
Actionable Insights Through Association Mining of Exchange Rates: A Case Study

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Abstract— **Association mining is the methodology within data mining that researches associations among the elements of a given set, based on how they appear together in multiple subsets of that set. Extensive literature exists on the development of efficient algorithms for association mining computations, and the fundamental**

motivation for this literature is that association mining reveals actionable insights and enables better policies. This motivation is proven valid for domains such as retailing, healthcare and software engineering, where elements of the analyzed set are physical or virtual items that appear in transactions. However, the literature does not prove this motivation for databases where items are "derived items", rather than actual items. This study investigates the association patterns in changes of exchange rates of US Dollar, Euro and Gold in the Turkish economy, by representing the percentage changes as "derived items" that appear in "derived market baskets", the day on which the observations are made. The study is one of the few in literature that applies such a mapping and applies association mining in exchange rate analysis, and the first one that considers the Turkish case. Actionable insights, along with their policy implications, demonstrate the usability of the developed analysis approach.

Keywords - ***association mining; case study; finance; exchange rates; investment science; portfolio management***

I. INTRODUCTION

Data mining is the field of computer science that aims at discovering interesting and actionable insights from data [1]. Association mining is the subfield of data mining that analyzes association patterns in a transactions given database for elements of a given set [2,3]. The transaction database consists of transactions that consist of subsets of the element set. The most fundamental results of association mining are *frequent itemsets* in the form $\{Item_1, Item_2, ..., Item_n\}$ and *association rules* in the form $\{Antec_1, Antec_2, ..., Antec_n\} \Rightarrow Conseq$, which respectively report the items that frequently appear together in transactions, and the antecedent items that signal the existence of a consequent item[1]. Frequent itemsets are characterized by *support*, the percentage of transactions among all transactions that the itemset appears in. Association rules are characterized by *confidence*, the conditional probability of observing the consequent when the antecedents exist, besides support.

While extensive literature exists on the development of efficient algorithms for association mining computations [2,4], the fundamental motivation is that association mining reveals actionable insights and enables better policies. The applicability and usefulness of association

[1] In this paper, we will only consider the case with a single item in the consequent

mining is well-known in domains such as retailing [5,6,7], healthcare [8], and software engineering [9], where the transaction database contains real or virtual items in *market baskets* (individual transactions). For example, in retailing, items are the actual physical products (ex: milk, bread) puchased by customers in their purchase transactions (ex: shopping receipt at the supermarket), and each transaction corresponds to a market basket. However, it is not always clear how association mining can be applied to model data that does not contain actual items, but rather *derived items*. How can the data in these domains be transformed to a form that will enable association mining? Will the results be meaningful? This study is an application of association mining on such a *derived market basket data*, where the items are not really items, but are patterns (discretized values of changes in exchange rates) that are represented as items.

The database used in this study is composed of exchange rates for US Dollar and Euro, and Gold in the Turkish economy, throughout an 11 year period. The changes in exchange rates for the present day, and the three days before the present day, are discretized to obtain derived items. For association mining, the data set being used needs to have one of two features [10]: Firstly, it should contain extensive historical data, translating into a large number of rows. 11 years of data is stored in the constructed database. Secondly, there has to be a large number of items, so that their analysis can yield interesting results. Our database consists of items that represent the four days of three commodities, that can take up to 61 values each (30 intervals in each direction, and the case of no change), resulting in 732 potential items (of which 644 are observed), and satisfying this second condition.

This study contributes to the literature in two ways:

1) Association mining is used for *derived items*, rather than items that correspond to actual entities. The applicability of the methodology for this type of data is illustrated through a case study in the field of finance.

2) Association mining is used for analyzing exchange rate data from Turkey for the first time in literature. While other data mining techniques have been applied extensively for analyzing and specifically predicting exchange rates [11,12,13,14,15], this is one of the very few applications of association mining for this domain, and, to the best of our knowledge, the only one for Turkey. Two very related studies investigate through association mining the change in foreign exchange rates: Refernce [16] investigates case of China and Hong Kong, and Reference [17] investigates case of Taiwan. Since the results of association mining are in the form of rules, they are easy to

understand, interpret, and apply. This is a major benefit over sophisticated models that involve complex –and even black box- computations.

II. METHODOLOGY AND PROCESS

A. *Data Selection*

Exchange rate data has been selected for this case study, due to its large size (many years of data), online availability, and due to the importance of financial decision making in individual as well as corporate context. The currency exchange rates have been acquired from the web site of Central Bank of the Republic of Turkey[2]. Currencies such as British Pound, Chinese Yen, and French Frank were not included since they currencies are not traded in large volumes in Turkey in recent years. To have a complete dataset, that includes all the currencies, it was decided to start the time frame based on the initial date for Euro.

B. *Data Cleaning*

Initially, Dollar, Euro, and Gold purchase and sales rates were taken, starting from 5 January 1999 and ending at 28 September 2010. However, only the sales rates have been used, due to strong correlation between the purchase and sales rates. The complete data preparation has been conducted using MS Excel, due to its intuitive interface and flexibility in implementing a variety of functions, including mathematical, logical and string manipulation functions. For each commodity, four columns have been constructed, corresponding to the exchange rate changes for the present day and the three days before that. The main idea in the created data set was to analyze the *percentage changes* in rates, rather than the rates themselves. This eliminated any distortions due to differences in scale. For each column, the difference in rates between the selected day and the day before it was obtained, and this change was then converted into percentage change. Since association mining requires discrete elements of a set, the percentage values were discretized based on intervals that represent 0.1% change.

C. *Naming the Variables*

Through string manipulation functions, the change intervals were given specific names that clearly tell the percentage change, as well as the number of days before. The intervals were given names according to the depth of the calculation. For example, the variable "DollarToday" tells how

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[2] http://www.tcmb.gov.tr/

the Dollar rate has changed today, compared to its value yesterday. The values under this column were based on the percentage differences.

The discretized values are labeled based on the amount of change, as well as the name of the column. For example DollarIncr00Today is the name of the derived item that represents the pattern (case) of Dollar purchase price increasing within the interval of 0%-0.1%, compared to its value yesterday. If this same amount of change was under the DollarDayAgo2 column, the derived item would be named as DollarIncr00DayAgo2. The string "Today" at the end of an item's name means that comparison is made to yesterday's rate, "DayAgo1" means the rate for yesterday is being compared to the rate for the day before, and so on. Fig. 1 illustrates one of the functions that have been implemented in MS Excel while transforming the tabular numerical data to market basket data.

D. Data Verification

Having finished the calculations in MS Excel, the database was ready for further and more detailed data cleaning. The next step was controlling and correcting any mistakes in the data set. Every step of the calculations was verified through a systematic quality control process and every resulting column was verified through sampling the rows. The resulting data set was composed of 4287 rows and 12 columns. Reference [18] reports that "exploratory data mining and data cleaning constitute 80% of the effort that determines 80% of the value of the data mining results". As typical in most data mining projects, the data cleaning process consumed a huge amount of time in our case study. Yet, this was a very critical step of the case study, since any mistakes at this point would destroy the validity of the remaining steps, and the case study.

E. Association Mining

Apriori algorithm has been used to perform association mining computations. Christian Borgelt's command line Apriori program[3], as well as its GUI version wxApriori[4] were used as the software tools. Once completed, the association mining results have been ported back to MS Excel for detailed analysis and interpretations. Apriori was selected due to prior experience of the authors with the software tools that implement Apriori. Computations were completed in less than one minute in the study, and were done only once for frequent itemsets and once for association rules. Thus, there was no need for using more efficient algorithms, such as FP-growth.

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[3] http://www.borgelt.net/apriori.html
[4] http://www.stkpp.org/

III. Analysis and Results

In this section, sample actionable insights obtained through association mining are presented. Alongside the insights, the policies that are derived from the insights are given. Where possible, the Tables from which the insights are derives are given, and the rows related with the insights are highlighted with bold font.

DollarPurchIncr01	=IF(H3=FALSE; IF(AND(D3<0; D3>=-0,001); "DollarPurchDecr00"; IF(AND(D3<=-0,001; D3>-0,002);
DollarPurchIncr00	"DollarPurchDecr01"; IF(AND(D3<=-0,002; D3>-0,003); "DollarPurchDecr02"; IF(AND(D3<=-0,003; D3>-
DollarPurchIncr03	0,004); "DollarPurchDecr03";IF(AND(D3<=-0,004; D3>-0,005); "DollarPurchDecr04";IF(AND(D3<=-0,005;
DollarPurchIncr05	D3>-0,006); "DollarPurchDecr05";IF(AND(D3<=-0,006; D3>-0,007); "DollarPurchDecr06";IF(AND(D3<=-
DollarPurchIncr00	0,007; D3>-0,008); "DollarPurchDecr07";IF(AND(D3<=-0,008; D3>-0,009); "DollarPurchDecr08";IF(AND(D3<
FALSE	=-0,009; D3>-0,01); "DollarPurchDecr09";IF(AND(D3<=-0,01; D3>-0,011); "DollarPurchDecr10";IF(AND(D3<
DollarPurchIncr00	=-0,011; D3>-0,012); "DollarPurchDecr11";IF(AND(D3<=-0,012; D3>-0,013); "DollarPurchDecr12";IF(AND(
DollarPurchIncr07	D3<=-0,013; D3>-0,014); "DollarPurchDecr13";IF(AND(D3<=-0,014; D3>-0,015); "DollarPurchDecr14";IF(
DollarPurchIncr03	AND(D3<=-0,015; D3>-0,016); "DollarPurchDecr15";IF(AND(D3<=-0,016; D3>-0,017); "DollarPurchDecr16";
FALSE	IF(AND(D3<=-0,017; D3>-0,018); "DollarPurchDecr17";IF(AND(D3<=-0,018; D3>-0,019);
DollarPurchIncr04	"DollarPurchDecr18";IF(AND(D3<=-0,019; D3>-0,02); "DollarPurchDecr19";IF(AND(D3<=-0,02; D3>-0,021);
DollarPurchIncr00	"DollarPurchDecr20";IF(AND(D3<=-0,021; D3>-0,022); "DollarPurchDecr21";IF(AND(D3<=-0,022; D3>-
FALSE	0,023); "DollarPurchDecr22";IF(AND(D3<=-0,023; D3>-0,024); "DollarPurchDecr23";IF(AND(D3<=-0,024;
FALSE	D3>-0,025); "DollarPurchDecr24";IF(AND(D3<=-0,025; D3>-0,026); "DollarPurchDecr25";IF(AND(D3<=-
FALSE	0,026; D3>-0,027); "DollarPurchDecr26";IF(AND(D3<=-0,027; D3>-0,028); "DollarPurchDecr27";IF(AND(D3<
FALSE	=-0,028; D3>-0,029); "DollarPurchDecr28";IF(AND(D3<=-0,029; D3>-0,03); "DollarPurchDecr29";IF(AND(
FALSE	D3<=-0,03); "DollarPurchDecr30";"DollarPurchZeroChange"))))))))))))))))))))))))))))))); H3)

Figure 1. Decreasing percentages calculation functions for MS Excel.

The insights and their accompanying policy suggestions appeal to investors with diverse backgrounds: Policies 1,2, and 3 are very intuitive and basic, and would contribute only to novice investors. The remaining policies, however, are not obvious, and can help investment professionals, as well.

Insight 1. Items related to gold have larger support values and gold appears in more frequent itemsets than Dollar or Euro. Among the top 100 frequent itemsets which have the highest support values, approximately 80% of them include an item related with gold. Therefore association patterns that involve gold have higher support.

Policy 1. Gold is a more predictable investment instrument, since its frequent patterns have high predictability.

TABLE I. SUPPORT LEVELS FOR DIFFERENT ITEMSETS

Item	*Support %*
GoldIncr00Today	**23.0**
GoldDecr00Today	**19.1**
GoldIncr01Today	17.9
GoldIncr02Today	10.0
GoldDecr01Today	9.8
GoldIncr03Today	5.1
GoldDecr02Today	3.9
GoldDecr03Today	3.2
GoldIncr04Today	2.6
GoldDecr04Today	1.5
GoldIncr05Today	0.9
GoldIncr08Today	0.8
GoldIncr09Today	**0.7**
GoldIncr07Today	0.5

Insight 2. (Table I) Gold is more likely to increase than decrease today, compared to yesterday. The number of all transactions that include Gold's increase today is more than those that include its decrease, as reflected in the support values. The daily decrease in Gold is at most 0.4% (observed in only 15 transactions). Gold's decrease being less than 0.1% (GoldIncr00Today) is observed in 715 transactions, with support value of 19.1%. However, gold was observed to increase up to 0.9% in a day. Also, its increase less than 0.1% (GoldDecr00Today) is observed in 931 transactions with 23% support value.

Policy 2. Gold is a good investment instrument if an investor wishes to avoid risk, and experience steady increase in value.

Insight 3. Only Dollar and Euro increase in very high percentage as 30% today with respect to yesterday. Gold increases maximum 9% today with respect to yesterday. Support value of Euro's increase 30% is 0.9%, higher than the 0.8% support for Dollar's 30% increase. Confidence of Dollar's increases 30%, if Euro increases 30% today is 0.875, due to the higher confidence value we could consider Dollar's increase can be connected to Euro's increase.

Policy 3. It is suggested to invest in Dollar or Euro if sudden jumps are desired and also these jumps are happening simultaneously between Dollar and Euro. Thus Dollar and Euro are better than Gold for risk-seeking investors, especially in times of crises when high increases are expected in exchange rates for Dollar and Euro. Gold is suggested if investors need a solid increasing pattern with small amounts. Dollar and Euro have more risk, but the sudden jumps yield much higher returns compared to gold.

Insight 4. If Gold decrease or increase less than 0.1% 1 day ago, it will most probably continue to decrease or increase less than 0.1% today. Confidence in the "decrease of Gold being less than 0.1% if it decreases less than 0.1% 1 day ago" is 98.6%. Confidence in the "increase of Gold being less than 0.1% if it increases less than 0.1% 1 day ago" is 97.4%.

Policy 4. Gold has a repeating pattern for two consecutive days, with a probability higher than 97%. For a risk-averse investor, it is recommended to invest in Gold if it increased yesterday less than 0.1% and not suggested to invest if it decreased less than 0.1%.

Insight 5. If Dollar increases less than 0.1% (DollarIncr00Today), one cannot make a certain guess about Euro, since Euro can either increase or decrease with almost the same probabilities (increase probability of 0.5012 vs. decrease probability of 0.4987). Also, if Dollar decreases by less than 0.1% today (DollarDecr00Today), we cannot make any certain guess about Euro for today, it can either increase or decrease again with close probabilities.

Policy 5. It is not suggested to invest at the days Dollar changed with a 0.1% increase or decrease. On these days, it is very hard to predict what will happen with the exchange rate of Euro, since the probability of "increase" and "decrease" events is almost the same.

Insight 6. (Table II) When Gold-related support values in are analyzed, it can be seen that when Gold increases (decreases) in the shown stable decreasing pattern for 3 consecutive days (increase or decrease by 0.4%, 0.3%, 0.2% consecutively), it always continues to increase (decrease) the next day by 0.1%. Table II shows that the support values of the 3 days process and 4 days process are the same; therefore the confidence in observing 0.1% increase (decrease) on the fourth day (today) is 100%.

Policy 6. Gold has a particular four days cycle pattern, that is guaranteed to take place if the first three days follow the pattern: Increase (or decrease) of 0.4%, 0.3%, 0.2%, and finally 0.1%. If the pattern is observed for the first three days, and if the trend is an increasing one, then it is suggested to invest into gold for the next day, since history has shown that the fourth day has always shown an increase. If the pattern is observed for the first three days, and if the trend is a decreasing one, then one should not invest in Gold on the fourth day.

TABLE II. EXCHANGE PATTERNS FOR GOLD

Itemset	*Support %*
GoldIncr04DayAgo3, GoldIncr03DayAgo2, GoldIncr02DayAgo1	**5.5**
GoldIncr04DayAgo3, GoldIncr03DayAgo2, GoldIncr02DayAgo1, GoldIncr01Today	**5.5**
GoldIncr04DayAgo3, GoldIncr03DayAgo2, GoldIncr02DayAgo1	**2.0**
GoldIncr04DayAgo3, GoldIncr03DayAgo2, GoldIncr02DayAgo1, GoldIncr01Today	**2.0**

TABLE III. SUPPORT LEVELS FOR CHANGE IN DOLLAR, IN COMPARISON TO THE PREVIOUS DAY

Item	*Support %*
DollarDecr00Today	**13.8**
DollarIncr00Today	**12.6**
DollarDecr01Today	**9.8**
DollarIncr01Today	**7.4**
DollarDecr02Today	**6.6**
DollarIncr02Today	**5.2**

TABLE IV. SUPPORT LEVELS FOR CHANGE IN EURO, IN COMPARISON TO THE PREVIOUS DAY

Item	*Support %*
EuroDecr00Today	**13.5**
EuroIncr00Today	**12.2**
EuroDecr01Today	**9.7**
EuroIncr01Today	**7.7**
EuroDecr00DayAgo1	7.2
EuroDecr02Today	7.0
EuroDecr01DayAgo1	6.9
EuroIncr00DayAgo1	6.3
EuroIncr01DayAgo1	5.9
EuroIncr02Today	5.6
EuroDecr00DayAgo2	5.6
EuroDecr02DayAgo1	5.3
EuroDecr03DayAgo1	4.9
EuroDecr02DayAgo2	4.9

Insight 7. (Table III) Dollar is more inclined to decrease than increase today (due to the higher support values of decreasing). For every percentage value, the support for decrease is higher than the support for increase.

Policy 7. Dollar rate has more tendency to decrease today compared to yesterday, so it is not a safe stable investment option.

Insight 8. (Table IV) When Euro's support values are observed in, one observes that Euro is more inclined to decrease than increase (just like Dollar).

Policy 8. Euro rate has more tendency to decrease today compared to yesterday, so it is not a safe stable investment option.

Insight 9. (Table V) The support and confidence levels of the first itemset composed of GoldIncr00DayAgo1 and GoldIncr00Today are very high. With 97.5% chance, yesterday's pattern of at most 0.1% increase results in at most 0.1% increase today. This pattern is observed in 41% of all transactions (days). At this point we can easily implement a policy.

Policy 9. We can say that if Gold is increased at most 0.1% yesterday it will increase 0.1% today with a 97.5% chance.

Insight 10. In Table VI, we are seeing association rules with two antecedent items and one consequent item. For example the first rule is telling us if gold is increased 0.1% yesterday and today, the Euro value will decrease 0.1% with a 98.8% confidence and this is seen 10.1% of all transactions.

Policy 10. For the days that the value of gold increased 0.1% (in the interval [0.1,0.2)) two days in a row, investing in Euro is not suggested, because with a very high confidence Euro value will decrease 0.1% (in the interval [0.1,0.2)).

Insight 11. In Table VII, an interesting case is observed. The confidence level of the first rule in the table is 100%. This means these three items are happening always together.

Policy 11. At this point we do not need to implement any policies with effort. Because it is lying there clearly when gold value is increased in the limits of Incr00 and the Dollar purchase value is decreased in the limits of Decr04 the next day the value of gold will increase within the limits of Incr00. Moreover it also has a reasonable support level at 2.6% as we compared it to the total number of transactions.

IV. DISCUSSIONS

This paper is showing a study of association mining on selected exchange currency rates (US Dollar and Euro) and Gold. Based on the association mining and the found associations, several actionable insights have been discovered, and have been interpreted with regards to policy making.

The suggested policies are not forecasts, but rather *rules of the game*, that are easy to understand and apply. Meanwhile, the insights and the policies generated do not involve any black-box models, such as neural networks. Instead, the policies can be applied without any further computations. Yet, the classic shortcoming of data mining applies in this study, as well: Data mining assumes that the future will repeat the past, and historical data can be used for deriving policies to be implemented in the future.

V. CONCLUSIONS

This study is an application of association mining on US Dollar, Euro, and Gold exchange rates in Turkey. The rates for these investment instruments were taken for an eleven year period starting from the year 1999 and ending at the year 2010. The data set created went through a data mining and association mining to find out associations between the changes in the exchange rates. While applying association mining to understanding exchange rates in Turkey for the first time, this study also demonstrated how association mining can be applied with *derived items*, and how it enables actionable insights.

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TABLE V. ASSOCIATION RULES FOR THE TWO-DAY PATTERNS OF GOLD

Support%	*Confidence%*	*Conseq*	⇐	*Antec1*	*Antec2*
41.0	**97.5**	**GoldIncr00DayAgo1**	⇐	**GoldIncr00Today**	
41.0	97.5	GoldIncr00Today	⇐	GoldIncr00DayAgo1	
28.9	96.6	GoldDecr00Today	⇐	GoldDecr00DayAgo1	
28.9	96.6	GoldDecr00DayAgo1	⇐	GoldDecr00Today	
15.2	96.0	GoldIncr02DayAgo1	⇐	GoldIncr02Today	
15.3	96.0	GoldIncr02Today	⇐	GoldIncr02DayAgo1	
10.4	97.8	GoldIncr00DayAgo1	⇐	DollarDecr00DayAgo1	GoldIncr00Today
10.4	98.4	GoldIncr00Today	⇐	DollarDecr00DayAgo1	GoldIncr00DayAgo1
10.4	96.9	GoldIncr00DayAgo1	⇐	DollarDecr00Today	GoldIncr00Today
10.3	97.7	GoldIncr00Today	⇐	DollarDecr00Today	GoldIncr00DayAgo1

TABLE VI. ASSOCIATION RULES REGARDING GOLD AND EURO

Support%	*Confidence%*	*Conseq*	⇐	*Antec1*	*Antec2*
10.1	**98.8**	**GoldIncr00Today**	⇐	**EuroDecr00Today**	**GoldIncr00DayAgo1**
9.4	97.3	GoldIncr00Today	⇐	DollarIncr00DayAgo1	GoldIncr00DayAgo1
9.4	97.5	GoldIncr00DayAgo1	⇐	EurpIncr00DayAgo1	GoldIncr00Today
9.4	97.3	GoldIncr00DayAgo1	⇐	DollarIncr00Today	GoldIncr00Today
9.4	97.5	GoldIncr00DayAgo1	⇐	EurpIncr00Today	GoldIncr00Today
9.4	97.3	GoldIncr00Today	⇐	EurpIncr00Today	GoldIncr00DayAgo1
9.4	97.8	GoldIncr00Today	⇐	EurpIncr00DayAgo1	GoldIncr00DayAgo1
9.3	99.0	GoldIncr00DayAgo1	⇐	DollarIncr00DayAgo1	GoldIncr00Today
9.3	98.5	GoldIncr00Today	⇐	DollarIncr00Today	GoldIncr00DayAgo1
7.8	97.0	GoldDecr00Today	⇐	EuroDecr00Today	GoldDecr00DayAgo1

TABLE VII. ASSOCIATION RULES REGARDING GOLD AND DOLLAR

Support%	*Confidence%*	*Conseq*	⇐	*Antec1*	*Antec2*
2.6	**100.0**	**GoldIncr00DayAgo1**	⇐	**DollarDecr04DayAgo1**	**GoldIncr00Today**
3.9	99.4	GoldIncr00Today	⇐	EuroIncr02DayAgo1	GoldIncr00DayAgo1
3.6	99.4	GoldDecr00Today	⇐	DollarIncr00DayAgo2	GoldDecr00DayAgo1
4.0	99.4	GoldDecr00Today	⇐	DollarIncr00DayAgo2	GoldDecr00DayAgo1
2.9	99.2	GoldDecr00Today	⇐	DollarIncr04DayAgo1	GoldIncr00DayAgo1
2.8	99.2	GoldDecr00DayAgo1	⇐	DollarDecr02DayAgo2	GoldDecr00Today
3.1	99.2	GoldDecr00Today	⇐	EuroDecr04DayAgo3	GoldIncr00DayAgo1
2.6	99.1	GoldIncr00Today	⇐	EuroIncr04DayAgo1	GoldIncr00DayAgo1
2.5	99.1	GoldIncr00Today	⇐	EuroDecr06DayAgo3	GoldIncr00DayAgo1
2.7	99.1	GoldIncr00Today	⇐	DollarIncr06DayAgo3	GoldIncr00DayAgo1