

Co-movement of European Stock Markets based on Association Rule Mining

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Abstract—Due to the fluctuation and complexity of the stock market, it is challenging to capture its non-stationary property and describe its moving tendency. Moreover, globalization increases the interdependence among countries. It is important for investors to understand the co-movement of international stock markets in order to make informed decisions which lead to profit. With the huge amount of data generated by the stock markets, researchers started to explore this problem using different approaches. In this paper, we apply one of the data mining techniques, namely, association rules, to illustrate knowledge patterns and rules of European stock markets. Especially, this paper investigates the co-movement of the European stock market indices with the leading global stock indices. This study shows a strong co-movement between stock market indices of Germany and United Kingdom. Moreover, the European stock markets seem to have strong co-movement with the US stock market. Their co-movement with the Brazil seems to be also strong. However, Brazil stock index does not assume the dominant role, as the US stock index does. This study also shows that there is a weak relationship between European and Japanese stock markets.

Keywords-co-movement; association rules; stock index; co-integration.

I. INTRODUCTION

International stock market linkages are of great importance for financial decisions of international investors. International diversification reduces total risk of a portfolio. Increase co-movement between asset returns can diminish the advantage of internationally diversified investment portfolios [18]. Changes in co-movement patterns call for an adjustment of portfolios [26].

Forecasting stock index is a challenging task due to its dynamic and complex nature. Forecasting stock index plays an important role in developing effective market trading strategies [14]. Stock markets can be influenced by various factors such as the international environment, government policies, political climate, economic growth, war, and natural disasters. Among these factors, some of them have long-term effect on the markets while others have only short-term effect [28]. Recently, globalization adds more complexity to the movement of stock markets. Globalization in finance and trade increases the interdependence among countries. Such relationships further cause the co-movement of the financial

markets between countries. Studies have confirmed that most of the world's stock markets are integrated and associated [22]. Loh [19] claims that understanding the dynamic co-movement between global financial markets plays an important role in predicting stock market returns, allocating assets and diversifying portfolios.

This paper extends the existing literature on stock market co-movement between the European stock markets with that of the US, Brazil, and the Japan. The major European markets include UK, Germany, and Turkey stock markets. The rest of the paper is organized as follows. In Section 2, we give the literature review. Section 3 presents data and research technique. Section 4 presents research findings and discussions. Section 5 concludes the paper.

II. LITERATURE REVIEW

The dynamic interdependence and market integration among major stock exchanges have been investigated by various studies using vector autoregression (VAR) and autoregressive conditional heteroscedastic (ARCH) models. Vuran [27] found that the ISE100 index is co-integrated with stock markets of the United Kingdom (FTSE), Brazil (BOVESPA), and Germany (DAX). Floros [9] demonstrated the linkages and co-integration among mature stock indices (such as S&P 500, Nikkei225 and FTSE-100) using a vector error correction model and the Granger-causality approach. Ozdemir and Cakan [23] claimed that there is a strong bidirectional nonlinear causality relationship between the US stock index and the stock market indices of the Japan, France and the UK using nonlinear causality tests. Some studies have demonstrated that the U.S stock market has a dominant impact on emerging markets [20] and some developed stock markets such as Japan and France [23]. These studies demonstrated the dynamic causal linkages among international stock market indices.

Contrary to these findings, Chan, Gup and Pan [6] concluded that stock markets are not co-integrated, by analyzing 18 stock market indices. Pascual [24] also found that there is no co-integration relationship between the French, German, and UK stock markets, by using quarterly data. Zhu et al. [30] rejected co-integration relationships between market returns in Shanghai, Shenzhen and Hong Kong. Dimpfl [8] further proved that international financial

markets are not co-integrated in the Engle and Granger [31] sense. In response to such a dilemma, data mining techniques have been introduced to investigate the co-movement between stock markets. Aghabozorgi and The [1] studied stock market co-movement using the three-phase clustering method. Liao and Chou [15] investigated the co-movement of the stock markets of Taiwan and Hong Kong using clustering methods and association rules. Association rules learning discovers interesting correlation patterns among data items in a large dataset by revealing attribute value conditions that co-occur frequently [29]. It aims at uncovering relationship between items that occur together in database. The association rules generated through mining represent an important class of regularities that exist in databases. Nowadays, stock markets across the world have some kinds of connection with each other. In addition, these markets generate huge amount of financial data each day. Thus, mining association rules becomes important since it can provide insights to investors and policy makers to make informed decision.

Since the introduction of the Euro, the European stock markets have become more integrated with the German stock market taking the leadership role [21]. Investing in European stock markets has grown since the European stock markets are one of the most attractive destinations of international funds. The European markets have assumed the leadership role that the US and Japanese markets experienced in the past [3]. Many studies have investigated linkages between European and US markets or among European markets. The majority of the studies focus on the co-movement among developed stock markets [3][21][25]. There are few studies examining the co-movement between developed and emerging markets [20][27]. Berger et al. [5] claimed that emerging markets provide significant diversification potential to investors due to the low integration of these markets with the developed markets worldwide. Therefore, it is important to understand and estimate the co-movement of the emerging markets and the developed markets. Empirical evidence concerning the dynamics of the co-movement of the European markets (including European emerging markets) with the US, Latin America and Japanese stock market is limited. This study intends to fill this gap by investigating the co-movement of the European stock markets within the region and its co-movement with the major global stock markets, such as the USA and Japanese markets.

III. RESEARCH METHOD

A. Data

This database was acquired from the UCI Repository of Machine Learning Databases [32]. Data sets include stock indices from both developed and developing markets, as shown in Table 1.

TABLE I. STOCK INDICES INVESTIGATED IN THIS STUDY

Stock Indices	Detail Information		
	Country	Stock Index	Stock Exchange
1	US	S&P500	New York Stock Exchange
2	Japan	NIKKEI 225	Tokyo Stock Exchange
3	Germany	DAX	Frankfurt stock Exchange
4	Brazil	BOVESPA	BM&F BOVESPA stock Exchange
5	Turkey	ISE100	Istanbul Stock Exchange
6	United Kingdom	FTSE-100	London Stock Exchange
7	Europe	EU	MSCI European Index
8	Europe	EM	MSCI emerging market index

Among the indices, the MSCI Europe Index captures large and mid-cap representation across 15 developed market countries in Europe, while the MSCI Emerging Markets index captures large and mi-cap representation across 21 emerging markets countries. The entire data set covers the period from January 5, 2009 to February 22, 2011. Missing values were replaced by the previous day's value.

B. Data Mining Techniques

With the development of information technology and software, large amounts of data on stocks traded by the hour and the minute can be easily collected. Therefore, extracting useful information from the huge amount of stock market data becomes critical to investment in stock markets. Data mining techniques have attracted more attention from investors interested in discovering patterns and predicting changes of the stock markets. For instance, Support Vector Machine (SVM) [11][12][13] and Neural Networks [4][7][12][17] have been used to improve the predictability of stock prices. Recently, mining association rules [1] from large data repositories have attracted considerable attention in various areas including financial domain. Association rule mining was originally used in marketing to discover association rules about which groups of products are likely to be purchased together. The goal of association rule analysis is to discover interesting association and correlation relationships among large sets of data items. Although there are many applications of association rules in the field of data mining problems, it is not common to estimate the co-movement of the stock markets using association rules. In the literature, only a few studies have utilized the association rules to study the behavior of stock markets. Liao, Ho, and Lin [16] implemented association rules learning on the Taiwan stock market to discover knowledge patterns and stock category association to aid portfolio investments. Na and Sohn [22] predicted the movement direction of the Korea Composite Stock Price Index using association rules.

The problem of mining association rules was first introduced by Agrawal et al. [2]. The association rule is defined as follows: Let $I = \{i_1, i_2, \dots, i_d\}$ be the item set

and $D = \{ t_1, t_2, \dots, t_N \}$ be the set of all transactions. A transaction t_j is said to contain an item set X if X is a subset of t_j . An association rule is an implication expression of the form $X \rightarrow Y$, where X and Y are disjoint item sets. The association rule means that the item set Y is likely to occur whenever the item set X occurs. The strength of an association rule can be measured in terms of support and confidence, which indicate the usefulness and certainty of a rule, respectively [10]. Support is denoted as $Sup(X, D)$, which represents the percentage of transaction D that contains the item set X . The higher the support value, the more important the transaction set D is. Accordingly, the support for the rule $X \rightarrow Y$ is denoted as $Sup(X \cup Y, D)$, which represents the percentage of transactions in D containing both X and Y item sets. The other measure of rule $X \rightarrow Y$, called confidence and denoted as $Conf(X \rightarrow Y)$, which can be expressed in terms of support such that $Conf(X \rightarrow Y) = Sup(X \cap Y) / Sup(X, D)$. It represents the percentage of transactions in D that contain X and also contain Y . In other words, confidence is an estimate of the conditional probability $P(Y|X)$. For the rules with the same confidence level, the rule with the highest support is preferred. However, both measures may not be sufficient to assess the descriptive power of a rule. For example, rules with high confidence may happen by chance. Therefore, the measure lift is used to assess the reliability of support and confidence, it is defined as: $Lift = Conf(X \rightarrow Y) / Sup(Y)$ [15]. If the lift value is close to 1, it implies that X and Y are independent and the rule is not useful. If the lift value is higher than 1, it indicates that the occurrence of X provides information about Y .

The goal of association rules discovery is to generate all transaction rules that have a certain level of minimum support and confidence. To obtain a small set of useful association rules from this dataset, we conducted association rule analysis using SAS enterprise miner 12.1[33]. The algorithm used to conduct association analysis is ASSOC procedure implemented in SAS data miner [33]. We also set the minimum support value at 10%, and the minimum confidence value at 70%, which were used in previous studies [16][22]. The maximum number of items in an association is set to 2 and 3.

IV. RESULTS

The extracted association rules ordered by confidence have been summarized in Table 2 and Table 3.

TABLE II. SET OF ASSOCIATION RULES BETWEEN TWO STOCK INDICES

Rule	Condition
R1: If BOVESPA is up, then EU is up	Confidence 100%, support 40%, Lift 2.22
R2: IF SP is down, then EU is down	Confidence 100%, support 35%, Lift 1.82
R3: IF EU is up, then SP is up	Confidence 100%, support 45%, lift 1.54
R4: If EU is down, then BOVESPA is down	Confidence 100%, support 55%, Lift 1.67
R5: If BOVESPA is down, then EU is down	Confidence 91.67%, support 55%, Lift 1.67
R6: If ISE is down, then EM is down	Confidence 81.82%, support 45%, lift 1.49
R7: If DAX is down, then EU is down	Confidence 80%, support 40%, lift 1.45
R8: If DAX is up, then FTS is up	Confidence 80%, support 40%, lift 1.45
R9: If DAX is down, then BOVESPA is down	Confidence 80%, support 40%, lift 1.33
R10: IF NIKKEI is up, then BOVESPA is down	Confidence 75%, support 45%, lift 1.25

A. Association Rules

According to Table 2, Rule 1 and Rule 4 indicate that the Brazil stock index has the highest confidence (100%) and high support with MSCI Europe Index. This reveals that BOVESPA is highly correlated with EU. That is, both indices will have the same trend of variation. Rule 2 and Rule 3 also show strong association between EU and SP. That is, US stock market may still play a dominant role in affecting European stock markets especially when the downward trend is present. Within Europe, the major stock index DAX is the driving force to other stock indices within the region according to Rule 7 and Rule 8. However, there seems to be an inverse relationship between NIKKEI and BOVESPA based on Rule 10. In addition, the lift values for all the rules listed in Table 2 are above 1, which implies that these rules are useful.

Table 3 shows association rules among three stock indices. Rule 1 and Rule 3 demonstrate that DAX and FTS are highly correlated with EU, since EU represents the developed markets in Europe. According to Rule 5 and Rule 6, when ISE and DAX are up, EU is up. However, when ISE and DAX are down, EU is also down. As to the global markets, SP still has a strong influence over European stock markets, as shown in Rule 7 and Rule 9.

TABLE III. SET OF ASSOCIATION RULES AMONG THREE STOCK INDICES

Rule	Condition
R1:If FTS and DAX are down, then EU is down	Confidence 97.77%, support 41.01%, Lift 1.86
R2:If EM and DAX are down, then EU is down	Confidence 97.42%, support 35.39%, Lift 1.86
R3:If FTS and DAX are up , then EU is up	Confidence 97.18%, support 38.76%, lift 2.04
R4: If EM and DAX are up, then EU is up	Confidence 96.36%, support 29.78%, Lift 2.03
R5:If ISE and DAX are down, then EU is down	Confidence 96.20%, support 33.15%, Lift 1.83
R6:If ISE and DAX are up, then EU is up	Confidence 95.83%, support 30.15%, lift 2.01
R7:If SP and DAX are down , then EU is down	Confidence 95.43%, support 35.21%, lift 1.82
R8:If NIKKEI is down and EU is up , then DAX is up	Confidence 93.85%, support 22.85%, lift 1.91
R9:If SP and EU are down, then DAX is down	Confidence 92.61%, support 35.21, lift 1.82
R10:If NIKKIE and EU are up, then FTS is up	Confidence 91.94%, support 21.33%, lift 1.88

B. Link Maps

In this study, we also conducted link analysis, which aims at highlighting the linkages between items of interest. The graph link shows the nodes of items within the dataset that are connected to each other. A link presents a connection between two items in a rule. The size of the node is determined by the transaction count, while the weight of the link is related to the confidence of the rule. The higher the confidence is, the thicker the link between nodes. The link graphs are given in Figure 1 and Figure 2. The link graphs are meaningful and interesting. More importantly, it is easy for investors and traders to identify the patterns of movement of these stock indices. Figure 1 shows a strong co-movement among DAX, FTS, EU, SP, and BOVESPA. That is, when these stock indices are rising, they also drive other stock indices (such emerging stock indices) to go up. On the other hand, when these stock indices are down, other stock indices also go down. Therefore, these stocks may be considered as the driving force to the others to move up or move down.

Figure 2 shows that when DAX, FTS and EU indices are down, all other markets tend to be down. The thick links originated from the nodes of these three indices represent that these indices have strong co-movements with other European stock indices and with the global stock indices, such as SP, NIKKEI, and BOVESPA.

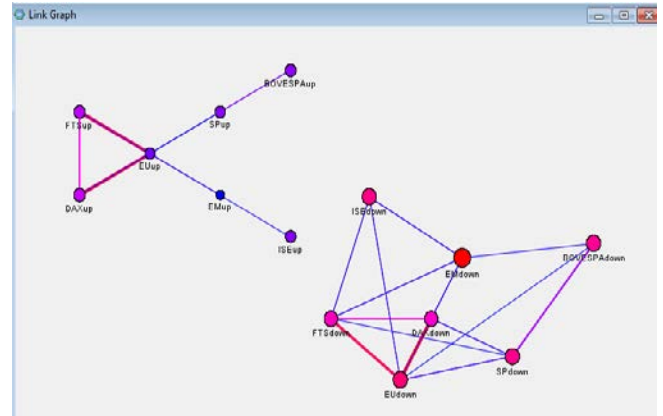


Figure 1. Link Map between two stock indices.

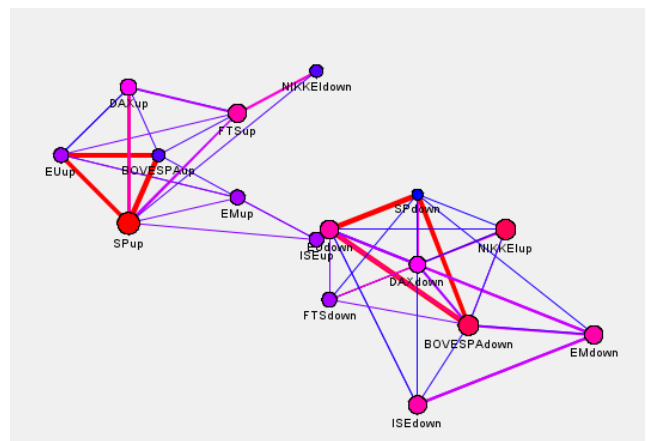


Figure 2. Link Map among three stock indices.

V. CONCLUSION AND FUTURE WORK

In conclusion, we found several interesting associations between European and leading global stock markets. The findings show strong co-movements among European stock indices. The European stock markets seem to have strong co-movement with the US stock market as well. More interestingly, European stock indices also have strong associations with the Brazil index. However, The Brazil stock index does not assume the dominant role as the US stock index does. This study shows that association rules seem to be an appropriate technique for effective exploration of underlying patterns in huge amount of stock market data. We expect that association rules can be used to provide information that can facilitate decision making with regard to predicting stock market returns, allocating assets and diversifying portfolios. However, the results of association analysis need to be interpreted with caution since an association rule does not necessarily imply causality.

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