribution of Premium Volume

(Billion ¨)	2015	2016	2017	2018	2019
Non-Life Companies	**26,4**	**34,3**	**38,3**	**45,9**	**55,00**
Direct	25,8	33,6	36,0	42,0	50,1
Endirect	0,6	0,7	2,3	3,9	4,9
Life / Pension Companies	**4,6**	**6,2**	**8,3**	**8,7**	**13,80**
Direct	4,5	5,9	8,0	8,3	13,3
Endirect	0,12	0,27	0,30	0,34	0,46
Premium Production	**31,1**	**40,5**	**46,6**	**54,6**	**68,8**
Non-Life Companies (%)	85,08	84,77	82,26	84,11	79,94
Life / Pension Companies (%)	14,92	15,23	17,74	15,89	20,06

Source: *T.R Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.39*

Compared to 2019, the increase in gross premiums (59%), in non-life (20%) and life / pension branches was higher than the inflation rate published in the same period (11.84%). The annual inflation figures for 2019 have been announced by the Turkish Statistical Institute (TUIK). The change observed in the Consumer Price Index (CPI) was realized as 0.74 percent in December 2019 compared to the previous month and 11.84 percent compared to December of the previous year. When the inflation figure is calculated according to the twelve-month averages, an increase of 15.18 percent has been observed. Premium amount paid per person in 2019 equals to 833 TL. The realized share of total premiums in GDP increased to 1.62%. The premium production per capita, which was 818 USD worldwide in 2019, is 134 USD (=134 USD x 5,9507.-TL. (Dollar Sales) = 797.-TL.) in Turkey. While the ratio of direct premium to GDP was 1.48% in Turkey, this ratio was equal to 7.23% in the world.[1]

Although the insurance industry produced 68.8 billion TL of the premium production in 2019, 129.3 trillion TL of the coverage was given to the insured. Seen that the GDP was 4.3 trillion TL in the same period, the direct premium production was equal to 1.48% of the GDP in the Turkish insurance sector and 30 times of the coverage was given to the policyholders. At the same time, it can be stated that the amount of funds accumulated in the private pension system was equal to 2.8% of GDP at the end of 2019.[2]

Since the insurance sector is part of the financial structure, it is one the sectors that is most quickly affected by the developments in the economy. While the GDP grew by 15% in nominal value in 2019, direct premium production had an increase of 11 points above the GDP which is equal to 26%. Similarly, the increase in direct premium production was 8 points above the GDP in real terms reaching a value of 9%.[3]

At the end of 2019, the total assets in the insurance sector increased by 32.6% and reached 236.6 billion TL. The shares of Life/Pension companies in the sector, with the effect of pension funds, is above 60%. While the share of companies in the insurance branch in the total assets of the sector was 62.8% in 2015, it reached 65.3% at the end of 2019 thanks to the rapid increase in private pension activity in recent years. At the end of 2019, it was observed that 32.6% of the total assets of the insurance sector belonged to non-life insurance companies, while the remaining 2.1% to reinsurance companies.[4]

The remarkable point in the insurance sector in recent years has been that the ratio of debts to the total liabilities of the balance sheet has increased, while the share of shareholders' equity is between 13% and 14%. Whereas the ratio of debts in total liabilities was 52.2% in 2015, the ratio of debts at the end of 2019 increased by 4.7 points reaching 56.9%. At the end of 2019, the ratio of the considered liabilities on the total liabilities was equal to 87% and the share of equity represented 13%. In 2019, the equity of the sector increased by 32% compared to the previous year, reaching 30.8 billion TL.[5]

The monetary value of the total profit realized for the insurance companies is equal to (=5.204,744.00. TL. (Non-Life Technical Balance) + 2.255.099.00.-TL. (Life Technical Balance) = 7.459.843,00.-TL.[6]

When Table 4 is examined, in the insurance sector, the amount of compensation paid, with recourse and salvage income deducted, increased every year, and reached 32.1 billion TL in 2019. In 2019, non-life companies paid 27.3 billion TL, and life / pension companies paid 4.8 billion TL. The share of non-life companies in the compensation amounts paid represents 85%, while the share of life / pension companies equals 15%. In the last five years, the total amount of compensation paid in the insurance sector on an annual basis has approximately increased by 102.8% in the last five years.[7]

Table 4

Distribution of Paid Losses

(Billion ¨)	**2015**	**2016**	**2017**	**2018**	**2019**
Non-Life Companies	**13,4**	**15,2**	**18,4**	**23,2**	**27,3**
From Direct Production	13,0	14,8	17,8	21,6	25,2
From Indirect Production	0,4	0,4	0,6	1,5	2,2
Life / Pension Companies	**2,6**	**3,0**	**3,3**	**3,6**	**4,8**
From Direct Production	2,5	2,8	3,1	3,4	4,5
From Indirect Production	0,1	0,2	0,2	0,2	0,3
Total Claims Payment	**15,9**	**18,1**	**21,7**	**26,8**	**32,1**
Non-Life Companies (%)	83,93	83,68	84,83	86,52	85,13
Life / Pension Companies (%)	16,07	16,32	15,17	13,48	14,87

Source: T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.26

1 *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.11, and T.C. Central Bank 31.12.2019 data*
2 *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.7*
3 *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.8*
4 *T.R Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.17 and Table 1A*
5 *T.R Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.19 and Table 1B*
6 *T.R Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, Table 6A*
7 *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, p.26*

In Table 5, the total profit for the period before tax of the insurance sector, compared to the previous year, increased by 47.0% reaching 10.6 billion TL in 2019. The profit after tax increased to 7.9 billion TL in 2019. Compared to the end of 2019, non-life insurance companies made a profit of 3.9 billion TL after tax, while life / pension companies made a profit of 3.6 billion TL. On the other hand, reinsurance companies operating in the insurance sector, closed the end of 2019 with a profit of 0.3 billion TL after tax.

Table 5

Profit-Loss Accounts

(Million ¨) Non-Life Companies	**2015**	**2016**	**2017**	**2018**	**2019**
Total Technical Income	18.451	24.780	28.616	33.050	39.116
Total Technical Outgoing	19.227	23.033	26.521	30.003	34.347
Technical Balance	-776	1.747	2.095	3.046	4.769
Investment Income	2.894	3.244	4.997	9.897	9.887
Investment Expenditures	2.726	3.016	4.570	8.910	9.027
Other Incomes/Expen.Prov	-150	-569	-253	-722	-201
Profit Before Tax	-759	1.407	2.269	3.312	5.427
Profit After Tax	-856	1.140	1.624	2.666	3.939
Life / Pension Companies					
Total Technical Income	6.090	7.685	10.069	11.647	16.439
Total Technical Outgoing	5.439	6.678	8.341	9.576	13.359
Technical Balance	651	1.007	1.729	2.071	3.080
Investment Income	821	917	1.123	1.993	2.300
Investment Expenditures	324	276	304	448	633
Other Incomes/Expen.Prov	-68	8	-19	-80	20
Profit Before Tax	1.079	1.656	2.529	3.536	4.767
Profit After Tax	826	1.322	2.005	2.746	3.637
Reinsurance Companies					
Total Technical Income	1.026	1.072	1.083	1.529	1.763
Total Technical Outgoing	1.058	1.011	1.023	1.429	1.683
Technical Balance	-31	61	59	100	79
Investment Income	292	302	474	1.374	1.022
Investment Expenditures	121	206	371	1.124	747
Other Incomes/Expen.Prov	-9	-19	-1	-14	7
Profit Before Tax	130	138	161	335	362
Profit After Tax	130	134	114	301	322
Total Profit Before Tax	**451**	**3.201**	**4.959**	**7.183**	**10.556**
Total Profit After Tax	**101**	**2.596**	**3.743**	**5.714**	**7.898**

When analyzing the last five years, there is a regular increase in technical and total net profits in life / pension insurance companies, while there is a regular[8] increase in the last four years in non-life companies.

4. METHODOLOGY AND DATA

4.1. Variables

The variables used in the study are divided into two main groups. Each parent group is divided into subgroups. The variables are shown in Table 6. The annual data of 16 life and pension insurance companies, 4 life insurance companies and 28 non-life insurance companies were used in the study between 2015 and 2019. All categorical variables and some numeric variables related to the management side (X1, X2, X3, X4) are derived from the activity reports of insurance companies. Categorical variables are divided into 3 groups. These include whether the chairman of the board of directors is male or female, the chairman of the board is a citizen of T.C or is a foreigner and the chairman and chief executive officer of the board of directors are or are not the same person. Numeric variables related to financial situations (X5, X6, X7, X8, X9, X10) were obtained from the balance sheet and income statements of the insurance companies.

Table 6
Variables

Categorical Variable		Numeric Variable			
Chairman of the Board of Directors (YKB) (Male/Female)	**K1**	Number of Members on the Board of Directors (Count YK Members)	**X1**	Loss/Premium Ratio Net (HP Net)	**X6**
		Number of Independent (Non-Executive) Board Members (Count as a Member of Bag.YK)	**X2**	Premium production (PREMIUM Pro.)	**X7**
Chairman of the Board of Directors (YKB) (Foreign/T.C Citizen)	**K3**	Number of Female Board Members (Count as Female YK Member)	**X3**	Total Assets (Tp Assets)	**X8**
		Number of Foreign Board Members (Yab YK Member Count)	**X4**	Equity	**X9**
Chairman and General Manager (YKB & GM) (same person)	**K5**	Loss/Premium Ratio Gross (HP Gross)	**X5**	Net Profit	**X10**

4.2. Clustering Analysis

As a general definition, clustering analysis is a solution method that helps subset pure groupings into subsets of unknown volumes and variables, or units and variables contained in any X data matrix.

In addition, clustering analysis is used to divide units or variables into homogeneous groups with the help of some measures calculated according to similarity and differences between variables.

Clustering analysis can be applied even if there are non-objective situations between observations. Clustering analysis can help make objective classifications in these cases.

Clustering analysis can be used for dimension reduction purposes. If there is more than one observed volume, they can be divided into small groups according to the specified variable. In addition, clustering analysis is used to determine the outlier or excessive observations between the variables examined. It is also used to observe hypotheses about the structure of the data used. The clusters obtained with the selected base variables are tested to see if they differ in terms of other variables that are not clustered. Clustering analysis generally consists of the following stages (Alpar, 2011, p.309-310; Özdamar 2010, p.267).

8 *T.R. Insurance and Private Pension Regulation and Supervision Agency, Report on Insurance and Private Pension Activities 2019, pp.26-27*

1) Creation of data matrix for units and variables observed from the population selected for research.
2) Determination of similarity or distance matrices for clustering analysis.
3) Determination of which clustering method to use for the solution method.
4) Interpretation of the results obtained.

4.2.1. TWO-STEP Clustering Method

A two-step clustering method is a scalable clustering analysis algorithm designed to run very large datasets. It is a method that can be used both for continuous variables and categorical variables. It consists of two steps: (IBM SPSS Statistics 23 Algorithms, 2014, p. 963).

1) Cases (or records) are preset in many small subsets.
2) Cluster subsets resulting from the preset step into the desired number of clusters. It can also automatically select the number of clusters.

4.2.1.1. Two-Step Clustering Process Stages

The two-step clustering process includes the following steps: (IBM SPSS Statistics 23 Algorithms, 2014, p. 964-965)

1) Presetting process. The presetting process uses a clustering method called sequential. After the saved data is scanned individually, it is a process in which it is decided whether to merge the existing record with the pre-generated clusters. It is also decided whether to create a new cluster based on the distance criterion.
2) Optional outlier value processing. When creating a cluster property tree, the process of handling excessive or values is initiated on demand in the research. The peculiarity of outliers is that they cannot belong to any set. If these values are less than 25% of the maximum cluster size, they are considered outliers. These values are checked and set aside before the cluster property tree is created.
3) Clustering process. In this step, it retrieves the subsets created after the preset process as inputs and groups them into a specified number of clusters. Traditional clustering methods can be used effectively because the number of calculated subsets is much smaller than the number of original entries. The two-step clustering method uses a bulk hierarchical clustering method because it is a process that works well with the automatic clustering method.

4.2.2. Distance Measurements

In general, the distance measurements used in clustering analysis are log-likelihood and Euclidean. In this study, log-likelihood distance measurement was used. This is because there are both continuous and categorical variables in the study.

4.2.2.1. Log-likelihood Distance Measure

The log-size offset measure can use both continuous and categorical variables. It is a measure of distance based on probability. The distance measure between the two sets is related to the decrease in log-probability because they are combined into a single set. When calculating the log-availability offset measure, it is assumed that there is normal distribution for continuous variables and multi-term distribution for categorical variables. In addition, before analysis, variables are assumed to be independent of each other and states are independent. For example, the distance between clusters j and i is defined as follows (IBM SPSS Statistics 23 Algorithms, 2014, p. 965-966):

$$d(i,j) = \xi_i + \xi_j - \xi_{\langle i,j \rangle} \quad (1)$$

the distance between sets $d(i,j)$= i and j, the cluster created by combining <i, j> =v, i i and j sets,

$$\xi_v = -N_v\left(\sum_{k=1}^{K^A} \frac{1}{2}\log(\hat{\sigma}_k^2 + \hat{\sigma}_{vk}^2) + \sum_{k=1}^{K^B} \hat{E}_{vk}\right) \quad (2)$$

K^A The total number of continuous variables used in Procedure, K^B the total number of categorical variables used in Procedure, $\hat{\sigma}_k^2$ the estimated variance of the kth continuous variable in the entire dataset, the estimated variance of the kth continuous variable in the $\hat{\sigma}_{vk}^2$= v set, the number of registered data in the N_v= v set.

$$\hat{E}_{vk} = \sum_{l=1}^{L_k} \frac{N_{vkl}}{N_v} log \frac{N_{vkl}}{N_v} \tag{3}$$

If the number of categories for the L_k k. categorical variable is not taken into account, the number of data records in the v set that receives the N_{vkl} k. categorical variable, the ξ_v (distance measure) and the $\hat{\sigma}_k^2$ (the estimated variance of the kth continuous variable in the entire dataset), the distance between the i and j sets when the two sets are merged will result in a decrease in the probability of full log-probability. the term $\hat{\sigma}_k^2$ is added to resolve the problem caused by $\hat{\sigma}_{vk}^2$ = 0, which causes the natural logarithm to be undefined. (This occurs, for example, when there is only one state in a cluster.)

5. Analysis and Findings

Clustering analysis for the categorical variables and numeric variables selected in the analysis results of the study was done as follows. In addition, a two-stage (Twosteps) clustering method was used.

- Categorical variables are introduced into clustering analysis among themselves.
- Categorical variables and management numeric variables were analyzed together.
- Categorical variables and financial variables were analyzed together.The results of the resulting clustering analysis are explained through the figures.

5.1. Clustering Analysis with Categorical Variables

Categorical variables and data about the board of directors, was obtained from the company's annual reports. These variables are encoded as K1, K3, K5.

The first finding obtained in the clustering analysis is shown in Figure 1, which shows the summary of the model created. When the figure was examined, a two-stage clustering algorithm was used, and 4 sets were obtained against 3 input variables. The quality of the resulting clusters is around 90%.

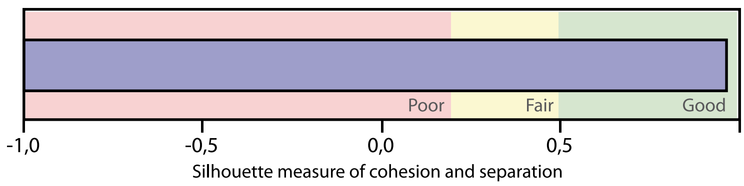
Figure 1

Model Summary for Categorical Variables

Model Summary

Algorithm	TwoStep
Inputs	3
Clusters	4

Clusster Quality



Within the set in Figure 2, the solution is followed by % values in volume of cluster sizes and weights of categorical variables, showing variables in which, the generated clusters are sorted by size. It is seen that the largest cluster with 48.9% in volume is cluster 3, and the smallest set with 2.2% in volume is cluster 4.

When cluster 3 is examined, it is seen that YKB is male and YKB and GM are not the same person. At the same time, it is seen that YKB is Turkish. When cluster 1 is examined, it is seen that YKB is male and YKB and GM are not the same person. Moreover, in this group, it is seen that YKB is foreigner. When cluster 2 is examined, it is seen that YKB is not the same person, YKB is a woman, YKB and GM are not the same person, but also YKB is Turkish. For cluster 4, it is seen that YKB is male, YKB and GM are the same person and YKB is foreigner.

Another important point is that YKB can be Turkish or a foreign national, but it has been observed that it is predominantly Turkish.

Figure 2

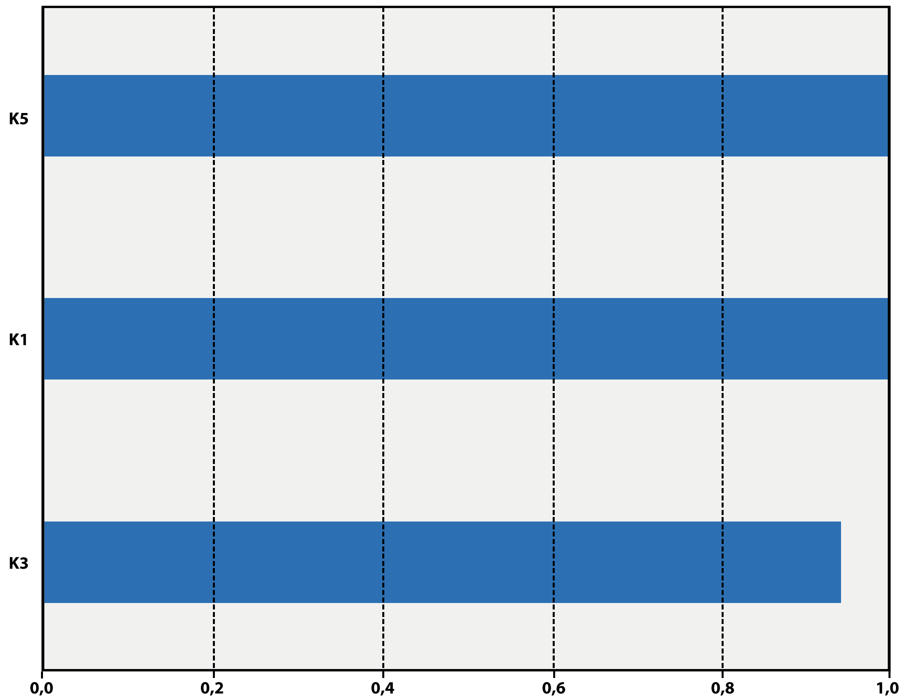
Categorical Variables Clustering Results

Cluster	**3**	**1**	**2**	**4**
Label				
Description				
Size	48,9 % (112)	39,7 % (91)	9,2 % (21)	2,2 % (5)
Inputs	K1 YKB is Male (100,0 %)	K1 YKB is Male (100,0 %)	K1 YKB is Female (100,0 %)	K1 YKB is Male (100,0 %)
	K5 YKB&GM is not same person (100,0 %)	K5 YKB&GM is not same person (100,0 %)	K5 YKB&GM is not same person (100,0 %)	K5 YKB&GM is not same person (100,0 %)
	K3 YKB is Turkish (100,0 %)	**K3 YKB is Foreign (100,0 %)**	**K3 YKB is Turkish (85,7 %)**	**K3 YKB is Foreign (80,0 %)**

The last part of the clustering analysis for categorical variables is the interpretation of Figure 3, which shows the importance of forecasters. When the figure is examined, it is seen that the most important variable in clustering with categorical variables is K5 (whether YKB and GM are the same person) and K1 (whether YKB is male or female). This means that in the insurance sector, the fact that the chairman of the board of directors and general managers are not the same people and the nationality and the gender of the chairman of the board of directors are important variables.

Figure 3

Categorical Variables Predictor Importance Chart



5.2. Clustering Analysis with Categorical Variables and Management Numeric Variables

K1, K3, K5, X1, X2, X3 and X4 variables were used in this part of the analysis. A summary of the model created as a result of the clustering analysis is shown in Figure 4. On the other side, 7 variables were used as two-stage clustering algorithms and inputs. As a result of the analysis, 2 clusters were obtained. The quality of the clusters created is good.

Figure 4

Categorical Variables and Management Numeric Variables Model Summary

Model Summary

Algorithm	TwoStep
Inputs	7
Clusters	2

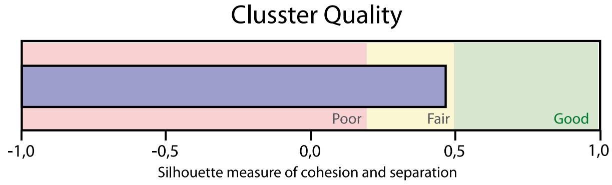


Figure 5 displays the size of the clusters created in volume and the order of variables in the sets. Cluster 2 has the highest percentage in volume. When cluster 2 is examined, when its variables are interpreted in order of importance, it is seen that YKB is Turkish and the number of Yab.YK members is 1.65 people on average and the number of board members is 7.48 people on average. For cluster 1, it is seen that YKB is foreign and the number of Yab.YK members is 4.21 people on average and the number of YK members is 6.18 people on average. Looking at the result in Figure 5, the following can be said. When YKB is Turkish, the number of foreign members in the board of directors is approximately 2 people. At the same time, YKB is male. Likewise, YKB & GM are not the same people. When YKB is foreign, it has approximately 5 foreign members on the board of directors. As a result, the nationality of the chairman of the board affects the formation of the board of directors.

Figure 5

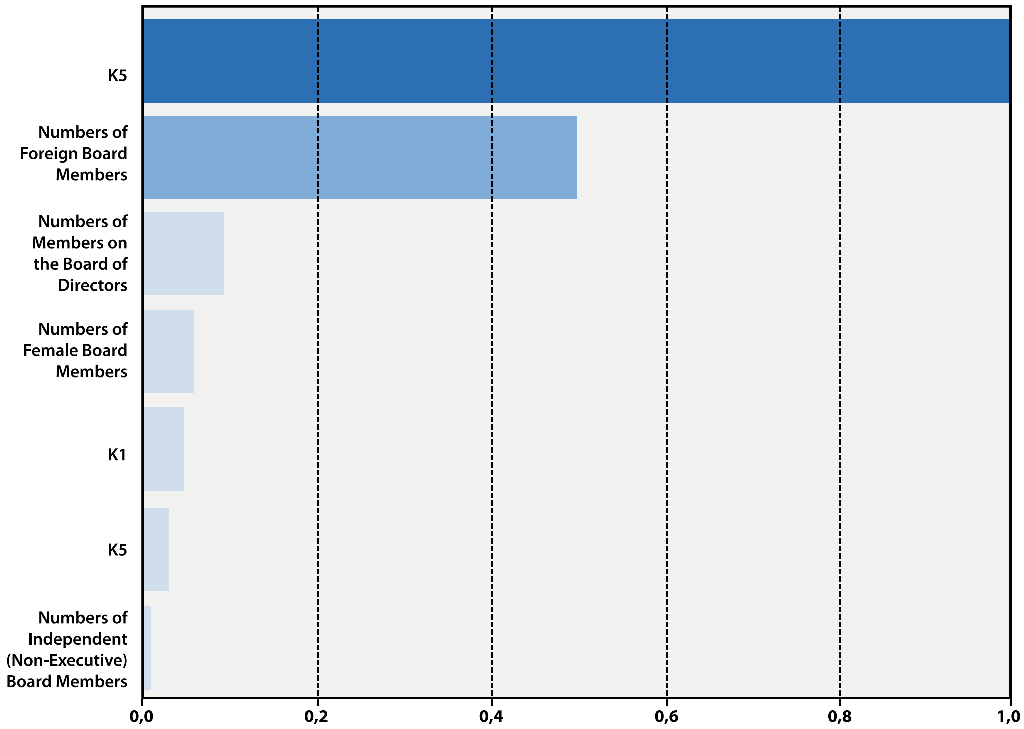
Categorical Variables and Management

Cluster	2	1
Label		
Description		
Size	57,2 % (131)	42,8 % (98)
Inputs	K3 YKB is Turkish (99,2 %)	K3 YKB is Foreign (99,0 %)
	Number of Foreign Board Members 1,65	Number of Foreign Board Members 4,21
	Number of Members on the Board of Directors 7,48	Number of Members on the Board of Directors 6,18
	Number of Female Board of Members 0,90	Number of Female Board of Members 0,44
	K1 YKB is Male (85,5 %)	K1 YKB is Male (98,0 %)
	K5 YKB&GM is not same person (100,0 %)	K5 YKB&GM is not same person (94,9 %)
	Number of Independent (Non-Executive) Board Members 0,47	Number of Independent (Non-Executive) Board Members 0,32

Numeric Variables Clustering Results

Figure 6, which shows the importance of predictors that the most important predictor in clustering is the K3 variable and the number of foreign board members.

Figure 6.
Categorical Variables and Management Numeric Variables Predictor Importance Chart



5.3. Clustering Analysis with Categorical Variables and Financial Variables

The results of the clustering analysis with categorical and financial variables are given in Figure 7, 9 input variables were used in the clustering analysis and 4 clusters were created. The quality of the clusters created is good.

Figure 7
Categorical Variables and Financial Variables Model Summary

Model Summary

Algorithm	TwoStep
Inputs	9
Clusters	4

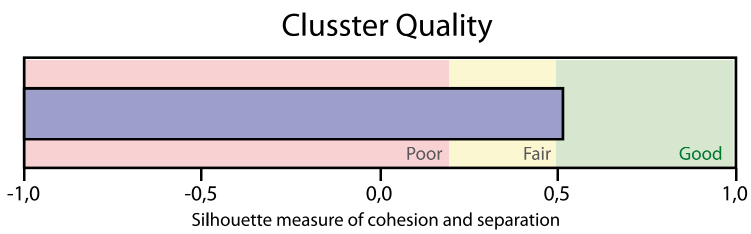


Figure 8 lists the volumes of the clusters created and the order of the variables. Cluster 4 is the largest in volume.

In cluster 4, the equity value is first with an average value of TL 265,710,259.05. At the same time, it is seen that YKB is Turkish. Total assets are worth an average of TL 2,225,145,835.23. Net profit is TL 60,104,931.13. And YKB appears to be male.

In cluster 1, the equity value is first with an average value of TL 192,315,332.56. At the same time, it is seen that YKB is foreign. Total assets are worth an average of TL 1,119,195,410.32. Net profit is TL 14,266,771.67 on average. And YKB appears to be male.

In cluster 3, the equity value is first with an average value of TL 1,214,488,042.72. At the same time, it is seen that YKB is Turkish. Total assets are worth an average of TL 10,783,321,239.00. Net profit is 279.516.042.31 TL on average. And YKB appears to be male.

In cluster 2, the equity value is first with an average value of TL 91,577,215.68. At the same time, it is seen that YKB is Turkish. Total assets are worth an average of TL 1,085,947,332.44. Net profit is -8.311.477.32 TL on average. And it appears that YKB is a woman.

Looking at Figure 8, the most important point is that when YKB is Turkish, some financial values, equity, total assets, and net profit are higher. In foreign managers, these values are lower. In this case, it can be said that Turkish managers are more successful than foreigners. The reason for this is that Turkish managers know the dynamics of the Turkish insurance sector better than foreigners and have worked in the sector for a long time. On the other hand, the values of other variables are close to each other.

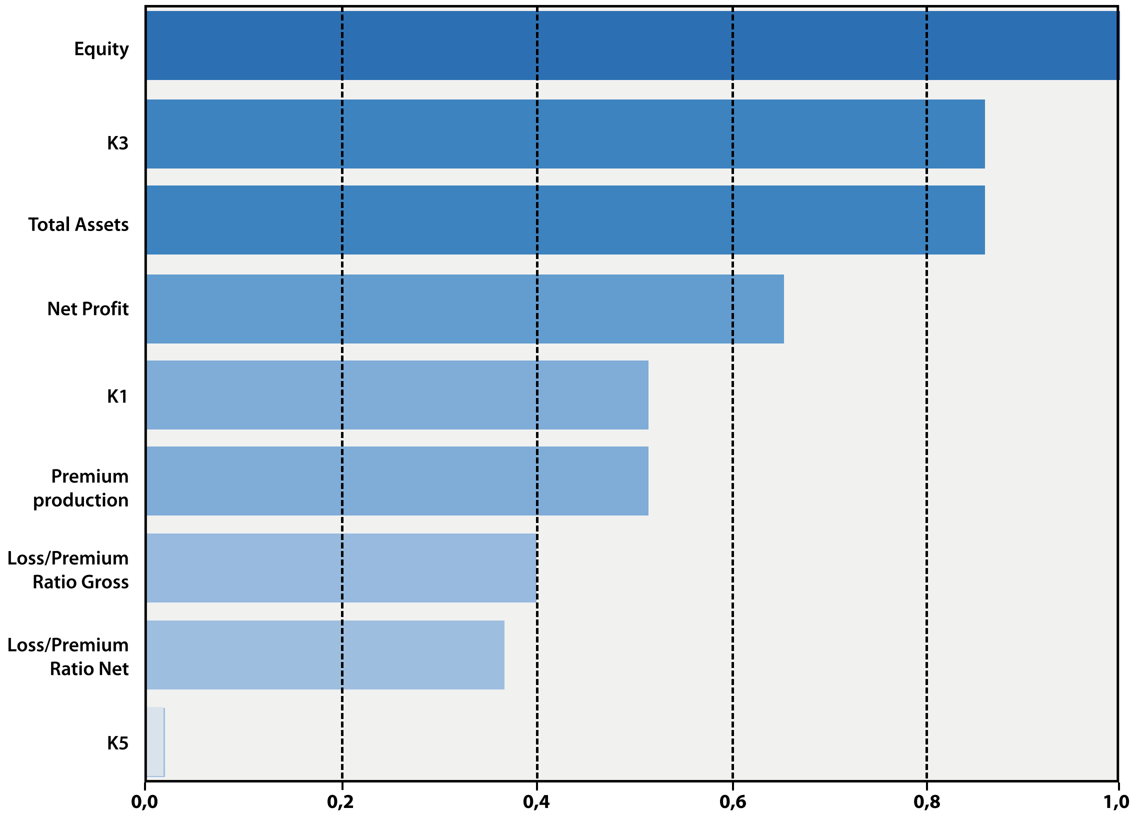
Figure 8

Categorical Variables and Financial Variables Clustering Results

Cluster	4	1	3	2
Label				
Description				
Size	37,6 % (86)	34,5 % (79)	17,0 % (39)	10,9 % (25)
Inputs	Equity 265.710.259,05	Equity 192.315.332,56	Equity 1.214.488.042,72	Equity 91.577.215,68
	K3 YKB is Turkish (100,0 %)	K3 YKB is Foreign (100,0 %)	K3 YKB is Turkish (79,5 %)	K3 YKB is Turkish (56,0 %)
	Total Assets 2.225.145.835,23	Total Assets 1.119.195.410,32	Total Assets 10.783.321.239,00	Total Assets 1.085.947.332,44
	Net Profit 60.104.931,13	Net Profit 14.266.771,67	Net Profit 279.516.042,31	Net Profit -8.311.477,32
	K1 YKB is Male (100,0 %)	K1 YKB is Male (100,0 %)	K1 YKB is Male (87,2 %)	K1 YKB is Female (64,0 %)
	Premium prodüction 686.478.732,74	Premium prodüction 516.583.786,04	Premium prodüction 2.635.447.454,64	Premium prodüction 270.690.251,16
	Loss/Premium Ratio Gross 0,54	Loss/Premium Ratio Gross 0,55	Loss/Premium Ratio Gross 0,60	Loss/Premium Ratio Gross 1,40
	Loss/Premium Ratio Net 0,56	Loss/Premium Ratio Net 0,59	Loss/Premium Ratio Net 0,63	Loss/Premium Ratio Net 1,53
	K5 YKB&GM is not same person (98,8 %)	K5 YKB&GM is not same person (94,9 %)	K5 YKB&GM is not same person (100,0 %)	K5 YKB&GM is not same person (100,0 %)

The predictor importance graph, which is important in creating a cluster, is given in Figure 9. The most important forecasters by shape are equity, K3, net profit and total assets.

Figure 9.
Categorical Variables and Financial Variables Predictor Importance Chart



CONCLUSION

Insurance companies play an important role in transferring risk because they cover financial losses from risks through premiums they collect from policyholders. Insurance companies themselves are exposed to risk because of their activities. Insurance companies need to be well managed in order to manage their own risks and continue their activities. For successful management, insurance companies need to carefully monitor their financial variables in the financial statements.

According to the results obtained in the study, three categories were created, and different sets were obtained for each category.

According to the clustering results with categorical variables, it is seen that the most important predictors are K5, K1 and K3. According to the results of the largest volume cluster, YKB & GM are not the same person and YKB is male.

According to the results of the clustering analysis with categorical variables and board variables, the most important predictors are that the YKB is Turkish according to the large volume cluster group. In addition, it was observed that the number of foreign board members was approximately 2 people.

As a result of the analysis with categorical variables and financial variables, it is seen that the most important forecasters are equity, K3, total assets. In other words, it was observed that YKB was Turkish according to the cluster with the largest volume.

According to the study, it is seen that the chairman of the board of directors is Turkish in the insurance companies in the Turkish Insurance Sector. Another important point is that the chairman of the board of directors is a man. At the same time, it has been observed that the chairman and chief executive officer are not the same people. Again, equity and total assets are important forecasters for clustering.

In conclusion, we can say the following. Managers in the Turkish insurance sector are predominantly

Turkish. In addition, the financial outputs of insurance companies in which Turkish are managers, they are more successful than foreign managers. In other words, it can be said that managers of Turkish origin manage insurance companies better. One of the keys to success in insurance companies is that the board of directors and the general manager are not the same person. In addition, the chairman of the board of directors is predominantly male.

The limitations of the study are the inability to obtain any more categorical and numerical variables of management and the inability to perform cluster analysis with financial variables alone.

As a contribution of this study to the literature, it is thought that insurance companies will give an idea of which variables are important in the related studies. It can also guide insurance companies as an indicator of which variable management is shaping up around.

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