Determination of the world stock indices' co-movements by association rule mining

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Abstract

Purpose – This study aims to provide preliminary information to the investor by determining which indices co-movement, with the data mining method.

Design/methodology/approach – In this context, data sets containing daily opening and closing prices between 2001 and 2019 have been created for 11 stock market indexes in the world. The association rule algorithm, one of the data mining techniques, is used in the analysis of the data.

Findings – It is observed that the US stock market indices take part in the highest confidence levels between association rules. The XU100 stock index co-movement with both the European stock market indices and the US stock indices. In addition, the Hang Seng Index (HSI) (Hong Kong) takes part in the association rules of all stock market indices.

Originality/value – The important issue for data sets is that the opening/closing values of the same day or the previous day are taken into account according to the open or closed status of other stock market indices by taking the opening time of the stock exchange index to be created. Therefore, data sets are arranged for each stock market index, separately. As a result of this data set arranging process, it is possible to find out co-movements of the stock market indexes. It is proof that the world stock indices have co-movement, and this continues as a cycle.

Keywords Data mining, Association rules, Stock market index, Global financial markets

Paper type Research paper

1. Introduction

Financial deepening and financial integration process that the world stock markets experienced increases the co-movement of world stock indexes. Investors need to foresee which direction other stock exchanges will move after the fall or rise of any stock market. This information will help investors take quick and efficient decisions. Ghosh *et al.* (1999) found that Hong Kong, India and Korea have a long-term relationship with the US market, while Indonesia, the Philippines and Singapore have long-term relationships with Japan. Johnson and Soenon (2009) found a significant association between the German and European Union stock markets. Kasibhatla *et al.* (2006) detected a long-run relationship between London (FTSE100), Frankfurt (DAX30) and Paris (CAC40) indices. Madaleno and Pinho (2012) investigated the long-term relationship between FTSE 100, Dow Jones 30, Nikkei

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225 and Bovespa, and concluded that the relationship is strong but not homogeneous. Vuran (2010) concluded that the Borsa İstanbul (XU100) Index is related to the FTSE 100, DAX, BOVESPA, MERVAL and IPC indices in the long term.

Chan *et al.* (1997) concluded that international diversification is important because stock markets do not co-movements in the long run. Caporale *et al.* (2016) could not determine the cointegration relationship between the US and European stock indices. Fu and Pagani (2012) state that there is a cointegration between international stock indices, but the evidence is weak. Dimpfl (2014) concluded that it would not be appropriate to investigate the relations and integration between financial markets through cointegration analysis, and cointegration is a coincidence. Can co-movement between stock markets, which cannot be determined by cointegration analysis, be analysed by another method? The association rule can answer this question. The association rule is a pattern of frequently used items appearing together. It reflects behaviours in which the same behaviour often occurs. With globalization, the potential of stock markets to exhibit common behaviours is increasing. In particular, return and volatility spillovers are frequently studied topics in the finance literature. These studies are also included in the literature part of this study. It is possible to show common behaviours with algorithms within the framework of association rule. In this study, the apriori algorithm, which is frequently used in the literature, is used. Also, Eclat and FP- Growth algorithms, which are other association rule algorithms, were used for the robustness of the results.

This study aims to consider the basic research question: Are the co-movement of stock indices present by the association rule? In this study, we investigate the co-movement of daily price changes of other stock market index values in the world for each of the index values of 11 world exchanges with the association rule algorithm. Association rule algorithm, one of the data mining techniques, is used to reveal this information. This method, also known as market-basket analysis, can help investors create investment plans using preliminary information. It is aimed to determine how the change in the opening/closing values of each stock market index is affected by the fluctuations in foreign markets and which international indices co-movement. Briefly, this study aims to provide preliminary information to the investor by determining which indices co-movement, with the data mining method. Details about the association rule give in the method section.

To be able to fill the gap in the literature and to guide the potential investors about alternative investment opportunities, this study aims to analyse world stock indices' co-movements by association rule mining selected samples in economies. To identify the gap in the literature, a literature review is presented in the second section. Then, the data set is presented in the third section. The methods and findings are indicated in the fourth and fifth sections, respectively.

2. Literature review

Studies on the co-movement and integration of stock markets focus on returns and volatility spillovers. Emerging markets, both in the long run and in the short run, are more affected by their own past shocks than developed markets (Li and Giles, 2015; Vo and Tran, 2020; Jung and Maderitsch, 2014). Wang and Wang (2010) stated that volatility spillovers are greater than price spillovers between China, Japan and US markets. This effect decreases with the openness of the markets and increases with the geographical distance. Yang *et al.* (2020) identified risk spillovers between Hong Kong and Shanghai. The study of Zhou *et al.* (2012) revealed that the volatility spillover between China, Japan and India markets is greater than the volatility spillover between China, the USA and the UK. These findings support the findings of Wang and Wang (2010) regarding geographical distance. Zhoung and Liu (2021) identified volatility spillovers between China and Singapore, Thailand, Indonesia, Malaysia and the Philippines. According to Hung (2019), China seriously affects Vietnam, Thailand, Singapore and Malaysia in terms of volatility spillover. There is mutual causality in the mean between

Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa (Korkmaz *et al.*, 2012). Majdoub and Mansour (2014) found that the conditional correlation estimates between the USA, Turkey, Indonesia, Pakistan, Qatar and Malaysia are insufficient. Volatility spillover from European markets to the US market is greater than that from the US to the European market (Savva *et al.*, 2009). Correlations between the BRICS countries and the markets of developed countries such as the USA, Europe and Japan that change over time (Mensi *et al.*, 2017; McIver and Kang, 2020) found bidirectional volatility and return spillover between BRICS and US stock markets. There is a one-way return spillover from the US markets to the Latin markets (Yousaf *et al.*, 2020). Farther of the closing hours between the stock exchanges affects the size of the volatility spillover (Baumohl *et al.*, 2018). When co-movement of financial data is evaluated with the use of the association rule algorithm, it is observed that the fluctuation movements of the stocks, indexes and exchange rates in various countries' financial markets are examined. Liao *et al.* (2008) investigated the problems that arise in stock market investments in Taiwan using the two-stage data mining method, and they applied the association rule and then used the k-means clustering method with 19 international indices. As a result of the analysis, Nikkei 225, Hang Seng and KOSPI stock indexes' co-movement with various stocks traded on the Taiwan Stock Exchange in the 60–75% confidence level. Hoon Na and Sohn (2011) used the association analysis, and they stated that the Korean Stock Exchange index moved in the same direction with the US and European stock exchange indices. Argiddi and Apte (2012) used the association rule for the exchange of stocks in the India Information Technology index. In addition, it is tried to find solutions with two different methods in the study. They created the data set from the opening prices of the relevant stocks for the last three years. The rules of association that emerged as a result of the analysis are interpreted. Liao and Chou (2013) examined the changes in Taiwan and China stock indexes in the stock market using the association rule method and cluster analysis between June 2008 and March 2011, strong co-movement between the electronics, finance, and insurance and semiconductors index and Taiwan Stock Index (TAIEX) in Taiwan Stock Exchange.

Arafah and Mukhlash (2015) studied the exchange of shares of 10 companies in Indonesia studied using the fuzzy association rules method. The data set is created by obtaining the closing prices of the relevant company stocks between January 2010 and December 2014. As a result of the analysis, they established rules at a minimum support level of 0.1, 0.07 and 0.06 and found that the increase in certain stocks caused increases and decreases over other stocks. Masum (2019) has examined the co-movement of the stocks of 36 companies listed on the Tehran stock market index. In total, 249,061 records are tested by association analysis. Many association rules and recommendations have been developed. The association rules with over 81% confidence value, over 1% support value and over two lift values are detected in three and four items.

When the above return and volatility spillover literature review is examined, it is found that stock markets affect each other in terms of return and volatility, and causal relationships are established. However, these studies do not reveal any findings concerning the up and down of other markets. In the studies conducted on the concept of association rule algorithm, it has been determined that the association rule is frequently used in the analysis of index co-movements. It is seen that the studies are mostly done on the indices in the Far East countries, and the focus is on the changes in the domestic markets. Globally, there is no study involving a total analysis of the movement of countries' stock indexes with other country stock indexes. For this reason, a research gap has been identified in this area.

3. Method

3.1 Data

In this study, data from 4,924 trading days between January 2001 and November 2019, which included 11 world stock market indices, are used. The resulting data set is Brazil (BVSP), USA

(S&P 500, DJI, IXIC), France (FCHI), Germany (GDAXI), UK (FTSE), China (SSEC), Hong Kong (HSI), Japan (N225) and Turkey (XU100) consists of opening and closing prices of the stock market. According to each stock market index, a total of 11 different data sets are created. The opening/closing values of the same day or the previous day are taken into account according to the open or closed status of other stock market indices by taking the opening time of the stock exchange index to be created. The opening/closing situations of the stock market indexes for each data set are shown in Table 1.

Since the association analysis used in the research can process categorical data due to its structure, the values in the data set have been converted to the form of "binary verbal expression". In this context, the values in the data set are coded as "Down" if the value of an index is in decrease compared to the previous day and "Up" in the increase. A sample of the data set (XU100 data set) is given in Table 2. The data are analysed using the "apriori" package in the R-Studio program. It has been tested with a variety of support and confidence values.

3.2 Procedure

The use of an association rule algorithm that determines this relationship has increased by researchers in recent years. Using this method in studies with the same purpose has ensured that the results are reliable and valid. The results of the study are thought to develop a suggestion system for individuals or institutions that will decide to invest in international stock market indices. In addition, as a result of the analysis of the data set customized according to each world index, it will be revealed how the world markets move in harmony with each other. Thus, a general map of the co-movement of the stock market index in the world will be created. Agrawal *et al.* (1993) stated that finding association rules is one of the important issues of data mining. The main use of the association rule algorithms is to reveal concurrent relationships by analysing random data. The data obtained can be used as reference information in the decision-making phase.

The association rule is defined as follows (Wang *et al.*, 2004, p. 428):

$I = \{i_1, i_2, \ldots, i_m\}$ shows each item from a particular community. The items in each T transaction are kept in the D database and are $T \subseteq I$. Each set of items T is a non-empty subset of items. This criterion, called support value for each $X \subset I$ item set, is calculated to determine the statistical significance of D. *Support* (X, D) shows the purchase rate of product X in the database D. If $X, Y \subset I$ and $X \cap Y = \varnothing$, the association rule is written as $X \rightarrow Y$. This rule indicates that if product X is purchased, product Y can also be bought. The confidence value is calculated for each rule. This value is calculated by the formula

Table 1. Opening/closing situations of stock market indices in data sets

Index data set	GSPC	DJI	IXIC	BVSP	FTSE	GDAXI	FCHI	XU100	SSEC	HSI	N225
GSPC	*O(t)*	C(t-1)	C(t-1)	O(t)	O(t)	O(t)	O(t)	O(t)	C(t)	C(t)	C(t)
DJI	C(t-1)	*O(t)*	C(t-1)	O(t)	O(t)	O(t)	O(t)	O(t)	C(t)	C(t)	C(t)
IXIC	C(t-1)	C(t-1)	*O(t)*	O(t)	O(t)	O(t)	O(t)	O(t)	C(t)	C(t)	C(t)
BVSP	C(t-1)	C(t-1)	C(t-1)	*O(t)*	O(t)	O(t)	O(t)	O(t)	C(t)	C(t)	C(t)
FTSE	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	C(t-1)	C(t-1)	O(t)	C(t)	C(t)	C(t)
GDAXI	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	C(t-1)	O(t)	C(t)	C(t)	C(t)
FCHI	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	O(t)	C(t)	C(t)	C(t)
XU100	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	O(t)	O(t)	C(t)
SSEC	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	C(t-1)	O(t)
HSI	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*	O(t)
N225	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	C(t-1)	*O(t)*

Note(s): O: Opening, C: Closing
Source(s): Own elaboration

Table 2. Sample data set (XU100)

Day	GSPC Closing(t-1)	DJI Closing(t-1)	IXIC Closing(t-1)	BVSP Closing(t-1)	FTSE Closing(t-1)	GDAXI Closing(t-1)	FCHI Closing(t-1)	XU100 Opening(t)	SSEC Opening(t)	DHSI Opening(t)	N225 Closing(t)
1	Up	Up	Up	Up	Up	Up	Up	Up	Up	Up	Down
2	Up	Up	Up	Down	Up	Up	Up	Up	Up	Up	Up
3	Up	Down	Down	Up	Down	Down	Down	Up	Up	Up	Up
–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	–	–	–	–	–	–	–
4,923	Down	Down	Down	Down	Down	Down	Down	Up	Up	Down	Down
4,924	Up	Up	Up	Up	Up	Up	Up	Down	Down	Up	Up

Source(s): Own elaboration

of *Confidence* $(X \rightarrow Y)$ = *Support* $(X \cup Y, D)/$*Support* (X, D). *Confidence* $(X \rightarrow Y)$ means that in the case of product X, it is high to purchase product Y too. While creating the association rule, large item sets are determined in the first stage, and then rules are created according to these elements. Minimum confidence and minimum support values are determined by the user, and the rules that meet the following two conditions are presented to the decision-maker: (1) $Support(X \cup Y, D) \geq support$, (2) $Confidence(X \rightarrow Y) \geq confidence$.

The easiest way to reduce the prejudices that may arise in the use of these measures is using a criterion with a lift value. Lift value is calculated by $Lift = Confidence(X \rightarrow Y)/Support(Y)$ formula (Wang *et al.*, 2004, p. 429; Liao and Chou, 2013, p. 1547). Apriori algorithm is frequently used in research (Agrawal *et al.*, 1993). This method is also used in this study. This method is first used in marketing, but today it is used in many fields such as medicine, telecommunications and finance. The method is used to reveal a large set of items. The algorithm calculates the support level for each subset and compares it to the minimum support level specified by the user. The algorithm continues until subsets exceed the specified support level (Han and Kamber, 2006, p. 235).

4. Results

The results of the association analysis of 11 different data sets, arranged according to each stock market index, are selected, and filtered as the related index. More precisely, each data set is arranged according to the relevant stock market index. The number of rules that appear at the level of different support values as a result of the association rule analysis is shown in Table 3 and Figure 1. As a result of the results obtained, it is seen that the stock index with the highest number of rules at all support levels is the Dow Jones Index (DJI). In addition, the confidence values of all these rules seem to be greater than 0.9. If we evaluate according to each stock market index, GSPC, DJI and BVSP stock exchange indexes reach the highest association rule numbers at 0.1, 0.2 and 0.3 support levels in the 0.9–1.0 confidence value range in Table 3. IXIC and XU100 stock indices reach the highest association rule numbers at the support levels of 0.1, 0.2 and 0.3, in the confidence value range 0.8–0.89.

In Table 3, the FTSE stock index reached the highest number of association rules in the 0.9–1.0 confidence value range at 0.1 support level, 0.5–0.59 confidence value range at 0.2 support level, and 0.8–0.89 confidence value range at 0.3 support level. GDAXI and FCHI stock indexes have reached the highest number of association rules in the confidence value range of 0.9–1.0 at 0.1 support level and 0.8–0.89 confidence value range at 0.2 and 0.3 support levels. SSEC and N225 stock indexes reached the highest number of association rules at support levels of 0.1, 0.2 and 0.3 in the confidence value range of 0.6–0.69. HSI stock index has reached the highest number of association rules in the confidence value range of 0.8–0.89 at 0.1 support level and 0.6–0.69 confidence level at 0.2 and 0.3 support levels. It is seen that rules are formed at high support levels in all support values. The comments on the rules will be disclosed under separate headings for each stock market index based on the highest support value (0.3).

GSPC (SandP500) results are shown in Table 4. It is seen that the GSPC Stock Index moves with BVSP, FCHI, FTSE, GDAXI, HSI, XU100 stock indices with a confidence value of over 95%. As an example, if the BVSP, FCHI, FTSE, GDAXI stock indices are opened with an increase in *t* time and the HSI stock index is closed with an increase in *t* time, it can be said that the GSPC stock index will increase with a probability of 96.1%. Likewise, if BVSP, FCHI, FTSE, GDAXI, XU100 stock indices are opened with a decrease in time, the GSPC stock index will be opened with a decrease in time with a probability of 95.5%. If the BVSP, FTSE, GDAXI stock indices are opened with an increase in time *t*, and the HSI stock index is closed with an increase in time, the GSPC stock index will be opened with an increase with a probability of 95.7%. In addition, if the XU100 stock index is opened with an

Table 3. Number of rules emerging according to different support and confidence values

Support	Confidence	GSPC	DJI	IXIC	BVSP	FTSE	GDAXI	FCHI	XU100	SSEC	HSI	N225
0.1	0.5–0.59	7	7	7	15	68	87	90	136	163	43	42
	0.6–0.69	13	14	26	28	121	90	88	160	879	686	1,383
	0.7–0.79	53	49	155	109	438	370	401	577	864	374	639
	0.8–0.89	403	355	2,310	935	821	893	833	1,185	157	955	0
	0.9–1	2,296	2,369	182	1,693	871	915	914	265	0	0	0
0.2	0.5–0.59	7	7	7	15	57	40	38	32	63	14	13
	0.6–0.69	4	3	5	3	15	23	23	67	93	126	147
	0.7–0.79	14	19	56	31	53	45	46	41	30	76	95
	0.8–0.89	135	115	487	199	52	64	56	84	0	94	0
	0.9–1	535	608	17	270	33	39	44	12	0	0	0
0.3	0.5–0.59	1	1	1	1	1	1	1	1	1	1	1
	0.6–0.69	2	2	3	2	1	5	5	5	3	15	15
	0.7–0.79	4	4	13	4	5	4	5	3	2	2	0
	0.8–0.89	36	34	74	36	5	7	6	5	0	1	0
	0.9–1	116	124	0	41	4	5	4	2	0	0	0

Source(s): Own elaboration

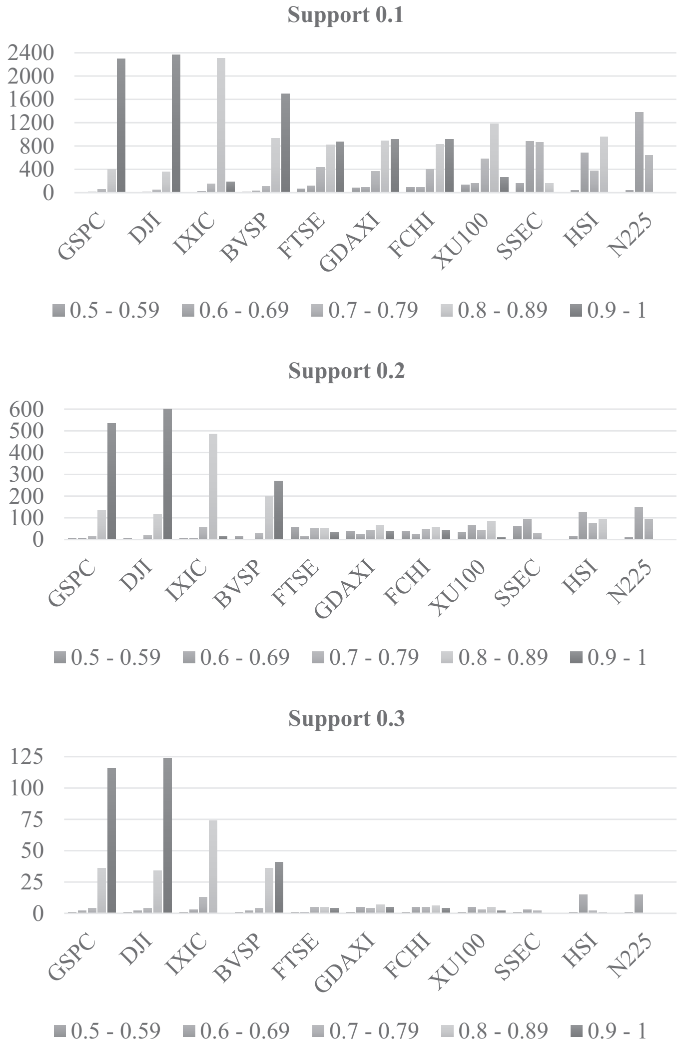

Figure 1.
Number of rules emerging according to different support and confidence values

increase in time *t*, the probability of the GSPC stock index to open with an increase will be 95.9%.

DJI stock index moves with high probability values of BVSP, FCHI, FTSE, GDAXI, XU100, HSI stock indexes are shown in Table 5. As an example of this situation, if the BVSP, FCHI, FTSE, GDAXI, XU100 stock indices are opened with an increase in time *t* and the HSI stock index is closed with an increase in time *t*, it can be said that the DJI stock index will be opened with an increase in time with a probability of 97.4%. According to another rule, if the BVSP, FCHI, FTSE, GDAXI stock indices are opened with an increase in *t* time and the HSI stock index is closed with an increase in *t* time, the DJI stock index will be opened with an increase of *t* in 97.2% probability. The opening of the DJI stock index with a probability of 97.1% with a decrease in time will occur when BVSP, FCHI, FTSE, GDAXI, XU100 stock indices are opened with a decrease in time.

It can be said that the IXIC stock index moves at 88% probability levels with BVSP, GDAXI, FTSE, FCHI, XU100, HSI stock indexes shown in Table 6. As an example of this situation, if the BVSP and GDAXI stock indices are opened with an increase in t time and the HSI stock index is closed with an increase in t time, the IXIC stock index will be opened with an increase in t time with a probability of 88.3%. The same situation arises by evaluating the FTSE stock index value instead of the BVSP stock index. In addition, it is determined that the IXIC stock index did not start the day with a decrease in the first five rules.

BVSP results are shown in Table 7. It is seen that the co-movement between the BVSP stock index and the FCHI, FTSE, GDAXI, XU100, HSI stock indices is approximately 95%. To exemplify, if the FCHI, FTSE, GDAXI, XU100 stock indices are opened with an increase in time t and the HSI stock index is closed with an increase in time t, the BVSP stock index will be opened with an increase in time with a probability of 94.9%. However, if the HSI stock index is not considered, the probability that the BVSP stock index will be opened with an increase in time decreases to 94.8%. In addition, among the first five rules, it is determined that the BVSP stock index did not start the day with a decrease.

It is determined that the FTSE stock index moves with the probability of 88.7–93.9%, together with the XU100, HSI, SSEC, N225 stock indexes as shown in Table 8. If the XU100 stock index is opened with a decrease in time t and the HSI stock index is closed with a decrease in time t, the FTSE stock index will be opened with a decrease in time with a probability of 93.9%. On the contrary, the XU100 stock index opens with an increase in time t and the HSI stock index is closed with an increase in time t, the FTSE stock index will be opened with an increase in time with a probability of 88.7%. Also, if the XU100 stock index is opened with a decrease in t time, it can be said that the FTSE stock index will be opened with a decrease in t time with a probability of 91.3%, but the opposite is not a rule.

It is determined that the GDAXI stock index moves with XU100, HSI, SSEC, N225 stock indexes with probabilities higher than 90% as shown in Table 9. If the XU100 stock index is opened with a decrease in t time and the HSI stock index is closed with a decrease in t time, it can be said that the GDAXI stock index will be opened with a decrease in 92.2% probability and vice versa. In addition, if the XU100 stock index is opened with a decrease in t time and the N225 stock index is closed with a decrease in t time, the GDAXI stock index will be opened with a with a probability of 92.2% and vice versa.

Antecedent	Consequent	Confidence	Lift
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, HSI = ↑	GSPC = ↑	0.961	1,884
BVSP = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	GSPC = ↑	0.959	1,880
BVSP = ↑, FTSE = ↑, GDAXI = ↑, HSI = ↑	GSPC = ↑	0.957	1,877
BVSP = ↑, FCHI = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	GSPC = ↑	0.957	1,876
BVSP = ↓, FCHI = ↓, FTSE = ↓, GDAXI = ↓, XU100 = ↓	GSPC = ↓	0.955	1,951

Source(s): Own elaboration

Table 4. Top 5 association rule with the highest confidence value in GSPC

Antecedent	Consequent	Confidence	Lift
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	DJI = ↑	0.974	1,904
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, HSI = ↑	DJI = ↑	0.972	1,901
BVSP = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	DJI = ↑	0.972	1,901
BVSP = ↓, FCHI = ↓, FTSE = ↓, GDAXI = ↓, XU100 = ↓	DJI = ↓	0.971	1,987
BVSP = ↑, FCHI = ↑, FTSE = ↑, XU100 = ↑, HSI = ↑	DJI = ↑	0.971	1,898

Source(s): Own elaboration

Table 5. Top 5 association rule with the highest confidence value in DJI

FCHI results are displayed in Table 10. It is determined that the FCHI stock index moves with XU100, HSI, SSEC, N225 stock indexes with probabilities higher than 89%. If the XU100 stock index is opened with a decrease in time *t* and the HSI stock index is closed with a decrease in time *t*, it can be said that the FCHI stock index will be opened with a probability decrease of 92% in time and vice versa. In addition, if the XU100 stock index is opened with a decrease in *t* time and the N225 stock index is closed with a decrease in *t* time, the FCHI stock index will be opened with a probability of 91.9% with a decrease in time and vice versa.

XU100 stock index moves with SSEC, N225, HSI stock indexes with a probability of over 84% as shown in Table 11. If the SSEC stock market index is opened with an increase in time *t* and the N225 stock index is closed with an increase in time *t* the XU100 stock index will be opened with a probability of 91.1% with an increase in time. In addition, if the SSEC and HSI stock indices are opened with an increase in time, the XU100 stock index will be opened with a 91% probability, while the opposite will be opened with a decrease with an 84.9% probability. In the rule where single unity is formed, if the SSEC stock index is opened with an increase in *t* time, the XU100 stock index will be opened with an increase with an 85.9% probability.

SSEC results are indicated in Table 12. It is determined that the SSEC stock market index moves with N225, BVSP, GSPC, DJI stock market indices with 61–77% probabilities. If the N225 stock index is opened with a decrease in *t* time, the SSEC stock index will be opened with a probability of 76.6% with a decrease in time and vice versa. If the BVSP stock index is closed with a decrease in t-1 time, the SSEC stock index will be opened with a decrease with a

Table 6. Top 5 association rule with the highest confidence value in IXIC

Antecedent	Consequent	Confidence	Lift
BVSP = ↑, GDAXI = ↑, HSI = ↑	IXIC = ↑	0.883	1,694
FTSE = ↑, GDAXI = ↑, HSI = ↑	IXIC = ↑	0.883	1,693
FCHI = ↑, FTSE = ↑, HSI = ↑	IXIC = ↑	0.875	1,679
BVSP = ↑, FTSE = ↑, HSI = ↑	IXIC = ↑	0.875	1,678
BVSP = ↑, XU100 = ↑, HSI = ↑	IXIC = ↑	0.872	1,673

Source(s): Own elaboration

Table 7. Top 5 association rule with the highest confidence value in BVSP

Antecedent	Consequent	Confidence	Lift
FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	BVSP = ↑	0.949	1,853
FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑	BVSP = ↑	0.948	1,853
FTSE = ↑, GDAXI = ↑, XU100 = ↑	BVSP = ↑	0.947	1,850
FTSE = ↑, GDAXI = ↑, XU100 = ↑, HSI = ↑	BVSP = ↑	0.946	1,849
FCHI = ↑, FTSE = ↑, GDAXI = ↑, HSI = ↑	BVSP = ↑	0.945	1,846

Source(s): Own elaboration

Table 8. Top 5 association rule with the highest confidence value in FTSE

Antecedent	Consequent	Confidence	Lift
XU100 = ↓, HSI = ↓	FTSE = ↓	0.939	1,872
XU100 = ↓, SSEC = ↓	FTSE = ↓	0.937	1,868
XU100 = ↓, N225 = ↓	FTSE = ↓	0.931	1,856
XU100 = ↓	FTSE = ↓	0.913	1,819
XU100 = ↑, HSI = ↑	FTSE = ↑	0.887	1,780

Source(s): Own elaboration

62.2% probability. If the GSPC stock index is closed with a decrease in t-1 time, the SSEC stock index will be opened with a decrease with a probability of 61.8%. If the DJI stock index is closed with a decrease in t-1 time, the SSEC stock market index will be opened with a decrease with a probability of 61.1%.

It is determined that the HSI stock market index moves with N225, GSPC, DJI, IXIC stock market indices with a probability of 69–82% as shown in Table 13. If the N225 stock index is opened with an increase in *t* time, it is found that the HSI stock index will be opened with a probability of an 81.3% increase in *t* and vice versa. In addition, if the US stock market indices are closed with an increase in t-1 time, it can be said that the HSI stock index will be opened with an increase in *t* time with a probability of 70.1%. If the IXIC and DJI stock index is closed with an increase in t-1 time, the HSI stock index is increased with a probability of 69.7% in time *t*, and if the IXIC and GSPC stock index is closed with an increase in t-1 time, it can be predicted that the HSI stock index will be opened with an increase in *t* time with a probability of 69.3%.

It can be said that the N225 stock index moves between 67 and 70% probabilities with US stock indexes, as shown in Table 14. It can be said that if the US stock market indices are closed with an increase in t-1 time, the N225 stock index will be opened with an increase in *t* time with a probability of 69.9%. In addition, if the GSPC stock index is closed with an increase in t-1 time, it can be said that the N225 stock index will be opened with an increase in *t* time with a probability of 67.6%. Apart from these rules, bilateral relations with US stock indexes are also determined. In addition, it is determined that the N225 stock index did not start the day with a decrease in the first five rules.

Antecedent	Consequent	Confidence	Lift
XU100 = ↓, HSI = ↓	GDAXI = ↓	0.922	1,935
XU100 = ↓, N225 = ↓	GDAXI = ↓	0.922	1,935
XU100 = ↑, HSI = ↑	GDAXI = ↑	0.913	1,744
XU100 = ↓, SSEC = ↓	GDAXI = ↓	0.905	1,899
XU100 = ↑, N225 = ↑	GDAXI = ↑	0.901	1,721

Source(s): Own elaboration

Table 9. Top 5 association rule with the highest confidence value in GDAXI

Antecedent	Consequent	Confidence	Lift
XU100 = ↓, HSI = ↓	FCHI = ↓	0.920	1,908
XU100 = ↓, N225 = ↓	FCHI = ↓	0.919	1,905
XU100 = ↑, HSI = ↑	FCHI = ↑	0.907	1,752
XU100 = ↓, SSEC = ↓	FCHI = ↓	0.905	1,877
XU100 = ↑, N225 = ↑	FCHI = ↑	0.893	1,724

Source(s): Own elaboration

Table 10. Top 5 association rule with the highest confidence value in FCHI

Antecedent	Consequent	Confidence	Lift
SSEC = ↑, N225 = ↑	XU100 = ↑	0.911	1,660
SSEC = ↑, HSI = ↑	XU100 = ↑	0.910	1,657
HSI = ↑, N225 = ↑	XU100 = ↑	0.873	1,590
SSEC = ↑	XU100 = ↑	0.859	1,564
SSEC = ↓, HSI = ↓	XU100 = ↓	0.849	1,882

Source(s): Own elaboration

Table 11. Top 5 association rule with the highest confidence value in XU100

4.1 Robustness checks

The results given in the findings section were revealed by the apriori algorithm, one of the association rule methods. For the robustness of the results, it is important to re-evaluate the data set with other methods used to reveal co-movement. While many methods are suggested for association rules, it can be said that these methods are generally variants and extensions of Agrawal *et al.* (1993), FP-Growth (Han *et al.*, 2000), and Eclat (Zaki, 2000) algorithms (Yu and Wang, 2014, p. 2116). For this reason, the basic FP- Growth and Eclat algorithms were used in the study, apart from the apriori algorithm. Since the main purpose of the study is to find out the co-movements in the price changes of the world stock markets, the study focused on the similarity of the results obtained, in other words, the robustness of the results, rather than the performances of the algorithms.

The characteristics of the algorithms used in the study are different. Apriori algorithm, which is the first algorithm used in the discovery of frequent patterns, is used in horizontal layout-based databases. Based on Boolean association rules, the algorithm finds candidate solutions by breadth-first search. The apriori algorithm uses the property that states "any non-empty subset of a frequent itemset is also frequent." Detailed information about the algorithm is given in the procedure section. The FP-Growth algorithm, which can be applied to projected type data sets, is a tree-based algorithm that uses the divide and conquer method. The algorithm first generates a list of common item sets and sorts them according to their support values from largest to smallest. The resulting lists are represented as nodes. All nodes except the root node contain item name, support value and node-link signal information which is

Antecedent	Consequent	Confidence	Lift
N225 = ↓	SSEC = ↓	0.766	1,468
N225 = ↑	SSEC = ↑	0.703	1,471
BVSP = ↓	SSEC = ↓	0.622	1,192
GSPC = ↓	SSEC = ↓	0.618	1,184
DJI = ↓	SSEC = ↓	0.611	1,172

Source(s): Own elaboration

Table 12. Top 5 association rule with the highest confidence value in SSEC

Antecedent	Consequent	Confidence	Lift
N225 = ↑	HSI = ↑	0.813	1,528
N225 = ↓	HSI = ↓	0.773	1,651
GSPC = ↑, DJI = ↑, IXIC = ↑	HSI = ↑	0.701	1,318
DJI = ↑, IXIC = ↑	HSI = ↑	0.697	1,312
GSPC = ↑, IXIC = ↑	HSI = ↑	0.693	1,303

Source(s): Own elaboration

Table 13. Top 5 association rule with the highest confidence value in HSI

Antecedent	Consequent	Confidence	Lift
GSPC = ↑, DJI = ↑, IXIC = ↑	N225 = ↑	0.699	1,342
DJI = ↑, IXIC = ↑	N225 = ↑	0.696	1,338
GSPC = ↑, IXIC = ↑	N225 = ↑	0.691	1,328
GSPC = ↑, DJI = ↑	N225 = ↑	0.683	1,312
GSPC = ↑	N225 = ↑	0.676	1,299

Source(s): Own elaboration

Table 14. Top 5 association rule with the highest confidence value in N225

linked on the FP tree and has the same item name. FP tree is created with these nodes. Starting from the leaf node, frequent patterns are revealed towards the root node. The algorithm, which uses less memory due to its projected layout feature, is also efficient in terms of storage. Eclat, a vertical database layout algorithm, uses the depth-first search method. The data which Eclat encodes as a bit matrix is represented by 0 or 1, depending on whether it is purchased or not. In the first step of the algorithm, it is necessary to create a prefix tree. The prefix tree is created using the intersection of the relevant line between the next lines. Frequent items are found with the depth-first search algorithm over the created prefix tree.

The rules and confidence values of the three algorithms are shown in Table 15. It has been observed that all three algorithms find the same rules with the same confidence value. Finding the same rules by algorithms with different search strategies shows the robustness and efficiency of the results. This situation can be interpreted as that the results are robust and that the emerging rules represent the real situation.

Eclat algorithm examines the whole data set at the beginning of the algorithm and then performs its operations over the prefix tree. For this reason, it is an important algorithm in terms of memory and efficiency (Garg and Kumar, 2013, pp. 29–30). The algorithms used in the study were run with a support value of 0.3 and a confidence value of 0.5, and the results were obtained.

5. Discussion and conclusions

Investors use alternative investments before making an investment. They consider both the risk and return. They make an investment decision based on risk and return. Portfolio management has become important even more with globalization. Thus, there is an increase in the number of alternatives in terms of financial instruments and markets for investors. This situation causes a higher level of interactions between the markets compared to the past.

Within this study, association rules according to 11 stock market indexes are found, and co-movements in the financial markets around the world are determined. Analyses are made by using the apriori algorithm, which is one of the association rule methods. Association rules for different support levels are simplified by filtering each stock market index as a consequence. Because of the results, it has been determined that the association rules with the highest confidence level are with the US stock indexes. It is observed that confidence levels decreased in Asian stock indexes. As a result, it can be said that the Asian stock indices are associated with the US stock indices, the European stock indices are associated with the Asian stock indices, and the US stock indices are associated with the European stock indices co-movement, and this continues as a cycle. Events that live in one-time-period affect the next period and lose their effect. When all association rules are analysed, it is observed that the XU100 stock index co-moves with both European stock market indexes and US stock indexes. HSI stock index is found to be in the association rules of all stock market indices. In this sense, perhaps the HSI stock index is more integrated with the world stock markets compared to other Far East stock indexes since the Hong Kong stock exchange is the international financial centre. Especially for investors, it can be said that the XU100 stock index is an important indicator of the Asian–European line. In addition, these results revealed investors should make an investment decision by considering the co-movement of the exchanges, as well as analysing a single stock index. According to the findings, there is an association between the Asian indices and the US indices, between the European indices and the Asian indices, and between the Brazilian and the US indices and the European indices. This turns into a constantly recurring cycle.

Estimation of stock price volatility is critical for investors to make the right investment decision. Accurate estimation of volatility is vital, especially in high volatility markets. This becomes even more important in global-scale financial events, such as the global financial crisis. However, the volatility estimates do not completely indicate the co-movement of stock

Antecedent	Consequent	Confidence Apriori	FP-Growth	Eclat
SSEC = ↑, N225 = ↑	XU100 = ↑	0.911	0.911	0.911
SSEC = ↑, DHSI = ↑	XU100 = ↑	0.910	0.910	0.910
DHSI = ↑, N225 = ↑	XU100 = ↑	0.873	0.873	0.873
FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, DHSI = ↑	BVSP = ↑	0.949	0.949	0.949
FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑	BVSP = ↑	0.948	0.948	0.948
FTSE = ↑, GDAXI = ↑, XU100 = ↑	BVSP = ↑	0.947	0.947	0.947
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, DHSI = ↑	GSPC = ↑	0.961	0.961	0.961
BVSP = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, DHSI = ↑	GSPC = ↑	0.959	0.959	0.959
BVSP = ↑, FTSE = ↑, GDAXI = ↑, DHSI = ↑	GSPC = ↑	0.958	0.958	0.958
BVSP = ↑, GDAXI = ↑, DHSI = ↑	IXIC = ↑	0.883	0.883	0.883
FTSE = ↑, GDAXI = ↑, DHSI = ↑	IXIC = ↑	0.883	0.883	0.883
FCHI = ↑, FTSE = ↑, DHSI = ↑	IXIC = ↑	0.875	0.875	0.875
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, DHSI = ↑	DJI = ↑	0.974	0.974	0.974
BVSP = ↑, FCHI = ↑, FTSE = ↑, GDAXI = ↑, DHSI = ↑	DJI = ↑	0.972	0.972	0.972
BVSP = ↑, FTSE = ↑, GDAXI = ↑, XU100 = ↑, DHSI = ↑	DJI = ↑	0.972	0.972	0.972
XU100 = ↓, DHSI = ↓	FTSE = ↓	0.939	0.939	0.939
XU100 = ↓, SSEC = ↓	FTSE = ↓	0.937	0.937	0.937
XU100 = ↓, N225 = ↓	FTSE = ↓	0.931	0.931	0.931
XU100 = ↓, DHSI = ↓	GDAXI = ↓	0.922	0.922	0.922
XU100 = ↓, N225 = ↓	GDAXI = ↓	0.922	0.922	0.922
XU100 = ↑, DHSI = ↑	GDAXI = ↑	0.913	0.913	0.913
XU100 = ↓, DHSI = ↓	FCHI = ↓	0.920	0.920	0.920
XU100 = ↓, N225 = ↓	FCHI = ↓	0.919	0.919	0.919
XU100 = ↑, DHSI = ↑	FCHI = ↑	0.907	0.907	0.907
GSPC = ↑, DJI = ↑, IXIC = ↑	N225 = ↑	0.699	0.699	0.699
DJI = ↑, IXIC = ↑	N225 = ↑	0.696	0.696	0.696
GSPC = ↑, IXIC = ↑	N225 = ↑	0.691	0.691	0.691
N225 = ↑	DHSI = ↑	0.813	0.813	0.813
N225 = ↓	DHSI = ↓	0.773	0.773	0.773
GSPC = ↑, DJI = ↑, IXIC = ↑	DHSI = ↑	0.701	0.701	0.701
N225 = ↓	SSEC = ↓	0.766	0.766	0.766
N225 = ↑	SSEC = ↑	0.703	0.703	0.703
BVSP = ↓	SSEC = ↓	0.622	0.622	0.622

Source(s): Own elaboration

Table 15.
Comparison of the algorithm results

markets. With the increase of globalization and capital movements, the importance of the mobility of financial markets is increasing. In this process, the mobility of these markets should be considered to form financial markets that are resistant to economic shocks. It is possible for investors to be competitive with the analysis of co-movement.

In future studies, co-movements and opening/closing direction information can be obtained by using a similar method for other stock market indices other than the sample. In this way, the interaction map between world stock indices is drawn. On the other hand, the analysis can be repeated by including the effects of determinants and breaks such as the global economic crisis. In addition, the co-movements obtained in this study can be analysed in terms of inter-exchange returns and volatility spillovers.

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