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Research Article

BAYESIAN NETWORK MODEL OF TURKISH FINANCIAL MARKET FROM YEAR-TO-SEPTEMBER 30TH OF 2016

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ABSTRACT

Bayesian Networks (BNs) are a useful graphical probabilistic structure for visualizing and understanding the dependencies of random variables. In this study, July 15 coup attempts' effects on Turkish Financial Market are analyzed with the BN approach. To this end, 31 Istanbul Stock Exchange (BIST) return indexes and seven foreign exchange rates (CNY, EUR, GBP, JPY, SAR, RUB, and USD) from year-to-September 30th of 2016 are examined. BN structure is learned (predict) via Greedy Thick Thinning algorithm with K2 prior from the dataset and is expertized. BN model is validated and trained from real dataset instead of generated data from the established model. The BN is called Trained Bayesian Network (TBN) model. TBN is validated and the beliefs of TBN are updated again by dataset via learning parameters with Expectation Maximization (EM) algorithm. BNs have not before been used to relate the presence/absence of BIST return indexes with foreign exchange rates. Accuracy rate (AUC) of the TBN model to generating the real data is calculated as 85.5% percent. TBN model has simplified the Market relations with conditional probability.
Keywords: Bayesian network, structure learning, Istanbul stock exchange return indexes, foreign exchange rate, Receiver Operating Characteristic (ROC).

1. INTRODUCTION

Bayesian Networks (BNs) are very popular and mostly used for understanding complex conditional relation structures. These techniques suggest a mathematical model for representing uncertain information with accruing probabilities of variables by Directed Acyclic Graph (DAG) structures [1, 2]. The structure of model is reflected by the graphical part of BNs, while local interactions among correlated variables are calculating via conditional probability distributions. These features make the BNs attractive for all decision-making and modelling areas.

In financial analysis, BNs are being used for bankruptcy or failure prediction [3-5], credit risk modelling or credit scoring [6-8], portfolio risk analysis [9], firm performance evaluation [10], company appraising [11], supply chain analysis [12] etc. on the business and finance area up to the present. BNs have ascending popularity especially, in the risk management and assessment area [13].

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As it is clear from the literature, researchers use BNs for financial risk assessment to evaluate an organization. BN model established in estimating stock prices for determination, validation and forecasting, respectively is a better predictor than AR, MA, ARMA and ARCH models [14]. For credit rating, different MCMC BN classifiers from the three real-life datasets are compared and performed very well with the support of the Markov Blanket concept [15]. The Czech engineering sector and its sub-sectors have been investigated by BN model established with expert knowledge and data on 4400 financial reports obtained between 1993 and 1997 [16]. BN is compared with neural network on financial rating analysis [17]. Ant Colony Optimized BN model is applied with two different algorithms (ChainACO and K2ACO) to find the factors that affect the rural property mortgages. ChainACO is cheaper than K2ACO, but K2ACO has better BN structure [18]. The results of the BN model developed for estimating the Up/down analysis of Nikkei, Dow30 and FSTE100 are compared with the psychological line and trend prediction analysis and the BN algorithm is given a higher profit than the conventional analysis [19]. In the studies with the credit rati ng system related to the BN evaluation model, the cause and effect relationship of the BN was used in developing a risk analysis tool for bank credits and the dynamic model is criticized for adaptation into new situation or environment by adding a node [20]. A review of BN references about maintenance applications, dependability of variables and risk analysis is presented and dependability analyses methods namely Fault Trees (FT), Markov Chains (MC) and Petri Nets (PN) are discussed [21]. BNs are used to improve risk profiles of contractors [13]. BN model is presented to analyze portfolio returns with basic economic variables from Polish financial market [22]. One of the studies takes advantage of BN using financial indexes to show the dissimilarities between different industries [23]. BN is used to turn an account for customer satisfaction [24]. BN models are proposed to demonstrate the practicability of financial risks' Bayesian modelling on e-logistics investments [25].

The aim of us is to predict the relation between the 31 return indexes of BIST and 7 foreign exchange by using BN. Three subheadings of BNs as structure learning, parameter learning and model validation, respectively have also been studied via GeNIe, which is general purpose-development environment for graphical decision-analytic models [26]. In the structure learning; Greedy Thick Thinning algorithm, which is heuristic search algorithm, with K2 prior has been used for structure learning of BN from the *training-dataset*. The BN is finalized after expert opinion by revising the direction of the arc between the nodes with taking into account the relations. In the parameter learning, parameter of model is learnt with EM algorithm and beliefs of BN are updated via the *validation-dataset*. And then, BN Model is validated on *test-dataset* via 10-fold cross-validation with zero seed. The model has been successfully obtained and tested. Consequently, The BN is interpreted with 12 different scenarios for decreasing, increasing and recession positions of indexes and foreign exchange rates. Four scenarios are queried from the TBN model.

2. MATERIALS AND METHOD

In this section, we mention examined datasets and methods, which is used for analysis.

2.1. Materials

In the present study, we examined 31 return indexes of BIST and 7 foreign exchange rates year-to-Sept 30, 2016. Data, which is presented in Appendix Table A.1, is collected from borsaistanbul.com and tcmb.gov.tr by the end of workday and organized with regard to the ratio of percentage change of BIST return indexes and foreign exchange rates. Since indexes are continuous variables and generally have a normal distribution. Those ratios are also continuous but are categorized to construct BN model. However, some methods are available discretizing the indexes [22]. Thus, the ratios are binned into intervals as decreasing (< -.05 percent), increasing

(> .05 percent) and recession (-.05< <.05). Afterward s, data was separated into three terms for analysis. *1st term data (training-dataset; January-April, 30th)* is used for constructing BN structure via Greedy Thick Thinning (GTT), which is a heuristic search method with K2 prior. *2nd term data (validation-dataset; May-July, 15th)* is used for training BN via learning parameters with EM algorithm and updating beliefs of BN. *3rd term data (test-dataset; July, 18th-September, 30th)* is used for validating TBN via 10-crossvalidation with zero seed and updating beliefs of TBN.

2.2. Method

The methods used in the study and the requirements for the use of these methods will be discussed in this section.

2.3. Bayesian Network

BNs are effective tools for modelling complex problems involving uncertain information [27]. Best of the inspiring characteristics of the BN's is evidence propagation. The mentioned characteristic allows updating probabilities of each node bi-directionally from one node through whole structure with a new knowledge [28]. BNs are used to construct mathematical models by taking advantage of the conditional probability values to determine the interaction and relationship between variables. BNs contain two main information; one of DAG for determining the relation of variables and the other is mathematical equations to make inference on parameters of the model. Features of graph and probability theory are combined [29, 30]. A DAG is a mathematical object defined as the pair $G=(B,C)$, where B is the set of nodes (variables) and C is the set of directed edges (arcs) connecting pair of nodes. An example of DAG is shown in Fig. 1. Arc represent dependencies between nodes(variables).

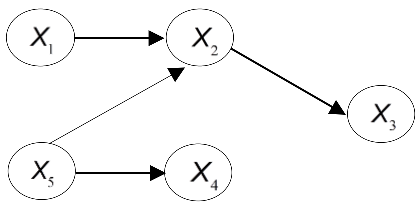

Figure 1. An Example of DAG

BN is given for K variables $(i=1,\ldots,K, K\in B)$. Each node X is associated with the conditional probability distribution of the corresponding variable of interest given its parents, $p\left(X / pa\left(X_i\right)\right)$. We can represent the joint probability distribution of $\left(X_1,\ldots,X_K\right)$ according to DAG is represented Eq. (1).

$$p\left(X_1,\ldots,X_K\right)=\prod_{i\in B} p\left(X_i / pa\left(X_i\right)\right) \tag{1}$$

Mathematical model of Fig. 1 is presented Eq. (2).

$$p\left(X_1,X_2,X_3,X_4,X_5\right)=p\left(X_1\right)p\left(X_3 / X_2\right)p\left(X_2 / X_1,X_5\right)p\left(X_4 / X_5\right)p\left(X_5\right) \tag{2}$$

The BN can generally be dealt with under three main headings: structure learning, parameter learning and model validation. Structure learning algorithms are categorized in two groups as score-based algorithms and constraint-based algorithms [2, 31]. At the base of score-based search algorithms is to assign a score to each possible BN and specify the network that maximizes this score by heuristic search algorithms. On the other hand, constraint-based algorithms learn the network structure by using the Markov properties of BNs together with conditional independence tests and examining the probabilistic relationship between variables. After that, network graph structure is constructed as a BN. Constraint-based structure learning algorithms are originally based on Inductive Causation (IC) algorithm [32]. Constraint-based structure learning methods with heuristic search algorithms are generally used to analyze BNs with relations between the variables as DAG structures. Although there is many search procedures in the literature, the greedy search algorithm is generally used as it is in this study.

2.4. Greedy Thick Thinning

In many studies on structure learning of BNs have been discussed the GTT algorithm with K2 prior [31, 33, 34] is more successful than the other Greedy Search algorithms [1, 24, 35-37].

Greedy search is one of the methods for escaping local maxima with random restarts and known as a useful simple heuristic search approximation algorithm [38, 39]. GTT, a constraint-based heuristic search algorithm for BN structure learning, is based on the Bayesian search approach [35]. Firstly, The GTT algorithm creates a null graph based on the probabilities of the variables (nodes) and their conditional probabilities. GTT then adds an edge between the nodes if there is no conditional independence between the nodes. Finally, because of repetitive checks, the edges of the connected nodes that are independent on the graph are subtracted if any. In short, the GTT algorithm is a topology optimizer that exploits variables and dependency relations.

If there is sufficient information about the sub-factors and interaction of the study, the BNs' DAG model can be manually constructed within the framework of the expert opinion. Although we have enough knowledge about the variables of our model, it is necessary to learn (predict) the model from the existing data in the construction of the DAG model of the complex structure about financial data. The final decision of the model's DAG structure with the expert opinion is important in that the analysis produces meaningful results.

3. RESULTS

One of the heuristic search algorithms known constraint-based structure learning method Greedy Thick Thinning algorithm with K2 prior used for constructing BN Model via GeNIe 2.2 Academic Edition.

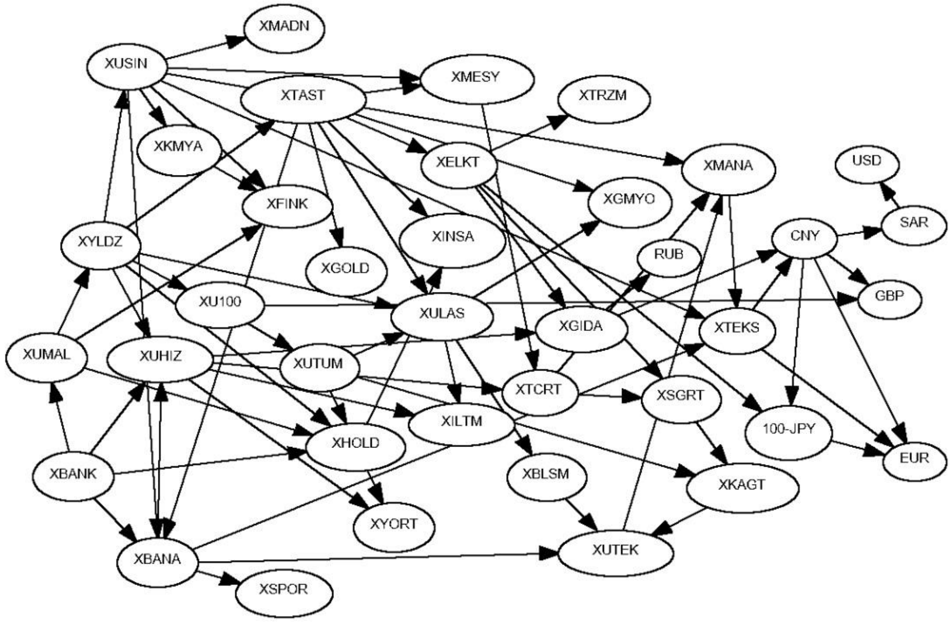

Figure 2. Trained BN(TBN) structure (Main Model) of return indexes and exchange rate

The BN structure of 31 return indexes and 7 exchange rates have calculated based on the 1st term data, using the GTT algorithm with K2 prior (see Fig. 2). BN is established by using the expert opinion to determine the dependency relations (parent/child) between the nodes.

BN model parameters are learnt (predict) from 2nd term data with $\log(p) = -998.574309$ via Expectation Maximization (EM) algorithm. BNs make it easy to see the model dynamically. After learning the parameters of BN model, The BN is validated via 10-fold cross-validation method with zero seed. In the new data stream of the model variables, the networks can be updated and new output can be generated by focusing only on the affected areas of the network. BNs can be transparent and supervised. Then, beliefs of BN main model are updated from the *2nd* term data and BN is called Trained Bayesian Network (TBN) Model.

In the performance analysis of the model where multiple nodes are targeted, the cross-validation scheme is quite successful [40]. TBN model is tested and is performed from *3rd* term data. XGMYO, XU100, XUTUM, XYLDZ indexes, which are the most effected variables on the TBN, are compared using the Receiver Operating Characteristic (ROC) curve, which is expressed as the ratio of true positives to false positives [41], the Area under the ROC (AUC) are shown in Fig. 3. Then, beliefs of TBN model are updated from the *3rd* term data.

AUC rates values, which are ranges between 0 and 1, are shown that how well the TBN model can distinguish between of BIST return indexes to foreign exchange rates (absence/presence) in Table 1.

Accuracy rate of the TBN model to generating the real data (*test-dataset*) is calculated as 85.5%. Note that this result is obtained for the overall accuracy rate with absence and presence accuracy rates. Usages of real data ensure that the TBN model is re-trained. Thus, it was possible to calculate the conditional probabilities in different situations in this model.

Three different return indexes (XUTUM, XUHIZ, XBANK) and one foreign exchange rate were examined for three different conditions (decreasing, recession, increasing), separately and 12 different scenarios are tested in *Table 2*.

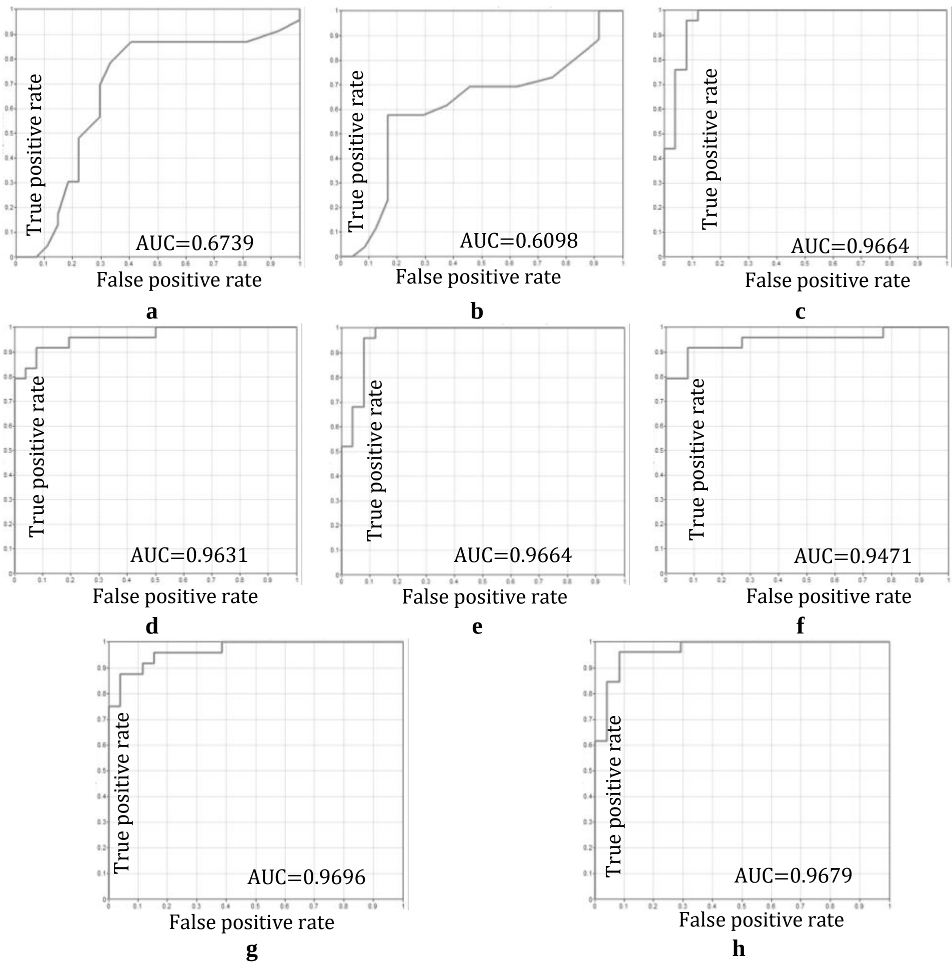

Figure 3. Receiver Operating Characteristic (ROC) curves and Area Under the ROC (AUC) for TBN model of us generated by Greedy Thick Thinning algorithm with K2 prior are shown; (a) ROC curve for decreasing condition of XGMYO, (b) ROC curve for increasing condition of XGMYO, (c) ROC curve for decreasing condition of XU100, (d) ROC curve for increasing condition of XU100, (e) ROC curve for decreasing condition of XUTUM, (f) ROC curve for increasing condition of XUTUM, (g) ROC curve for decreasing condition of XYLDZ, (h) ROC curve for increasing condition of XYLDZ.

Table 1. Accuracy rates (in percentage) of four indexes for BN model

Indexes	**Accuracy**	**Absence**[1]	**Presence**[2]
XGMYO	70.0	57.7	87.0
XU100	92.0	91.67	96.0
XUTUM	90.0	91.67	92.0
XYLDZ	90.0	87.5	92.3

1. Accuracy rate for index value decreasing.
2. Accuracy rate for index value increasing.

Table 2. Evidential Scenarios About Some Important Variables

	SCENERIOS											
	I. Scenario			**II. Scenario**			**III. Scenario**			**IV. Scenario**		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
XUTUM												
Decreasing	100			72.5	58.4	19.8	86.2	72	11.5	51.4	46	48.9
Recession		100		3	3	1	3.4	2.9	.9	2.2	2	2.2
Increasing			100	24.5	38.7	79.2	10.5	25.1	87.6	46.4	52	48.9
XU100												
Decreasing	99.98	.10	.04	72.5	58.3	19.7	86.1	71.9	11.4	51.4	46	48.9
Recession	.01	99.75	.01	3.1	3	1	3.4	3	.9	2.3	2	2.2
Increasing	.01	.15	99.95	24.4	38.6	79.3	10.4	25.1	87.6	46.4	52	48.9
XYLDZ												
Decreasing	99.96	86.1	.01	75.3	60.5	20.5	89.5	74.7	11.9	53.3	47.7	50.8
Recession	.03	13.6	.02	.4	1.1	.3	.2	.3	.6	.4	.4	.4
Increasing	.01	.3	99.7	24.4	38.4	79.2	10.3	25	87.5	46.3	51.9	48.8
XUHIZ												
Decreasing	74.5	70.7	26	100			79	24.2	25.3	52	47.1	51
Recession	9.2	10.8	6.3		100		7.4	24.2	7	7.6	6.5	8.3
Increasing	16.3	18.5	67.7			100	13.6	51.6	67.7	40.4	46.4	40.6
XGMYO												
Decreasing	62.2	46.2	26.9	53.8	47.7	33.2	58	52.9	31.1	45.5	43.1	44.7
Recession	2	4.1	4.5	2.3	3.2	4.4	2.3	2.7	4.2	3.2	3.4	3.2
Increasing	35.8	49.7	68.6	43.9	49.1	62.4	39.7	44.4	64.7	51.3	53.4	52.1
XGIDA												
Decreasing	58	57.2	42.4	57.4	69.6	38.2	57.4	54.7	43.2	48.3	33	56.2
Recession	7.7	7.6	3.7	9	11.7	.6	7.9	5.3	3.7	5.6	4.8	6.1
Increasing	34.3	35.2	53.9	33.6	18.7	61.2	34.7	40	53.2	46.1	62.2	37.7
XBANK												
Decreasing	83.3	74.5	10.5	74.3	45.1	15.9	100			49.7	44.5	47.2
Recession	5.7	5.3	2	1.9	12.1	4.9		100		4	3.8	3.9
Increasing	11.1	20.3	87.5	23.8	42.8	79.2			100	46.3	51.7	48.9
XHOLD												
Decreasing	82.3	24.1	10.6	63.9	51.1	24.1	75.2	62.9	16.6	47.8	43.8	45.9
Recession	10.1	56.8	3	10.7	11.9	3.8	12.1	20.4	2.1	7.8	7.2	7.6
Increasing	7.7	19.1	86.4	25.9	37	72.1	12.7	16.6	81.3	44.4	49	46.4
XGOLD												
Decreasing	51.2	51.4	52.8	52.1	51.6	51.9	51.4	51.6	52.6	51.9	52	52
Recession	2.3	2.4	3.4	2.3	2.8	3.5	2.4	2.6	3.3	2.8	3	2.8
Increasing	46.5	46.2	43.8	45.6	45.7	44.6	46.2	45.8	44.1	45.2	45	45.2
USD												
Decreasing	45.3	44.9	42.3	44.7	42.5	43.1	45.4	44.4	42.3	100		
Recession	9	9.1	10.6	9	8.1	11	9	9.5	10.5		100	
Increasing	45.7	46	47.2	46.3	49.4	45.9	45.6	46.1	47.2			100

Some evidential scenarios have given in Table 2. Each scenario gives a percentage of 100% for one case. All cases are especially conditional probabilities. This means that, for example if we know XUTUM will decrease, XU100's decreasing probability will be 99.98%. On the other hand, posterior probabilities of recession and increasing are .01%.

Note that, the probability values of indexes and foreign exchange rate, which are given in following Fig. 4-7, are only the evidence values. They are not to be the conditional probabilities. DAG models which are sub models of TBN are given following for illustrate the Scenarios.

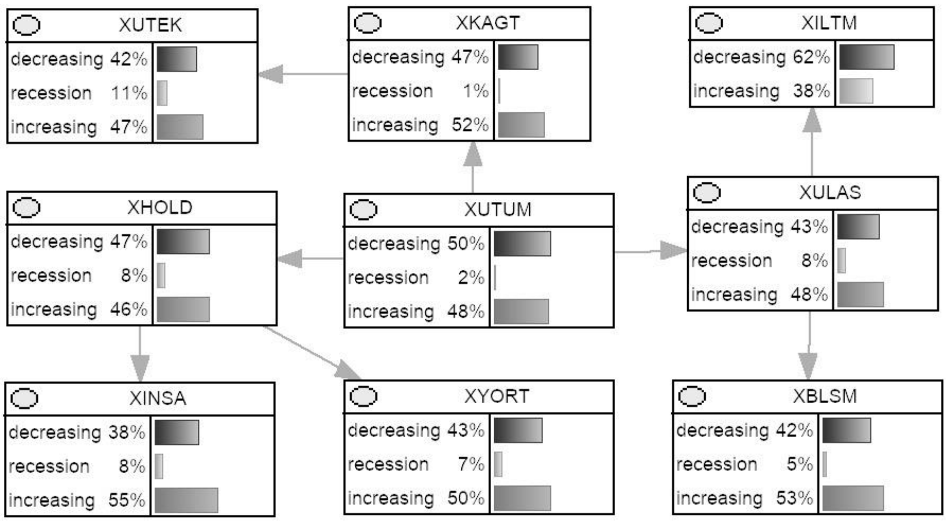

Figure 4. DAG model of Scenario-A with Evidence values

Scenario-A: Index values of XUTUM are examined as Scenarios-A for decreasing, recession, and increasing conditions,respectively. The mathematical model of Scenario-A is given in Eq. (3).

$$\begin{aligned}&p\left(XUTUM,XULAS,XKAGT,XHOLD,XBLSM,XILTM,XINSA,XYORT\right)=p\left(XUTUM\right)\\&p\left(XKAGT/XUTUM\right)p\left(XILTM/XULAS\right)p\left(XULAS/XUTUM\right)\\&p\left(XBLSM/XULAS\right)p\left(XINSA/XHOLD\right)p\left(XHOLD/XUTUM\right)p\left(XYORTXHOLD\right)\end{aligned} \tag{3}$$

DAG of Scenario-A is an abbreviated version of BN model given in Fig. 5. Decreasing, recession and increasing probabilities of model are similar for XHOLD, XKAGT, XULAS and XUTUM. XUTUM index directly affect previously mentioned indexes. In the Table 2, XBANK, XHOLD and XUHIZ indexes are made their declining and upward trends in enormous quantities with XUTUM. In addition to this, predicted probabilities of XGMYO are obtained 62.2% for decrease, 2% for recession and 35.8% for increase. The predicted probabilities of the XGOLD are 51.2%, 2.3% and 46.5%, respectively. If XUTUM index known recession, as can be understood from the Table 2, XGOLD index will not be much affected by the XUTUM index probabilities. The estimated probability of returns indexes and foreign exchange rates are not affected by the stock market indexes such as XGOLD. When XUTUM index given recessing, posterior probability of the XYLDZ index is 86.1% decreasing. But estimated recession probability is 13.6%. Likewise, posterior probabilities of other stock market indexes are calculated like the first scenario in Table 2. In other words, other financial instruments have not been affected by the prior knowledge of the XUTUM index. Furthermore, the conditional probabilities of the other indexes and the foreign exchange rates are calculated when the XUTUM index is given as evidence of an increasing. The calculated probabilities are similar to the decrease of the XUTUM index.

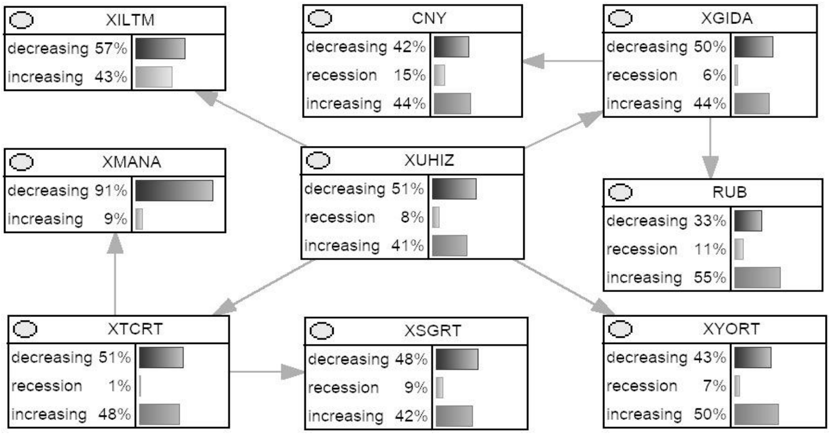

Figure 5. DAG model of Scenario-B with Evidence values

Scenario-B: Index values of XUHIZ are examined as Scenarios-B for decreasing, recession and increasing conditions, respectively. The mathematical model of Scenario-B is given in Eq. (4).

$$\begin{aligned} &p\left(XUHIZ, XYORT, XGIDA, XILTM, XBANA, XTCRT, RUB, CNY, XMANA, XSGRT\right) = p\left(XUHIZ\right) \\ &p\left(XYORT / XUHIZ\right) p\left(XBLSM / XUHIZ\right) p\left(RUB / XGIDA\right) p\left(XYORT / XUHIZ\right) p\left(CNY / XGIDA\right) \\ &p\left(XMANA / XTCRT\right) p\left(XTCRT / XUHIZ\right) p\left(XSGRT / XTCRT\right) \end{aligned} \tag{4}$$

In this scenario, while decreasing condition of XUHIZ index is known XUTUM, XU100, XYLDZ, XBANK indexes will be decreased by 70% - 75%. Besides, the probability of XGOLD, XGMYO and XGIDA indexes to take a decreasing value is between 50% and 55%. On the other hand, exchange rates are maintained the general probability values. They have an insignificant amount of relation to XUHIZ. It is shown Table 2 that, when the XUHIZ index is to be recession, other variables are moving in the range of 45% to 55% of the probability that they are not influenced by this situation. Also, increasing probabilities of the XUHIZ indexes are similar to decreasing probabilities.

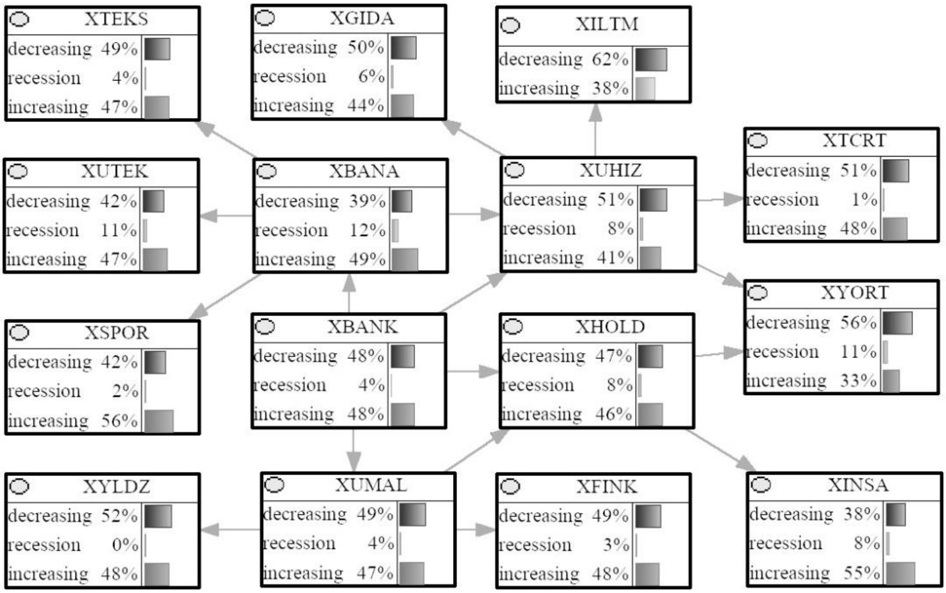

Figure 6. DAG model of Scenario-C with Evidence values

Scenario-C: Index values of XBANK are examined as Scenario-C for decreasing, recession and increasing conditions, respectively. The mathematical model of Scenario-C is given in Eq. (5).

$$
\begin{aligned}
&p\left(\begin{array}{l} XBANK, XUHIZ, XBANA, XUMAL, XHOLD, XYORT, XTCRT, XILTM, XGIDA, \\ XTEKS, XUTEK, XSPOR, XYLDZ, XFINK, XCONST \\ \end{array}\right) = p\left(XBANK\right) \\
&p\left(XTCRT / XUHIZ\right) p\left(XUHIZ / XBANA, XBANK\right) p\left(XBANA / XBANK\right) p\left(XILTM / XUHIZ\right) \\
&p\left(XGIDA / XUHIZ\right) p\left(XTEKS / XBANA\right) p\left(XUTEK / XBANA\right) p\left(XSPOR / XBANA\right) p\left(XYLDZ / XUMAL\right) \\
&p\left(XUMAL / XBANK\right) p\left(XFINK / XUMAL\right) p\left(XINSA / XHOLD\right) p\left(XHOLD / XUMAL, XBANK\right) \\
&p\left(XYORT / XHOLD, XUHIZ\right)
\end{aligned}
\tag{5}
$$

In Fig. 7 it is understood that, XBANK have a direct relation with XBANA, XUMAL, XHOLD and XUHIZ indexes and indirect relation with other variables. The Turkish banking sector is important in terms of showing the strength of the Turkish financial market. For this reason, Scenario-C has been formed with the XBANK index. In these scenarios, it is understood that the XBANK index and XUTUM, XU100, XYLDZ and XHOLD indexes generally act jointly. While XUHIZ index is shown a decreasing tendency in decreasing condition of the XBANK index, it is observed to be less affected in other cases. These arguments of XBANK index have negligible effect on the conditional probabilities of other variables.

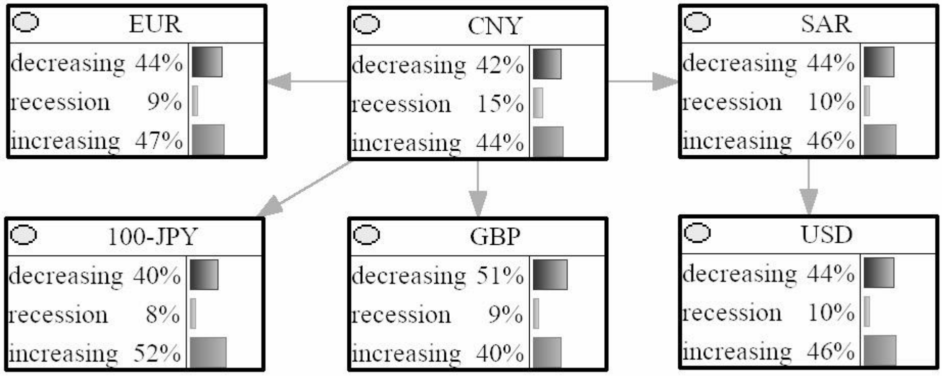

Figure 7. DAG model of Scenario-D with Evidence values

Scenario-D: Foreign exchange rate values of CNY examined as Scenario-D for decreasing, recession and increasing conditions, respectively. The mathematical model of Scenario-D is given in Eq. (6).

$$p\left(CNY,GBP,SAR,100-JPY,USD,EUR\right)=p\left(CNY\right)p\left(USD/SAR\right)p\left(SAR/CNY\right)$$
$$p\left(EUR/CNY\right)p\left(100=JPY/CNY\right)p\left(GBP/CNY\right) \quad (6)$$

CNY exchange rate has a direct relation with EUR, SAR and GBP. But, USD has an indirect relation with CNY. This information explains the positive trade relations that have developed in recent years with Asia and Africa. In addition, agreements for the use of national exchange rates in foreign trade may be effective in revealing the relationship between foreign exchange variables.

In addition, in Table 2 decreasing is given as prior for USD, EUR and GBP affected negatively. Although those were not affected in the recession prior, there was a tendency to increase in the given ascending prior state. XGIDA has shown a positive trend in the case of USD's recession and a negative trend with negligible impact from USD's increasing prior.

As a result, when the all scenarios are examined, XGOLD and foreign exchanges are not influenced by the tendency of the stock market indexes. It can be said that the characteristics of these three different types of investment instruments are different. Their interactions with each other are minimal. On the other hand, there is a similarity in homogeneous type of instrument data. It is maintained that, index variables have influenced by index variables, foreign exchange variables influenced by other foreign exchange variables. In addition, gold index shows an independent change from other two types of investment tools.

4. CONCLUSION

The model is designed for the day-to-day of 31 BIST return indexes and 7 foreign exchange rates from the beginning of the year to September 30, 2016. Predictions are made on the main model for the period after the coup attempt. The model has been established to monitor the first impact of the attempt on the market and so, does not reflect the profound impact that may arise in the long term.

The model has been set up differently from the normal BN and has been validated with real data set instead of the generated data from the established model. As a result, accuracy rate of the model has been calculated from the real dataset 85.5% percent. Usages of real data ensure that, BN model can be re-trained. Thus, it is possible to calculate the conditional probabilities of variables in different conditions in TBN model.

The results of analysis showed that BNs are an effective method for market research, considering the interaction between BIST returns indexes and foreign exchange rates. The government, using the information in the TBNs and the knowledge of Turkey Financial Market, they can make decisions backed by scientific and objective tool. To summarize, the dynamic nature of BNs not only defines the real situation, it also allows the Turkish economy to simulate any external impact (i.e., coup attempt) in real time.

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Conflict of interest

None of the authors of this paper have a financial or personal relationship with other people or organizations that could inappropriately influence or bias the content of the paper.

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Appendix

Appendix A: Codes and Descriptive Statistics

Table A.1 Variable Names, Codes and Desriptive Statistics

	INDEX CODE	INDEXES	MEAN	STDANDART DEVIATION
1	100-JPY	100 JAPANESE YEN	0.114	0.988
2	CNY	CHINESE YUAN	0.003	0.591
3	EUR	EURO	0.032	0.563
4	GBP	BRITISH POUND	-0.051	0.776
5	RUB	RUSSIAN ROUBLE	0.101	1.125
6	SAR	SUUDI ARABIA RIAL	0.018	0.631
7	USD	UNITED STATES DOLLAR	0.018	0.631
8	XGOLD	GOLD INDEX	0.126	1.093
9	XBANA	BIST MAIN	0.062	1.598
10	XBANK	BIST BANKS	0.065	1.818
11	XBLSM	BIST INF. TECHNOLOGY	0.058	1.397
12	XELKT	BIST ELECTRICITY	0.026	1.609
13	XFINK	BIST LEASING FACTORING	0.170	1.301
14	XGIDA	BIST FOOD BEVERAGE	0.027	1.622
15	XGMYO	BIST REAL EST. INV. TRUSTS	0.072	1.508
16	XHOLD	BIST HOLD. AND INVESTMENT	0.058	1.504
17	XILTM	BIST TELECOMMUNICATION	0.008	1.493
18	XINSA	BIST CONSTRUCTION	0.034	1.717
19	XKAGT	BIST WOOD PAPER PRINTING	0.003	1.333
20	XKMYA	BIST CHEM. PETROL PLASTIC	-0.018	1.346
21	XMADN	BIST MINING	0.198	3.720
22	XMANA	BIST BASIC METAL	0.158	1.903
23	XMESY	BIST METAL PRODUCTS MACH.	0.098	1.511
24	XSGRT	BIST INSURANCE	0.017	0.778
25	XSPOR	BIST SPORTS	0.295	2.892
26	XTAST	BIST NONMETAL MIN. PRODUCT	0.044	1.218
27	XTCRT	BIST W. AND RETAIL TRADE	-0.005	1.504
28	XTEKS	BIST TEXTILE LEATHER	0.123	1.560
29	XTRZM	BIST TOURISM	-0.018	1.940
30	XU100	BIST 100	0.045	1.409
31	XUHIZ	BIST SERVICES	-0.024	1.221
32	XULAS	BIST TRANSPORTATION	-0.172	1.875
33	XUMAL	BIST FINANCIALS	0.041	1.183
34	XUSIN	BIST INDUSTRIALS	0.052	1.262
35	XUTEK	BIST TECHNOLOGY	0.047	1.573
36	XUTUM	BIST ALL SHARES	0.042	1.356
37	XYLDZ	BIST STARS	0.040	1.372
38	XYORT	BIST INVESTMENT TRUSTS	-0.005	1.018