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CLUSTERING OF BANKS OPERATING IN TURKEY ACCORDING TO FINANCIAL INDICATORS AND EMPLOYEE PROFILE WITH K-MEANS ALGORITHM

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ABSTRACT

This paper concentrates on the clustering analysis of Turkish Banking System to investigate the similarities of public, private and development and investment banks with respect to their financial indicators and employee profiles by using K-means algorithm based on Euclidean distance. In other words, we cluster the 46-unit banks with respect to two different type of variable groups (group one consists of 6 variables related to capital adequacy and group two consists of 12 variables related to employee profile) and compare the results. When we compare the findings, it was observed that public banks were all in the same cluster with different number of private banks. In addition, when we change the evaluation variables from financial indicators to employee profile, only 4 banks replace their clusters.

Keywords- Turkish Banking System, Financial Indicators, Employee Profile, K-Means Clustering

I. INTRODUCTION

Banks are among the major financial actors in any country's economy in terms of their role in bringing the funds they collect from savings into the economy and in using capital in different sources. Especially with the rally of foreign capital banks into the market in the union with financial liberalization caused increased competition in the markets due to the growth of the sector. Banks are known as institutions that collect the savings of domestic and foreign depositors in the form of deposits. In order for savers to entrust their savings to the bank, banks and the financial markets need to be trusted. Therefore, it is very important to establish a trust environment for investors in any country.

With the impact of globalization, banks have an important role in the growth and development of any country's economy. Banks work actively and efficiently to adapt the increase competition, economic activities in a country with a sound financial infrastructure should be created to be fulfilled. The fragility experienced especially during crisis periods can have negative effects on the banks.

With the transition to a free market economy after 24 January 1980 [1], the Turkish banking system was affected by macroeconomic and financial factors. The banking sector-based crises in the 90s and 2000s in Turkey and the world have had a negative impact on the banking and financial sector [2]. High inflation, high real interest rates and the inability to repay loans caused a loss of confidence in the sector. Therefore, the ability to deal with the risks faced by the banking sector has become more important for the whole sector.

Capital adequacy was established by the Basel I criteria published by the Basel Committee on Banking Regulation and Supervision in 1988 [3]. Thus, the minimum amount of capital that victims must hold in order to minimize their losses in the event of the bank's bankruptcy was standardized. According to Basel II standards published in 2004 [4], market and credit risk must be taken into account as well as the operational risk. The authority to determine the capital adequacy ratio of banks operating in Turkey belongs to the Banking Supervision and Regulation Authority (BRSA). The BRSA wants this rate to be above 12% in order to keep banks' financial structures stronger [5].

As of May 2020, there are 48 banks operating in Turkey [6]. 34 of the banks are deposit banks, 14 of the banks are development and investment banks. 3 of the deposit banks are public, 9 of them are private, and 21 of them are foreign banks. Since one of these banks is transferred to the Savings Deposit Insurance Fund (SDIF), it is not included to the study (Table 1).

TABLE 1. BANK GROUPS OPERATING IN TURKEY [6]

Bank / Group Name	**Banks**	**Domestic Branch**	**Overseas Branch**
Banking System of Turkey	***48***	***10081***	***71***
Deposit Banks	**34**	**10018**	**71**
Public Capital Deposit Banks	3	3670	33
Private Equity Deposit Banks	9	3728	28
Banks with Foreign Capital	21	2619	10
Development and Investment Banks	**14**	**63**	**0**
Development and Investment Banks with Public Capital	3	40	0
Private Equity Development and Investment Banks	7	19	0
Foreign Capital Development and Investment Banks	4	4	0

As illustrated in Table 1, from 14 development and investment banks 3 of them are public, 7 of them are private, and 4 of them are foreign development and investment banks. Table 2 illustrates the key indicators of the deposit banks operating in Turkey as of March 2020. Accordingly, the total assets of development and investment banks are TL 322,039. Its equity is TL 45,209 while its total loans are TL 219,412.

TABLE 2. BASIC INDICATORS OF DEPOSIT BANKS (BILLION TL) [7]

	Deposit Banks (Total)	Deposit Banks		
		Banks with Public Capital	Banks with Private Capital	Banks with Foreign Capital
Loan	2.511.738	1.082.859	832.649	596.230
Stocks and Bonds	666.842	319.493	234.220	113.129
Deposit	2.550.987	1.003.335	917.851	629.801
Equity	429.824	134.747	172.032	123.045
Total Assets	4.232.167	1.656.218	1.522.060	1.053.889

In another perspective deposit banks consist of 3 types: public, private, and foreign (foreign capital). Accordingly, while the total asset size of the sector is TL 4.23 billion, the largest share in terms of asset size belongs to deposit banks with public capital. As can be seen from Table 2, the equity size of deposit banks with public capital is higher than that of other types of banks. In this context, it can be said that the use of foreign resources in public banks is lower than in other types of banks. Furthermore, by the help of these values we can mention that public banks are more successful in terms of converting deposits into loans.

TABLE 3. BASIC INDICATORS OF DEPOSIT, DEVELOPMENT AND INVESTMENT BANKS (BILLION TL) [7]

	Deposit Banks	Development and Investment Banks
Loan	2.511.738	219.412
Stocks and Bonds	666.842	23.489
Deposit	2.550.987	--
Equity	429.824	46.209
Total Assets	4.232.167	322.039

The banking system in Turkey consists of deposit banks (public, private and foreign) and development and investment banks (public, private, foreign). In this study, banks are split into three groups: private (domestic and foreign banks), public deposit banks and development and investment banks. This is because, although banks with public capital are located within deposit banks, as stated above, they are separated from private and foreign capital banks in terms of their asset size and other indicators. In this context, deposit banks split into two groups.

47 banks operate in the Turkish Banking System and a total of 189,507 employee exists in this sector. The total number of employees in deposit banks is 184,324. Private capital banks have the highest proportion of deposit banks based on number of employees and number of branches.

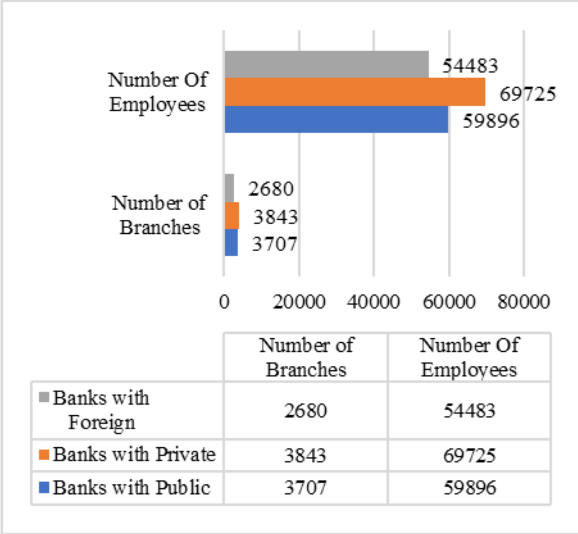

FIGURE 1. BRANCH AND EMPLOYEE NUMBERS BASED ON DEPOSIT BANKS (FOREIGN, PRIVATE, PUBLIC) [6]

As shown in Figure 2, the total number of employees in development and investment banks is 5183 people and the number of branches is 58.

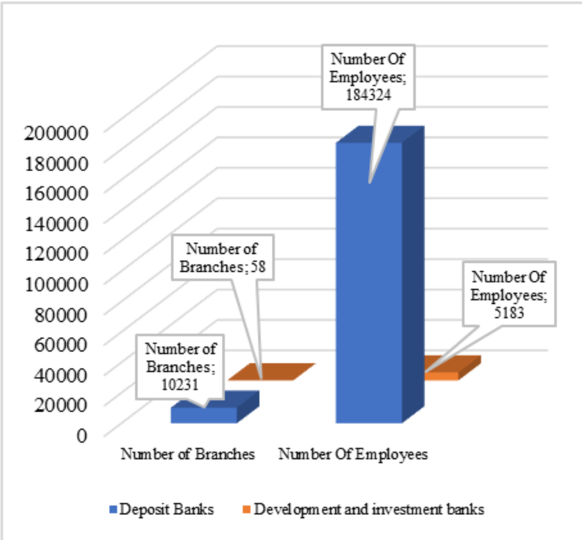

FIGURE 2. BRANCH AND EMPLOYEE NUMBERS BASED ON DEPOSIT, DEVELOPMENT, AND INVESTMENT BANKS [6]

Figure 3 illustrates the educational status of employees in the Turkish Banking System. According to this, 79,890 of the 95,937 women working in the sector graduated from a higher education institution. 67,893 of the total male employees (93,570) have graduated from high school. In addition, the number of women working in the sector is higher than the number of men.

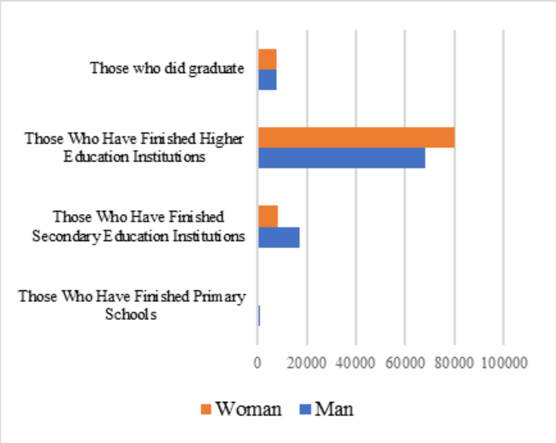

FIGURE 3. TRAINING STATUS OF EMPLOYEES [6]

The research question of this study is: Are the findings that obtained when the banks are clustered with respect to training and gender of their employees are similar to clustering results obtained when they are clustered with respect to capital adequacy variables? Regarding this question, we decided to cluster Turkish banks with two different type of variable sets and then compare the results from each cluster analysis. The K-means algorithm was used to perform the clustering analysis. For this purpose, variables belonging to 6 financial indicators and 7 employee profiles of public, private, development and investment banks operating in the Turkish Banking System were included in the analysis. The study primarily includes studies in the literature that investigate the similarities of banks with various methods using financial indicators, compare and/or rank banks. After the third part where the method of the research is introduced, the findings and results from the research are given.

II. LITERATURE REVIEW

Alam et al. (2000) analyzed the banks ' net profit-loss ratios for 1992 using the fuzzy clustering and artificial neural networks approach [8]. The aim of the study is to classify banks that have potentially failed by taking advantage of financial ratios. According to the results obtained from the analysis, it was determined that both methods had consistent and successful results in classification.

Boyacıoğlu and Kara (2007), tried to estimate the financial strength ratings of 18 banks between 2001 and 2005 using artificial neural networks and multivariate statistical analysis techniques [9]. When the validity of the model was tested, it was found that there was no significant difference between the predictive performances of the applied techniques.

Keçek and Cinser (2008) classified Turkish commercial banks with clustering analysis and discriminant analysis of rates derived from their 2005 financial statements [10]. In the study, banks with similar characteristics in terms of their financial ratios were grouped by clustering analysis. Discriminant analysis was applied to reveal variables of greater importance in groups obtained by clustering analysis.

Doğan (2008) analyzed the financial ratios of commercial banks operating in the Turkish Banking System between 1998 and 2006 with a clustering analysis [11]. The aim of the study is to determine the financial performance of banks using the clustering analysis technique and to identify financially similar banks and to create a complementary technique to the techniques used by banks.

Wu et al. (2009), they sorted banking performance using TOPSIS, VIKOR and SAW methods [12]. The main criteria and sub-criteria of finance, customer, internal process, learning and development were used in the study. The bank with the best performance was determined by ranking the three banks whose performance was evaluated in the analysis.

Unvan and Tatlıdil (2011) analyzed logistics, probit regression and discriminant analysis according to the financial ratios of banks operating in the Turkish Banking System between 2002 and 2008 [13]. The aim of the study is to determine the best model of the financial ratios that are effective in the probability of bankruptcy of banks with the help of the methods used. The result was that discriminant analysis was the most appropriate method with selected variables to predict the financial situation of the banks.

Gökgöz et al. (2013), March, June, and September 2012 "Financial Robustness Indicators" of Turkish deposit and participation banks using Fuzzy c-Means Clustering analysis classified [14]. The results of the study concluded that the financial size of the banks did not have a significant effect on grouping and that the participation banks were clustered together.

Aydın and Başkır (2013) classified the 2012 capital adequacy ratios of 44 banks operating in Turkey using clustering analysis and multidimensional scaling method [15]. According to the results obtained from the analysis, similar results were reached in terms of classification in both methods.

Akgül and Başkır (2013) compared the similarities in terms of the asset size of the banks in the Turkish Banking System between 2008 and 2012 with the results of clustering analysis using Ward technique and PAM algorithm [16]. According to the results from the study, it was determined that the cluster groups obtained when the data used in the analysis was standardized were the same. However, the cluster groups obtained when the data used was processed without being standardized differed by years.

Yilmaz and Uzgören (2013) classified the provinces in Turkey according to their banking performance using nine criteria [17]. According to the results obtained from the study, it was determined that 6 groups were formed when the provinces in Turkey were grouped and that Istanbul and Ankara formed a separate cluster group on their own.

Ginevičius and Podviezko (2013) evaluated the financial stability of commercial banks in Lithuania between 2007-2009 using the methods SAW, TOPSIS, COPRAS and Promethee 2 [18]. According to the findings of the analysis, it was concluded that banks operating in Lithuania experienced a fluctuation in terms of financial stability.

Sedaghat (2013) aimed to determine the importance of human resources, management, and property performance to improve the efficiency of banks (state, private and semi-private) operating in Iran [19]. To achieve this goal, TOPSIS, VIKOR and SAW methods were utilized. According to the results, among the three productivity dimensions, management performance is of greater importance in human resources and financial efficiency is of the highest importance for all private banks.

Saçcı ve Sayılgan (2014) classified 28 local banks of systemic importance in Turkey using their 2012 financial indicators using clustering analysis method [20]. The result was that 7 banks of the highest systemic importance were clustered separately from other banks.

Çelen (2014) evaluated the financial performance of 13 Turkish deposit banks in 2010 using the TOSIS method using capital weights, balance sheet, liquidity, profitability ratios, income-expense structure, and asset quality criteria [21]. The normalisation process was applied with the TOPSIS method and the maximum and minimum values were determined between the alternatives and the comparisons were made and consistent results were obtained.

Wanke et al. (2016), 88 banks operating in South Asia between 2010 and 2013 were subject to performance evaluation based on capital adequacy, earnings, asset quality, liquidity, market sensitivity criteria [22]. Using fuzzy multi-criteria decision-making techniques, the variables included in the analysis were found to have a significant effect on the efficiency of banks.

Çalış and Baynal (2016) aimed to cluster two hundred customers belonging to a bank branch operating in Turkey with twelve different variables and to develop sales strategies according to customer profile in the resulting cluster groups [23]. Three cluster groups were obtained in the study. The first cluster consisted of 45-51 years old, primary school graduates and retired male customers, while all of the customers in this cluster were found to have disrupted their credit payments. The second cluster has created a customer profile consisting of 24-30 years old, working single customers with normal payment status in credit payments. The last cluster was made up of male customers aged 38-44, public employees, and there were no problems with loan payments.

Rençber and Avcı (2018) evaluated the WASPAS method using the capital adequacy ratios of banks traded in BİST between 2012 and 2017 [24]. The results of the study showed that Albaraka, Development and TSKB Banks were the best in terms of capital adequacy, while QNB Finansbank and Deniz bank were the lowest in terms of capital adequacy.

Tekin and Temelli (2020) examined the banks operating in Turkey between 2009 and 2018 using 7 different capital ratios using K-means clustering method [25]. According to the results obtained in the analysis, it was observed that public banks were in the same cluster together in all years, while private banks had no significant co-clustering status.

III. K-MEANS CLUSTERING ALGORITHM

Clustering is one of the widely used knowledge discovery techniques to reveal structures in a dataset that can be extremely useful to the analyst [26]. K-Means is a kind of classical partitioning method, which partitions a collection of documents into k clusters (groups, which is determined at the beginning) ([27], [28]).

The k-means algorithm is an iterative algorithm, which can be described by the following steps [29].

Step 1: Determine the number of clusters (determine value for k)

Step 2: Select k points (objectives) at random as cluster centers,

Step 3: Assign points to their closest cluster center

Step 4: Calculate new centers

Step 5: Repeat steps 2, 3 and 4 until the same points are assigned to each cluster.

IV. DATA DESCRIPTION AND ANALYSIS

We cluster 46-unit banks with K-means algorithm using Euclidean distance with parameters: Total Assets, Total Credits, Total Deposits, Total Equity, Paid in Capital, Net Profit/Loss. Since there are three different type of banks in the banking system of Turkey, we assume the value of k of the algorithm is three. In other words, we split the banks into three clusters with respect to six parameters which are related to banks' capital adequacy and also related to their financial performance. Since the second step of the algorithm is to randomly select k points as initial cluster centers, we can randomly select any k points inside or outside the dataset. These points will initially be the centroid of each cluster. Since different cluster centers may lead different findings for any k-means analysis, this step can be thought as one of the drawbacks of the algorithm ([30], [31], [32]). To minimize this drawback, we decided to use all possible initial centers which are derived from inside the dataset. Since there are 46-unit banks in the Turkish Banking System and since we split the banks into three clusters, there are 15810 different choices to select initial centers. To minimize this drawback, we run the k-means algorithm 15810 times. Table 3 presents 4 Cluster

Groups built by k-means algorithm with number of occurrence frequencies with respect to financial indicators.

TABLE 3. RESULTS OBTAINED FROM K-MEANS CLUSTERING WITH FINANCIAL INDICATORS

Cluster Groups	Cluster 1	Cluster 2	Cluster 3	Frequency
Cluster Group 1	A, B, C, E, K, L, AJ	D, F, G, H, I, M, N, O, P, R, S, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AY, AZ	J, T, AF, AV	14328
Cluster Group 2	A	B, C, E, K, L, AJ	D, F, G, H, I, J, M, N, O, P, R, S, T, U, Z, V, Y, Z, AA, AB, AC, AD, AE, AF, AG, AH, AI, AK, AL, AM, AN, AO, AP, AR, AT, AS, AU, AV, AY, AZ	846
Cluster Group 3	A, B, C, K	D, F, G, H, I, J, M, N, O, P, R, S, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	E, L, T, AF, AJ	4
Cluster Group 4	A, B, C, E, K, L, AJ	D, F, G, H, I, J, M, N, O, P, R, S, T, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AF, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	------	2

As seen from Table 3, four different cluster groups (Cluster Group 1, 2, 3 and 4) constructed when we split the banks into three clusters with respect to financial indicators. Compared to the other cluster groups, Cluster Group 1 has the highest occurrence frequency value. In other words, Cluster Group 1 was obtained with 14328 different initial centers. Only Cluster Group 4 could not split naturally into three clusters. In addition, Cluster Group 4 only built by two different initial centers and banks naturally split into two clusters.

Since the existence of positively high and statistically significant relation between frequencies and Silhouette index is known ([33], [34], [35]) we consider the frequencies of the cluster group and decide the most accurate one. Silhouette index is well known way of estimating the number of clusters in a dataset [36] and also same method can be used to decide which cluster group is more accurate. For this reason, we construct Table 4 to examine each cluster of cluster group with the highest frequency (Cluster Group 1). In other words, Table 4 illustrates the type of banks in each cluster belongs to Cluster Group 1.

TABLE 4. CLUSTER GROUP 1: FINANCIAL INDICATORS

Clusters	Members	Type of Members
Cluster 1	A, B, C, E, K, L, AJ	**3 Public Bank,** 4 Private Bank
Cluster 2	D, F, G, H, I, M, N, O, P, R, S, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AY, AZ	24 Private Bank, 12 Development and Investment Bank
Cluster 3	J, T, AF, AV	3 Private Bank, 1 Development and Investment Bank

As seen from Table 4, all public banks are belonging to same cluster with 4 private banks. Private Banks are distributed to all clusters, but they are mostly belonging to Cluster 2 with development and investment banks. Cluster 2 and Cluster 3 both consist of private banks and development and investment banks.

In the second part of the analysis, our aim is again to split the banks into three clusters with k-means algorithm using Euclidean distance according to the training status and gender of its employees. In this study, we named these variable group as employee profile. This group consists of 12 variables, such as total number of employee (men/women), graduation from different type of education (elementary, high school, bachelor, master and PhD) system (men/women) and total number of branches of each bank. As in the first part of the analysis, we run the k-means algorithm 15810 (number of possible initial centers from inside the dataset) times. Table 5 presents 6 Cluster Groups built by k-means algorithm with number of occurrence frequencies with respect to employee profile. As seen from Table 5, six different cluster groups (Cluster Group 1, 2, …, 6) constructed when we split the banks into three clusters with respect to employee profile. Cluster Group 1 has the highest frequency, which implies that this cluster group is more accurate than the other groups. However, it has seen that there are lots of different methods ([37], [38], [39], [40], [41]) that we can apply when we need to examine which cluster group is more accurate. Generally, these methods are valid to decide the parameter k of the K-means clustering method. In other words, they are helpful to find accurate number of clusters which gives the most similarity and/or dissimilarity of the dataset (objectives).

TABLE 5: RESULTS OBTAINED FROM K-MEANS CLUSTERING WITH EMPLOYEE PROFILE

Cluster Groups	Cluster 1	Cluster 2	Cluster 3	Frequency
Cluster Group 1	A, B, C, E, K, L, T, AF, AJ	H, J, AA	D, F, G, I, M, N, O, P, R, S, Y, U, V, Y, Z, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	13043

Cluster Group 2	A, B, C, K, L, AJ	E, J, T, AF	D, F, G, H, I, M, N, O, P, R, S, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	1243
Cluster Group 3	A, K	B, C, E, J, L, T, AF, AJ	D, F, G, H, I, M, N, O, P, R, S, U, Z, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AR, AT, AS, AU, AV, AY, AZ	386
Cluster Group 4	A, B, K, AJ	C, E, J, L, T, AF	D, F, G, H, I, M, N, O, P, R, S, U, Z, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AR, AT, AS, AU, AV, AY, AZ	230
Cluster Group 5	A, B, K	C, E, J, L, T, AF, AJ	D, F, G, H, I, M, N, O, P, R, S, U, Z, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AR, AT, AS, AU, AV, AY, AZ	205
Cluster Group 6	A, B, C, K, AJ	E, J, L, T, AF	D, F, G, H, I, M, N, O, P, R, S, Y, U, V, Y, Z, AA, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	73

As we mentioned before, Cluster Group 1 was obtained with 13043 different initial centers which means that this group is more accurate than the other cluster groups in case of their occurrence frequencies. To examine the most accurate cluster group (Cluster Group 1), Table 6 is constructed.

TABLE 6. CLUSTER GROUP 1: EMPLOYEE PROFILE

Cluster	Members	Type of Members
Cluster 1	A, B, C, E, K, L, T, AF, AJ	**3 Public Bank**, 6 Private Bank
Cluster 2	D, F, G, I, M, N, O, P, R, S, Y, U, V, Z, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AV, AY, AZ	21 Private Bank, 13 Development and Investment Bank
Cluster 3	H, J, AA	3 Private Bank

As seen from Table 6; when we cluster the banks according to their employee profile, it has been determined that all public banks are in the same cluster with 6 private banks (Cluster 1). All development and investment banks are in the same cluster with 21 private banks (Cluster 2). The results obtained so far point out that the remarkable finding is the distribution of private banks in all clusters. In addition, three private banks built Cluster 3.

Table 7 illustrates the accurate cluster group based on financial indicators and employee profile.

TABLE 7. COMPARISON OF CLUSTER GROUP 1: FINANCIAL INDICATORS & EMPLOYEE PROFILE

Cluster	Type of Members (Financial indicators)	Type of Members (Employee Profile)
Cluster 1	**A, B, C, E, K, L, AJ**	**A, B, C, E, K, L, AJ** T, AF
Cluster 2	D, F, G, H, I, M, N, O, P, R, S, Y, U, V, Y, Z, **AA**, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, AY, AZ	D, F, G, I, M, N, O, P, R, S, Y, U, V, Y, Z, AB, AC, AD, AE, AG, AH, AI, AK, AL, AM, AN, AO, AP, AS, AR, AT, AU, **AV**, AY, AZ
Cluster 3	J, T, AF, **AV**	H, J, **AA**

When we compare the banks clustered in terms of both financial indicators and employee profile, it is seen that the public banks are in the same cluster in both analyses with different number of private banks. When we examine Cluster 1 derived from analysis with respect to financial indicators, we observe that the banks A, B, C, E, K, L and AJ belong to same cluster. The remarkable finding derived from the analysis with respect to employee profile, the banks T and AF are belong to same cluster with A, B, C, E, K, L and AJ (which construct Cluster 1 of the analysis with respect to financial indicators). In addition, T and AF are private banks.

We have one more remarkable finding. This finding shows that the difference between Cluster 2 and Cluster 3 is the banks AA and AV belongs to different clusters. All other banks belong to the same cluster.

V. CONCLUSION

This research conducted financial performance and employee profile analysis on 46 unit-banks from Turkish Banking System using K-means algorithm. To minimize the drawback of K-means, we run the algorithm for all possible initial centers inside the dataset and decide the accurate cluster group by their occurrence frequencies. In other words, banks are divided into three different clusters by the help of all possible initial centers from inside the dataset based on two different type of variable groups. One of the variable group consists of financial indicators related to capital adequacy of banks and the other one consists of employee profile variables related to their training status (men/women) and gender of their employee. The main aspect of this study is to determine the similarities or/and dissimilarities in the findings obtained from these two different analyzes.

In conclusion, the findings of this study can be summarized as follows: 1-All public banks are in the same cluster with some of private banks. 2- It was observed that all private banks are distributed to all clusters. 3- Development and Investment banks are belong to two clusters when we examine the similarities based on capital adequacy. Development and Investment banks belongs to one cluster when we examine the banks based on employee profile. 4- It was observed that only 4 banks (T, AF, AA, AV) replace their clusters when we changed the analysis based on financial indicators to employee profile. Three of them (T, AF, and AA) are private banks and one of them is investment and development bank.

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