UNIVERSITY OF TECHNOLOGY SYDNEY

32513 Machine Learning

Assignment2: Practical Workplace Related Data Analytics Project

Student ID & Name: Qing Ding 13101023

Student ID & Name: Dongxu Fan 12833291

Content

Business of Understanding

This research investigates if there is a critical time varying between national stock market and iShares market among the four countries, like iShares USA, UK, France and Germany and their counterparties country index. The study uses cointegration theory in long-term investigation and vector autoregressive model to test the short-term relationship among the given index. In addition, the research will benefit investors who wants to have overseas market portfolio and gain the diversification in both national stock markets and iShares market.

Business of Objective

iShares, initially well known as WEBS(the full name is world equity benchmark shares), in addition Miffre (2007) investigates that the investors in USA have high level of returns in trading a national country funds, and benefits profits from short-term iShares. In this research, we want to figure out the good portfolio of iShares products and national products.

MSCI	Country index
USA (United State of America)	DJAI
UK (United Kingdom)	FTSE100
FRA (France)	CAC40
DE (Germany)	DAX30

Table 1 iShares index and country index

Data Source

The data is downloaded from Bloomberg and the period ranges from 26th of June 2006 to 16th of June 2017.The number is daily measurement, and the data is the close index. We picked up four national indexes, namely DAX30 (Germany), CAC40 (France), FTSE100 (UK), and DJAI (US).

Measure of Success

The indicator that predicts which indicator is the most investment-oriented depends on which indicator is related to more attributes in the process of this calculation test. Based on the trends between these Attributes and divided into long-term and short-term situations, we finally derive the relationship between these Attributes.

Course's Action

We begin to understand and analyze our data by using statistical data, histograms, tables, discrete graphs, etc. to describe its presentation. After a clear understanding of the data set, we can perform the subsequent pre-processing and conversion process to get the data attributes needed for the analysis. We choose the right algorithm and evaluate the model that best fits our business goals.

Data Understanding

Data Description

Attribute	Format	Description
USA	INT	MSCI of United State of America
UK	INT	MSCI of United Kingdom
FRA	INT	MSCI of France
DE	INT	MSCI of Germany
DJAI	INT	Country index of United State of America
FTSE100	INT	Country index of United Kingdom
CAC40	INT	Country index of France
DAX30	INT	Country index of Germany

Table 2 Data Description

Statistical Description of Dimensions

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
USA	153.7072	142.1126	244.55	68.11	41.06894	0.320311	2.071999	146.6558
UK	36.3466	35.34	54.44	18	6.753244	0.333218	2.99296	51.22953
FRA	26.30339	25.31	40.09	14.44	5.203306	0.730533	3.08653	247.0669
DE	25.48858	25.755	36.5	12.73	4.598055	-0.081236	2.552714	26.11859
DJAI	13762.01	13021.33	21374.56	6547.05	3245.482	0.263412	2.247843	97.25866
FTSE100	9730.038	9534.628	13974.21	4894.534	1672.472	0.03731	3.039992	0.826652
CAC40	5504.962	5275.609	8459.06	3184.383	1128.752	0.845722	3.127837	331.8517
DAX30	9981.047	10166.95	14451.45	4635.253	2051.801	-0.178229	2.234784	82.18869

Table 3 Statistical Description

Figure 1. The Histogram of attribute USA shows that the maximum value of the ishares index is 244.55, the minimum is 68.11. Mean is 153.7072. In the interval of (101.001, 137.002), the number is the largest. Moreover, attribute USA has a higher value and a smaller number.

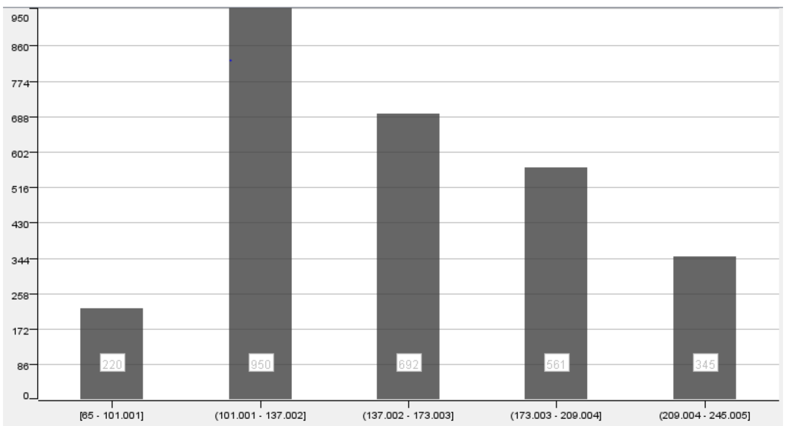

Figure 1 USA Histogram

The figure below shows the changes in the different values and quantities of Attribute UK. In the total amount of data 2768, attribute UK is in the range of (32.594, 38.891), half of which shows the basic trend of the value. The maximum number is concentrated in the middle section, and the number of the two ends has a decreasing trend.

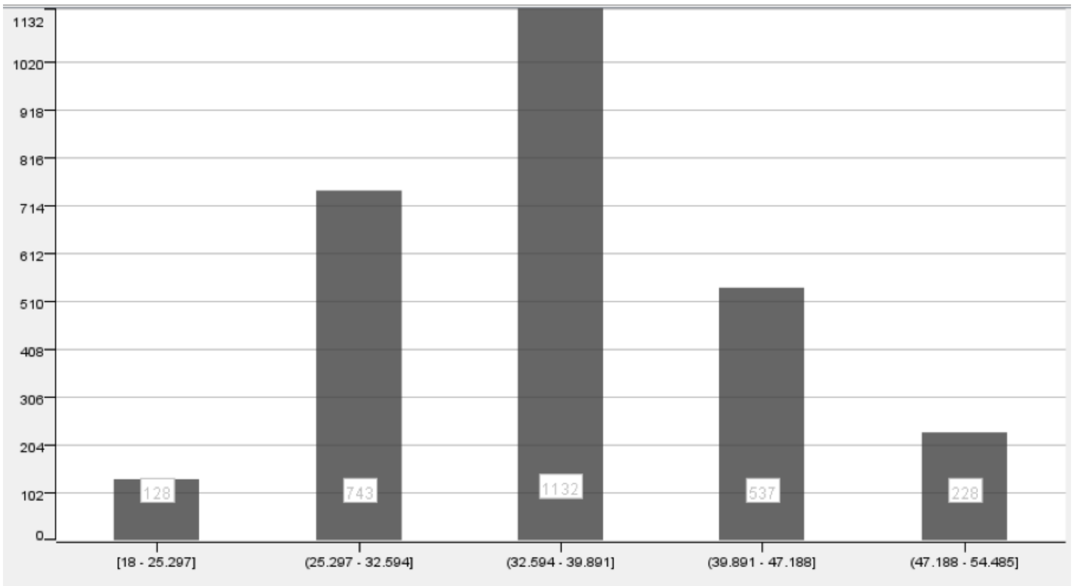

Figure 2 UK Histogram

The figure below shows the quantitative relationship of the Fist Histogram. Attribute FRA values are mainly concentrated in the (19.22, 29.66) numerical segment, accounting for about two-thirds. In this numerical interval, it is worthy of reference.

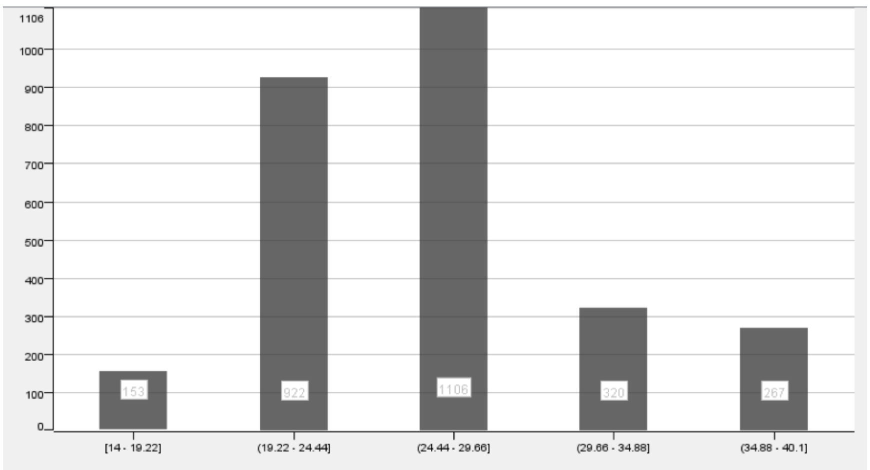

Figure 3 FRA Histogram

The graph of DE's Histogram shows the simple number relationship of attribute DE. The maximum value is 36.555 and the minimum value is 12. Median is 25.75. The overall data also shows a phenomenon in which there are many intermediate values and few values at both ends.

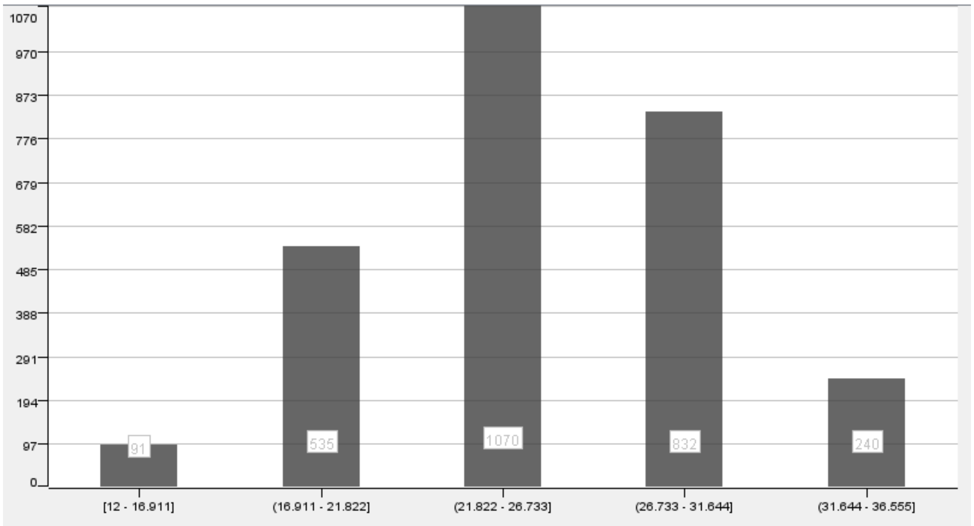

Figure 4 DE Histogram

The diagram of DJAI's Histogram shows the simple quantitative relationship of attribute DJAI. Median is 13021.33. The overall data also shows a phenomenon in which there are many intermediate values and few values at both ends.

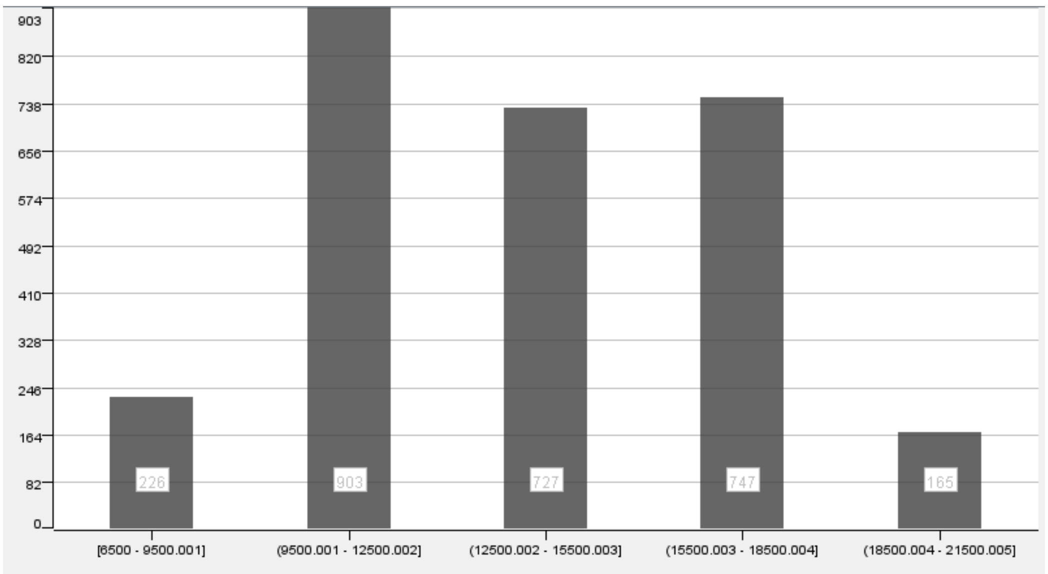

Figure 5 DJAI Histogram

The FTSE100's Histogram plot shows the simple quantitative relationship of the attribute FTSE100. Median is 9534.628. In the middle of the data segment, the value is the most, and the values at both ends are decreasing.

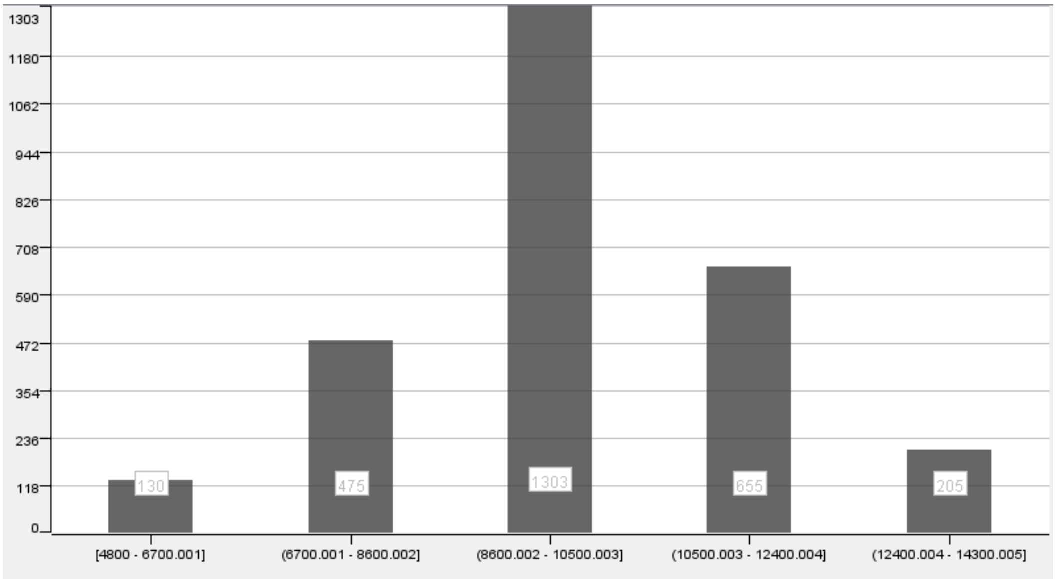

Figure 6 FTSE100 Histogram

The graph of the Histogram of CAC40 shows the simple quantitative relationship of attribute CAC40. Median is 5275.609. The overall data also shows a phenomenon in which there are many intermediate values and few values at both ends.

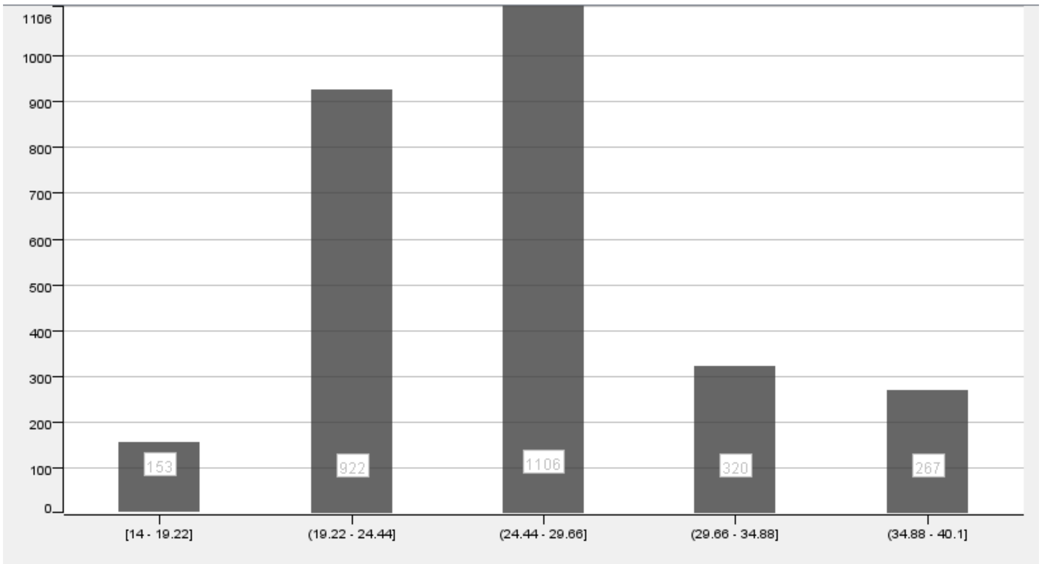

Figure 7 CAC40 Histogram

The DAX30's Histogram plot shows the simple quantitative relationship of the attribute DAX30. Median is 10166.95. The overall data also shows a phenomenon in which there are many intermediate values and few values at both ends.

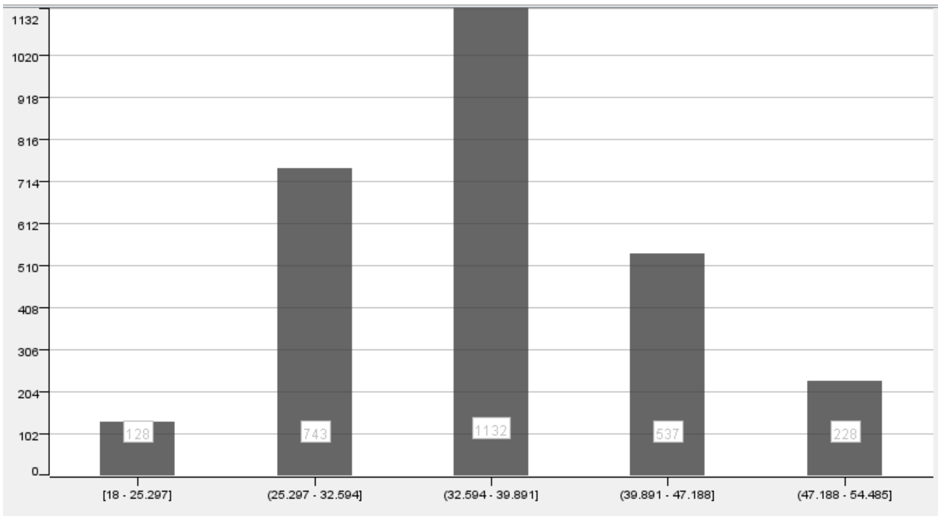

Figure 8 DAX30 Histogram

Boxplots and Outliers

The figure below shows the boxplots showing attribute UK, where we can see many outliers. The median is 35.34. There are several extreme outliers for the values at both ends.

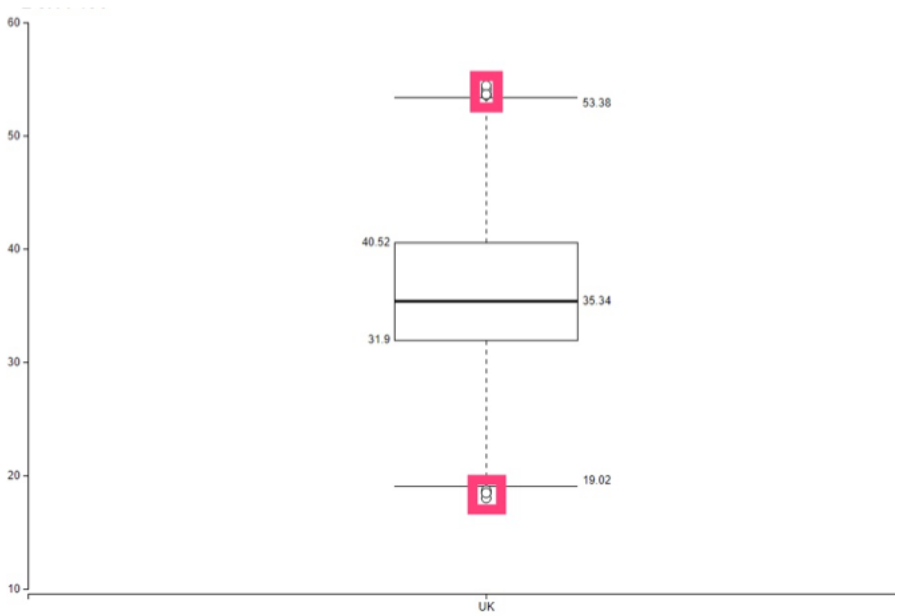

Figure 9 UK Boxplots

The following figure shows the boxplots showing attribute FRA, where many outliers are highlighted.

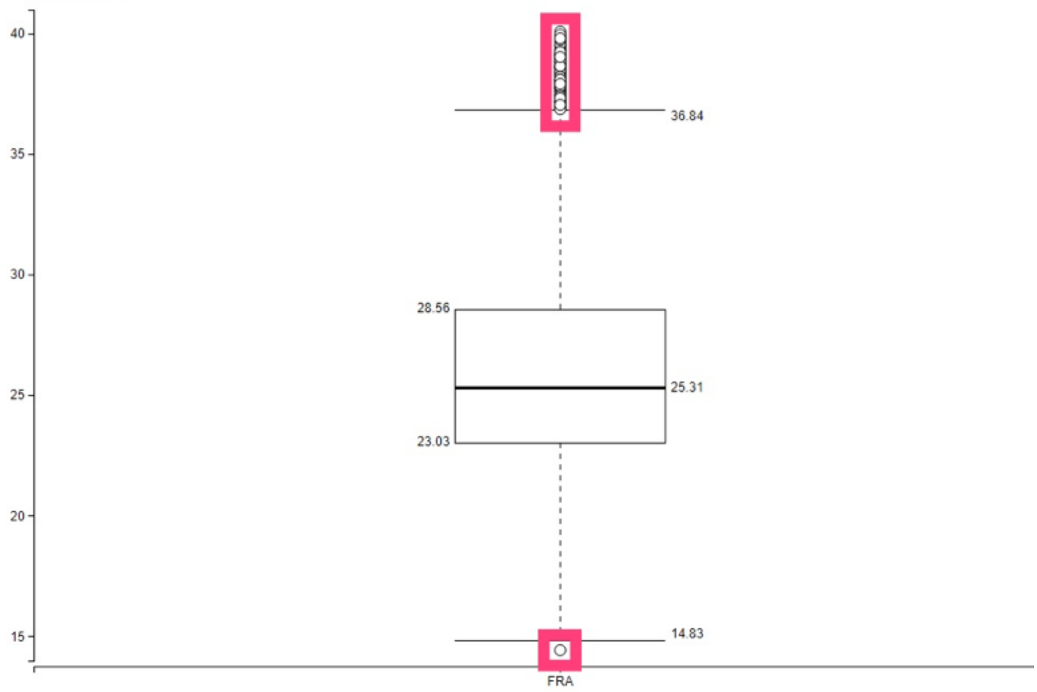

Figure 10 FRA Boxplots

The following figure shows the boxplots showing attribute FTSE100, where many outliers are noted.

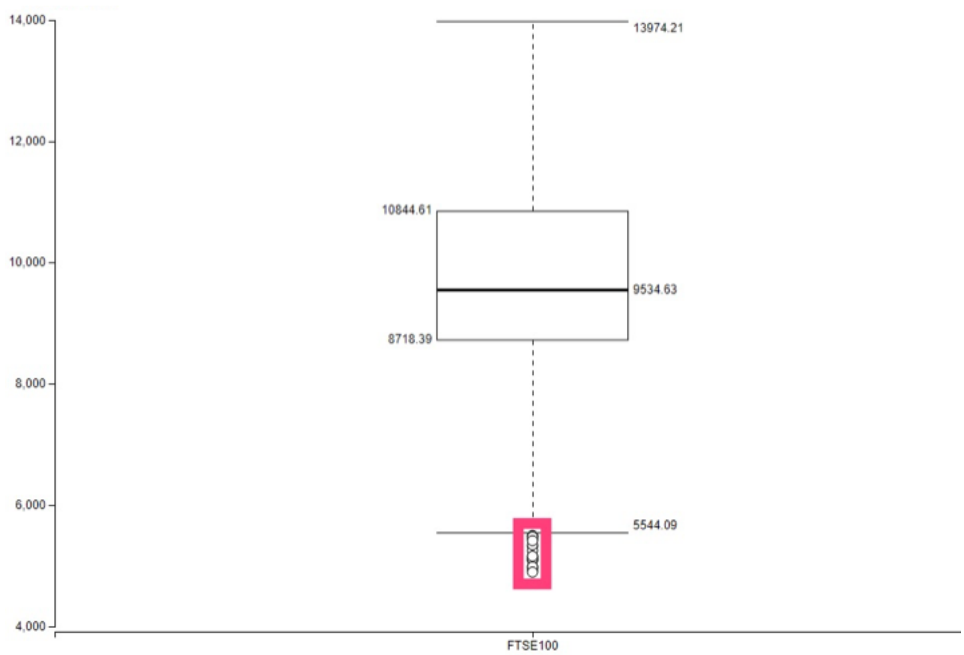

Figure 11 FTSE100 Boxplots

The following figure shows the display of attribute CAC40 boxplots, wherein the marked out many outliers.

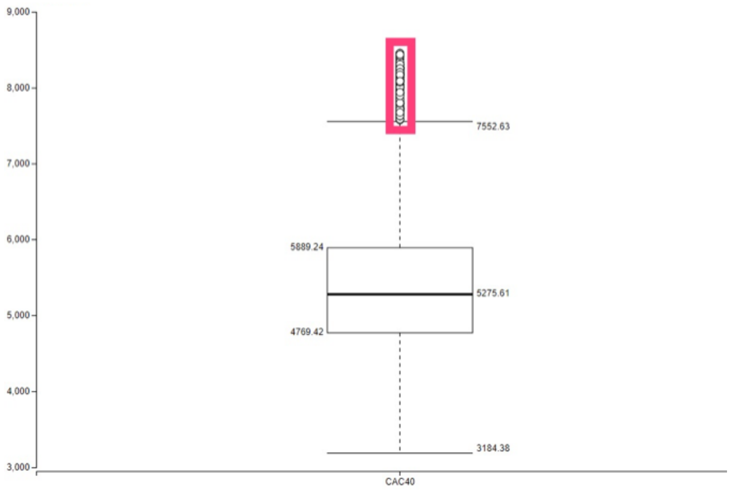

Figure 12 CAC40 Boxplots

Missing and Empty Values

Correlations

This image shows the correlation between the data. In general, red indicates a negative correlation and blue indicates a positive correlation. Figure 1 shows that there is a positive correlation between the data. The shade of the color indicates the degree of correlation between the two attributes. Based on the depth of blue, attribute USA is more correlated with DJAI and DAX30, and may have a relationship that deserves further study. Conversely, the correlation between attribute USA and Attribute CAC40 is the lowest because the color is the shallowest. The correlation between the two attributes is relatively small. (As shown below)

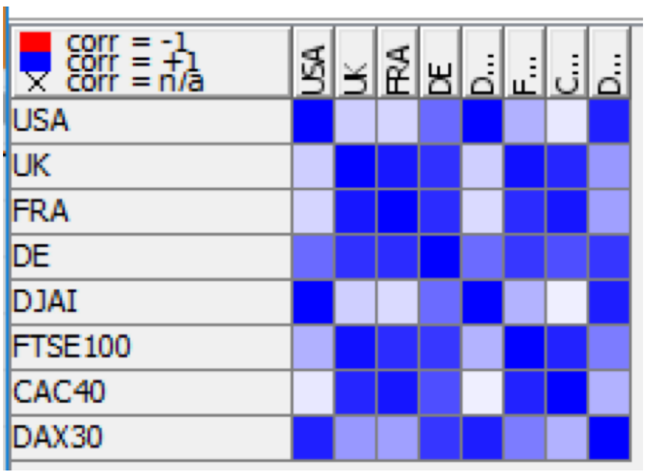

Figure 13 Correlation of data

This table is represented by [-1, 1] by using the correlation coefficient. The greater the correlation, the larger the correlation coefficient. For example, Attribute USA and Attribute DJAI, the correlation coefficient of the two attributes reached 99.4%, indicating that the correlation between the two is very high, we can predict that attribute DJAI may be the main influencing factor of attribute USA.

Table "Correlation values" - Rows: 8 | Spec - Columns: 8 | Properties | Flow Variables

Row ID	D USA	D UK	D FRA	D DE	D DJAI	D FTSE100	D CAC40	D DAX30
USA	1.0	0.19387610904137...	0.16635162409632...	0.5844989461518...	0.9947751820016...	0.3062643917697...	0.09204966209075...	0.8789626746130...
UK	0.19387610...	1.0	0.9144130510405513	0.810079215762549	0.1874150860830...	0.9392669788812...	0.8540602656720754	0.4036146010472...
FRA	0.16635162...	0.9144130510405513	1.0	0.8314643073494...	0.1448380179556...	0.8331242965538...	0.9158510319348838	0.3707338978648...
DE	0.58449894...	0.810079215762549	0.8314643073494135	1.0	0.5822065716294...	0.7841049390894...	0.694859585120611	0.7863856824391...
DJAI	0.99477518...	0.18741508608307...	0.1448380179556835	0.5822065716294...	1.0	0.2974186216102...	0.0638526432748286	0.8847209373746...
FTSE100	0.30626439...	0.9392669788812997	0.8331242965538306	0.7841049390894...	0.2974186216102...	1.0	0.8679148720780903	0.5132822373173...
CAC40	0.09204966...	0.8540602656720754	0.9158510319348838	0.694859585120611	0.0638526432748...	0.8679148720780...	1.0	0.302416311937844
DAX30	0.87896267...	0.4036146010472236	0.3707338978648137	0.7863856824391...	0.8847209373746...	0.5132822373173...	0.302416311937844	1.0

Figure 14 Correlation

Scatter Plots

In the figure, attribute DJAI is the X axis and Attribute USA is the Y axis. As can be seen from the figure below, there is a clear linear relationship between attribute USA and attribute DJAI, which has a high correlation and almost no discrete values. There is a high reference value in the stock market.

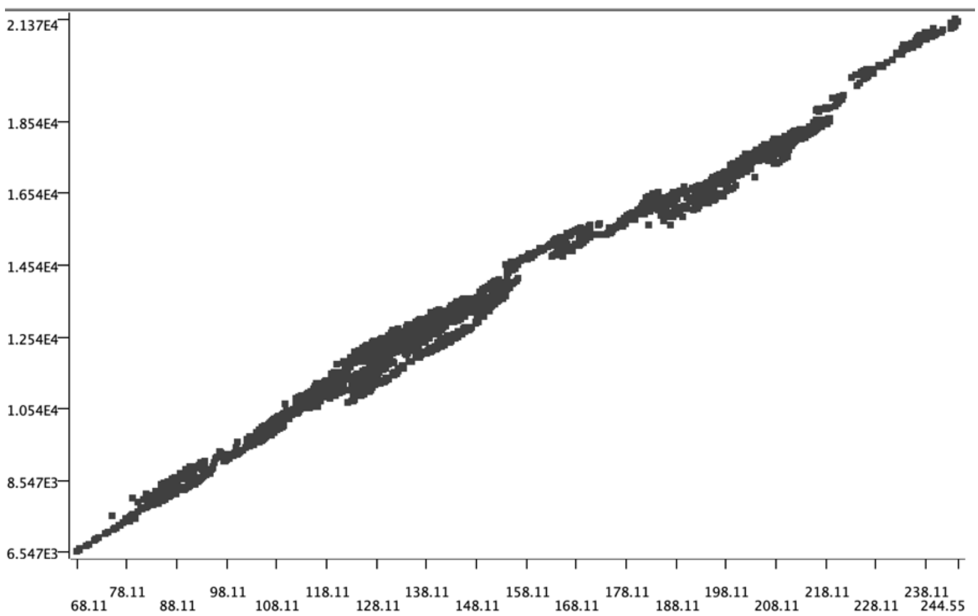

Figure 15 Scatter Plots of DJAI and USA

The figure below shows a scatter plots of time with the X axis and other attributes for the Y axis. As can be seen from this picture, there is a certain correlation between these attributes in the long run. In the stock market, these factors may have some cointegration equilibrium relationship. So in this paper, we will study the relationship between these attributes in both long-term and short-term.

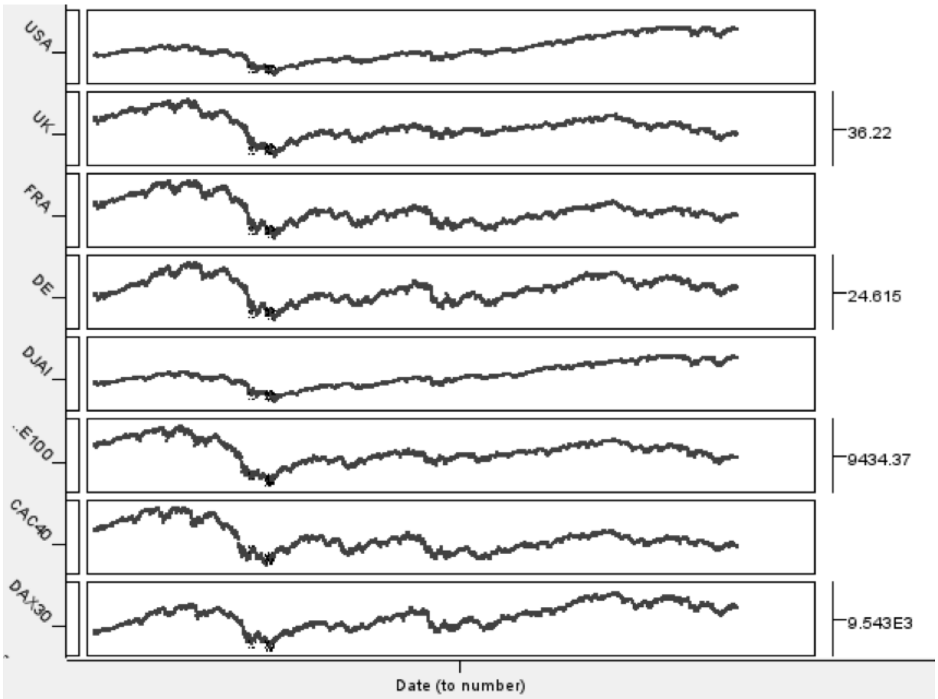

Figure 16 Scatter Plots of all attributes

Data of Preparation

Data of Cleaning and the Observations

Data of Cleaning:

Our initial data set contains 15 attributes. Only eight were chosen because they are significant in analyzing business issues. The remaining attributes have been removed from the data set.

Data Observation:

In the overall data, there is no missing value by observation. Also, by using Knime analysis, import the data to see if there are missing values. Overall, the entire set of data can be used.

Data Pre-processing and transformations

We analyze the overall data and refer to relevant information to determine the reliability of the overall data in order to better classify the data. The overall data is to make people more convenient and easier to refer to the investment index. The values for USA, UK, FRA, DE are indices based on US dollars, while the remaining four attributes are determined according to the national currency. For example, the standard for the FTSE 100 is the pound.

Modelling

Stationary test

The theory of ADF

Before analysis the cointegration test of iShares index of four countries USA, UK, France and Germany and their national stock counterparties, the unit root tests should be tested. The most well-known stationary test is the ADF test which is launched by Augmented Dickey-Fuller(Ajay Khorana, Edward Nelling 1998). The unit root test is used to confirm a series is stationary or not. The null hypothese of ADF test is that there is a unit root, and if the p-value of the test is no more than 0.05, the null hypothesis is rejected. Thus, the tested series is stationary.

The result of ADF test

In [ ]:
```
#ADF stationary test
result = ts.adfuller(x, 1)
adfResult = sm.tsa.stattools.adfuller(data,maxlags)
print = pd.DataFrame(index=['Test Statistic Value', "p-value", "Lags Used", "Number of Observations Used",
                            "Critical Value(1%)", "Critical Value(5%)", "Critical Value(10%)"],
                     columns=['value'])
 print ['value']['Test Statistic Value'] = adfResult[0]
 print ['value']['p-value'] = adfResult[1]
 output['value']['Lags Used'] = adfResult[2]
 output['value']['Number of Observations Used'] = adfResult[3]
 output['value']['Critical Value(1%)'] = adfResult[4]['1%']
 output['value']['Critical Value(5%)'] = adfResult[4]['5%']
 output['value']['Critical Value(10%)'] = adfResult[4]['10%']
```

ADF statistics in developed market					
	iShares index				
	name	Levels		Fisrt difference	
		t-Statistic	Pro.	t-Statistic	Pro.
1	USA	-1.52	0.82	-56.92	0.00
2	UK	-1.99	0.61	-58.12	0.00
3	FRANCE	-1.95	0.63	-57.48	0.00
4	GERMANY	-2.04	0.58	-56.11	0.00
	Country stock index				
1	DJAI	-1.53	0.82	-57.76	0.00
2	FTSE100	-2.11	0.54	-53.81	0.00
3	CAC40	-2.11	0.5400	-54.44	0.00
4	DAX30	-2.31	0.43	-52.17	0.00

Table 4 ADF test

At level, the absolute values of p-value from all the index are more than 0.05 under the 95% confidential interval. Thus, the null hypothesis is accepted and there is a unit root at levles of all the factors. On the contrary, the absolute values of t-statistics in the first difference of all the factors are more than critical value under the confidence interval, so the null hypothesis is rejected. All the series on the first difference is stationary.

VAR Model

VAR Theory

VAR model normally is used to check the relationship between the dependent variables and independent variables within the short time(Phengpis & Swanson 2009). VAR (vector autoregressive model)is indicated by Sims(1980).VAR is used to test more than one dependent variables, and investigates the relationship between simultaneous equations and univariable time series models(Durand & Scott 2003). This article, the VAR models are used to test the short-term relationship between iShares index and the national stock market index in these four countries.

The result of VAR

The result of the VAR model. Thus, there is a short time relationship between the USA iShares index and the rest other index. To be specific, there is a positive trend with CAC40 index in lag 1 and lag 2, DAX 30 index in lag2, Germany iShares index in lag 1 and lag 2, DJAI in lag 1, French iShares index in lag 2. However, the other all index have negative trend with USA iShares index in the short time.

```
In [ ]: #VAR model
lnDataDict = {'lnSHFEDiff':lnSHFEDiff,'lnXAUDiff':lnXAUDiff}
lnDataDictSeries = pd.DataFrame(lnDataDict,index=lnSHFEDiffIndex)
data = lnDataDictSeries[['lnSHFEDiff','lnXAUDiff']]
```

USA = 0.000686239074403*D(CAC40(-1)) + 0.000354707560405*D(CAC40(-2)) - 0.000438277471008*D(DAX30(-1)) + 0.000766053484409*D(DAX30(-2)) + 0.622268923803*D(DE(-1)) + 0.423881393219*D(DE(-2)) + 6.07191927482e-05*D(DJAI(-1)) - 0.00101450443345*D(DJAI(-2)) - 0.810687941995*D(FRA(-1)) + 0.00417733759064*D(FRA(-2)) - 0.000141454377319*D(FTSE100(-1)) + 5.18110892606e-05*D(FTSE100(-2)) + 0.0899153156859*D(UK(-1)) - 0.123362620862*D(UK(-2)) + 0.946333568012*USA(-1) + 0.0538660929115*USA(-2) + 0.0137429035713

The stationary test of the VAR model

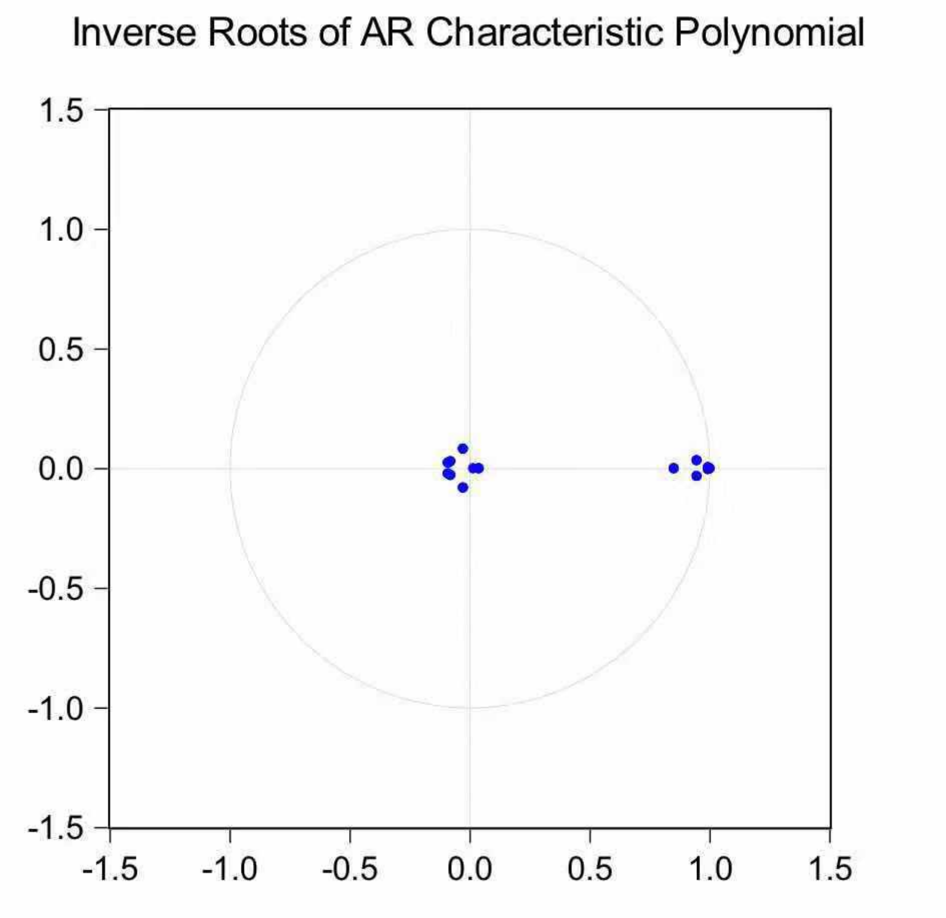

Figure 17 Inverse Roots of AR Characteristic Polynomial

The inverse roots of AR characteristic polynomial is used to check the stable function of the VAR model. In this result, all the points are in the unit one circle, so the VAR model is stable.

The lag of VAR model

In the test of lag observations, AIC suggested that the lag should be 2 under the 5% confidence interval.

Sample: 1 2768

Included observations: 2765

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-114961.6	NA	1.80e+26	83.16065	83.17779	83.16684
1	-68044.31	93529.15	3.45e+11	49.27039	49.42467*	49.32611*
2	-67929.94	227.3269	3.33e+11	49.23395*	49.52537	49.33921
3	-67844.76	168.8261*	3.28e+11*	49.21863	49.64719	49.37342

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Table 5 lag test

Cointegration test

The cointegration test is first introduced by Granger (1980).This test is used to check the long-term relationship among more than two series which are not stationary(Aroskar 2007).In this research, the cointegration test is applied to test whether there is a long-term equilibrium among the stock market index from four countries of national index and the iShares index. The theory of cointegration indicates two or more nonstationary series move closely to each other and their difference series is cointegrated. Normally, in the test results, there are two types of cointegration, namely, the maximum eigenvalue tests and the trace tests(Rompotis 2009).

In [ ]:
```
# Cointegration test
def coint(y0, y1, trend='c', method='aeg', maxlag=None, autolag='aic',
          return_results=None):
    coint_johansen(df,0,1)
```

Unrestricted Cointegration Rank Test (Trace)					
Hypothesized		Trace	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.090985	627.2970	159.5297	0.0000	
At most 1 *	0.070223	363.7250	125.6154	0.0000	
At most 2 *	0.041793	162.5491	95.75366	0.0000	
At most 3	0.006897	44.59224	69.81889	0.8436	
At most 4	0.004162	25.46971	47.85613	0.9056	
At most 5	0.002741	13.94474	29.79707	0.8437	
At most 6	0.002185	6.362298	15.49471	0.6527	
At most 7	0.000115	0.317877	3.841466	0.5729	
Trace test indicates 3 cointegrating eqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)					
Hypothesized		Max-Eigen	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.090985	263.5720	52.36261	0.0001	
At most 1 *	0.070223	201.1759	46.23142	0.0000	
At most 2 *	0.041793	117.9569	40.07757	0.0000	
At most 3	0.006897	19.12253	33.87687	0.8144	

At most 4	0.004162	11.52497	27.58434	0.9501	
At most 5	0.002741	7.582440	21.13162	0.9274	
At most 6	0.002185	6.044421	14.26460	0.6075	
At most 7	0.000115	0.317877	3.841466	0.5729	
Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					

Table 6 Cointegration test

The result of cointegration is that there are at most 2 pairs of cointegration relationships among all the pairs of long-term relationships.

Granger Causality test

Since VAR models include a number of lags from independent variables, it is quite difficult to estimate the effects between the independent variables and dependent variables. The Granger test is applied to check the effects of exogenous variables(Barari, Lucey & Voronkova 2007). The Granger test is able to indicate the correlation between the current value and the previous value from one factor to another, rather than the changes from only one variable(Brooks 2008).

The null hypothesis is A does not Granger cause B. If the p-value is less than critical value, the null hypothesis is rejected. Thus, A causes Granger B in this situation. In the following results, there are 19 pairs of factors have granger cause. There are three pairs of index have relationship, like FTSE 100 index and CAC 40 index, DJAI index and Germany iShares index, and the last pair is Germany iShares index and USA iShares index. Thus, there is obvious relationship between American market and German market in term of national index and iShares index.

In [ ]:

```
#Granger test
from statsmodels.tsa.stattools import grangercausalitytests

n = 1000
ls = np.linspace(0, 2*np.pi, n)

df1 = pd.DataFrame(np.sin(ls))
df2 = pd.DataFrame(2*np.sin(1+ls))

df = pd.concat([df1, df2], axis=1)

df.plot()

grangercausalitytests(wb, maxlag=3)
```

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
DAX30 does not Granger Cause CAC40	2765	0.49288	0.6872
CAC40 does not Granger Cause DAX30		5.97665	**0.0005**
DE does not Granger Cause CAC40	2765	2.07257	0.1017
CAC40 does not Granger Cause DE		9.84556	**2.E-06**
DJAI does not Granger Cause CAC40	2765	1.31424	0.2679
CAC40 does not Granger Cause DJAI		1.84528	0.1368
FRA does not Granger Cause CAC40	2765	1.11659	0.3410
CAC40 does not Granger Cause FRA		33.4230	**3.E-21**
FTSE100 does not Granger Cause CAC40	2765	24.9533	**6.E-16**
CAC40 does not Granger Cause FTSE100		4.70712	**0.0028**
UK does not Granger Cause CAC40	2765	0.73622	0.5303
CAC40 does not Granger Cause UK		11.6455	**1.E-07**
USA does not Granger Cause CAC40	2765	1.49432	0.2141
CAC40 does not Granger Cause USA		1.61526	0.1837
DE does not Granger Cause DAX30	2765	1.08740	0.3531
DAX30 does not Granger Cause DE		16.0590	**2.E-10**
DJAI does not Granger Cause DAX30	2765	3.61147	0.0128
DAX30 does not Granger Cause DJAI		9.34883	**4.E-06**
FRA does not Granger Cause DAX30	2765	0.38769	0.7619
DAX30 does not Granger Cause FRA		7.48989	**5.E-05**
FTSE100 does not Granger Cause DAX30	2765	3.72465	0.0109
DAX30 does not Granger Cause FTSE100		0.94969	0.4156
UK does not Granger Cause DAX30	2765	0.14771	0.9312
DAX30 does not Granger Cause UK		9.83555	**2.E-06**
USA does not Granger Cause DAX30	2765	3.03314	0.0282
DAX30 does not Granger Cause USA		9.94601	**2.E-06**

DJAI does not Granger Cause DE	2765	5.35197	**0.0011**
DE does not Granger Cause DJAI		4.59472	**0.0033**
FRA does not Granger Cause DE	2765	2.32362	0.0731
DE does not Granger Cause FRA		3.21928	0.0219
FTSE100 does not Granger Cause DE	2765	15.5420	**5.E-10**
DE does not Granger Cause FTSE100		1.13236	0.3346
UK does not Granger Cause DE	2765	2.85500	0.0359
DE does not Granger Cause UK		4.84868	**0.0023**
USA does not Granger Cause DE	2765	5.38623	**0.0011**
DE does not Granger Cause USA		5.55353	**0.0008**
FRA does not Granger Cause DJAI	2765	4.36929	**0.0045**
DJAI does not Granger Cause FRA		2.08925	0.0995
FTSE100 does not Granger Cause DJAI	2765	0.71452	0.5432
DJAI does not Granger Cause FTSE100		0.97873	0.4017
UK does not Granger Cause DJAI	2765	1.54331	0.2012
DJAI does not Granger Cause UK		0.62923	0.5961
USA does not Granger Cause DJAI	2765	0.60100	0.6143
DJAI does not Granger Cause USA		0.73603	0.5305
FTSE100 does not Granger Cause FRA	2765	15.8719	**3.E-10**
FRA does not Granger Cause FTSE100		1.58412	0.1911
UK does not Granger Cause FRA	2765	0.88973	0.4456
FRA does not Granger Cause UK		1.36963	0.2502
USA does not Granger Cause FRA	2765	2.46472	0.0606
FRA does not Granger Cause USA		5.23703	**0.0013**
UK does not Granger Cause FTSE100	2765	3.05912	0.0272
FTSE100 does not Granger Cause UK		33.2095	**4.E-21**
USA does not Granger Cause FTSE100	2765	0.43852	0.7255
FTSE100 does not Granger Cause USA		0.75287	0.5206
USA does not Granger Cause UK	2765	0.66040	0.5764
UK does not Granger Cause USA		1.84905	0.1361

Table 7 Granger test

Evaluation

This article mainly discussed the portfolio of international investment among iShares index and national index in the given four countries. The results indicate that there is a positive effect between USA national index and German index as well as iShares index in Germany. In the long-term, the result of cointegration is that there are at most 2 pairs of cointegration relationships among all the pairs of long-term relationships. From the Granger causality test, there is obvious relationship between American market and German market in term of national index and iShares index. The econometrics results indicate that the investors in USA have high level of returns in trading a closed-end country funds in the short-term, and benefits profits from long-term iShares which will have a forecast in Germany iShares index and Germany national index.

Reference

Ajay Khorana, Edward Nelling, and J.J.T. 1998, 'The Emergence of Country Index Funds', *The Journal of Portfolio Management*, vol. 24, no. 4, pp. 78–84.

Aroskar, R. 2007, 'DYNAMIC RELATIONSHIPS BETWEEN ISHARES AND COUNTRY FUNDS : THE CASE OF EUROPE AND ASIA', *The International Journal of Business and Finance Research*, vol. 1, no. 1, pp. 1–10.

Barari, M., Lucey, B.M. & Voronkova, S. 2007, 'Re-assessing co-movements among G7 equity markets: evidence from iShares', *Applied Financial Economics*, vol. 18, no. 2015, pp. 863–77.

Brooks, C. 2008, *Introductory Econometrics for Finance*, S. Edition (ed.),.

Durand, R.B. & Scott, D. 2003, 'iShares Australia: A clinical study in international behavioral finance', *International Review of Financial Analysis*, vol. 12, no. 2, pp. 223–39.

Granger, C.W.J. 1980, 'Testing for causality', *Journal of Economic Dynamics and Control*, vol. 2, pp. 329–52, viewed 26 July 2017, <http://linkinghub.elsevier.com/retrieve/pii/016518898090069X>.

Miffre, J. 2007, 'Country-specific ETFs: An efficient approach to global asset allocation', *Journal of Asset Management*, vol. 8, no. 2, pp. 112–22.

Phengpis, C. & Swanson, P.E. 2009, 'IShares and the US market risk exposure', *Journal of Business Finance and Accounting*, vol. 36, no. 7–8, pp. 972–86.

Rompotis, G.G. 2009, *Performance and Trading Characteristics of iShares : An Evaluation*, vol. 15, no. 7.

Sims, C.A. 1980, 'Macroeconomics and Reality', *Sims Source: Econometrica*, vol. 48, no. 1, pp. 1–48.

GitHub Link：< https://github.com/Aqua-13101023/Ass2>