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The Co-Movements Analysis of Military Expenditure Based on Complex Network Approach

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Abstract. Because of the importance of military expenditure to the security of nation, it has been a crucial and hot point in military research for decades. In the paper, we develop co-movement network of international military expenditure with the empirical mode decomposition method and Granger causality test. The results demonstrate that the most influential nations on different time scales are similar despite that the short-term components are disturbed. As the time scale increases, the pattern tends to be more clarified that the nations with developed economy or powerful military force, e.g., UK and USA are the most influential countries in co-movement of military expenditure. our paper provides a novel network approach to study the co-movement military expenditure path among nations from short- and long-term time-scale, where affectees and influencers are distinctive.

Keywords. Military expenditure, Complex network, Empirical mode decomposition method, Granger causality test

1. Introduction

Recently, complex network has been used as a useful tool to various fields, such as finance[1, 2], biology[3], genes[4], meteorology[5] and so on. Generally, there are several ways to construct network. For example, in research of stock market, stocks' price, return or volatility are used to construct the correlation-based networks, with the filtering method of threshold [6, 7], Minimal Spanning Tree [8] or Granger causality [9, 10].

Empirical mode decomposition (EMD) method, as a data-adaptive multiresolution technique, has been widely used in various domains[11]. This method could decompose non-linear and non-stationary series into components with different resolutions, i.e., intrinsic mode functions (IMF) components.

Generally speaking, we still not clear the co-movement of military expenditure among different nations via complex network. So, we do a study on this point. Intuitively, with different time scales, the relations among co-movement of international military expenditure should be different. In this research, we use the EMD

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model to separate the historical 44 national military expenditure time series into components with different time scales. Then we develop network with pairwise Granger-causality test to identify statistically significant co-movement relations among 44 nations.

The paper is presented as follows: we do a data description in Section 2. Section 3 introduces the EMD model. Section 4 explains the experiments, with EMD and Granger causality method. In Section 5, we do robustness checks. Finally, we make a conclusion.

2. Data

In order to measure the military input of a certain nation, we choose the military expenditure to represent it. In our paper, we collect the yearly military expenditure from SIPRI dataset. The dataset ranges from 1949-2020, recording yearly military expenditure of 196 nations. Because of the shortage of military expenditure data of early periods, we only choose the nations have full data from 1956-2020, which could cover 90% of whole time periods (from 1949 to 2020). With such filtering method, we have 44 nations left. Due to the lack of military expense from 1949 to 1955, China is not included in these 44 nations. The military expenditure value of 44 nations from 1956-2020 are demonstrated in millions of US$ at current prices and exchange rates.

Table 1 presents the statistics of 44 nations' military expenditure during our sample period, i.e.,1956 – 2020. From table 1, we could see the average, maximum and minimum military expenditure during 1956 – 2020, and we rank these nations from high to low according to the value of average military expenditure. we find that top 5 nations with highest military expenditure are USA, UK, France, Germany and Japan. Especially, as the superpower, the average yearly USA military spending is more than 9 times of UK.

Table 1. Ranking of 44 nations' military expenditure (millions of US$)

Ranking	Country	Mean	Min	Max
1	USA	311473.4	46072.64	778232.2
2	UK	33467.7	4960.01	73448.03
3	France	26959.04	3049.87	56441.46
4	Germany	25328.04	1535.94	52764.76
5	Japan	25146.74	451.39	60762.21
6	India	16901.79	654.89	72887.45
7	Italy	15033.87	867.25	36839.99
8	Korea, South	12664.19	132.13	45735.39
9	Brazil	10013.58	342.34	36936.21
10	Canada	8989.08	1574.7	22754.85
11	Australia	8812.19	437.92	27691.11
12	Spain	8514.87	225.48	22227.72
13	Israel	7045.46	159.03	21704.45
14	Turkey	6850.87	301.33	20603.38

15	Poland	6116.21	1493.91	17379.52
16	Netherlands	5776.43	396.03	12578.37
17	Greece	3315.5	149.02	10641.35
18	Pakistan	3255.12	153.35	11732.13
19	Belgium	3069.04	366.24	6295.82
20	Norway	2972.27	143.36	7541.06
21	Switzerland	2539.61	200.09	5701.81
22	South Africa	2301.92	60.55	4594.15
23	Thailand	2280.29	58.74	7340.19
24	Denmark	2155.08	142.75	4953.36
25	Mexico	2082.77	67.84	6758.69
26	Chile	1995.2	91.07	5686.75
27	Portugal	1957.27	83.19	4949.69
28	Malaysia	1745.28	42.47	4919.25
29	Finland	1661.32	69.12	4161.14
30	Austria	1613.57	82.56	3746.73
31	Romania	1596.87	545.38	5726.84
32	Morocco	1355.4	35.4	4830.96
33	Peru	1072.77	42.29	3312.21
34	New Zealand	934.55	89.04	3011.39
35	Lebanon	704.3	18.65	2775.56
36	Ecuador	682.88	16.5	2786.52
37	Jordan	612.56	45.36	2077.04
38	Ireland	568.7	23.04	1582.89
39	Sri Lanka	536.17	10.74	2057.87
40	Tunisia	320.83	6.41	1157.37
41	Ethiopia	280.84	15.07	785.05
42	Guatemala	125.48	11.95	342.77
43	Luxembourg	121.18	5.26	489.53
44	El Salvador	116.08	4.38	372.28

In figure 1, we show the historical military expenditure value from 44 nations including USA. From the evolution of American military spending, we find that since the Eastern European drastic change and Soviet Union disintegration in 1991, the input of American military spending decreased slightly and then remained stable. Due to the September 11 attacks of 2001, the America then kept on increasing the military spending to fight terrorism. These ups and downs of American military spending were in accordance with reality.

From figure 2, which depicting the evolutional military spending of remaining 43 nations without USA, we see that from 1991 to 2001 the general trend of these remaining 43 nations are stable, and dramatic increases appear since 2001. These conclusions are consisted with USA, which show a strong influence of American military spending on the others nations.

However, the values of military spending of different nations don't change synchronously, and raw signals of military spending are mussy. Then, we do a decomposition of the signals into clarified patterns. In the next section, we analyze the co-movement of military spending across nations.

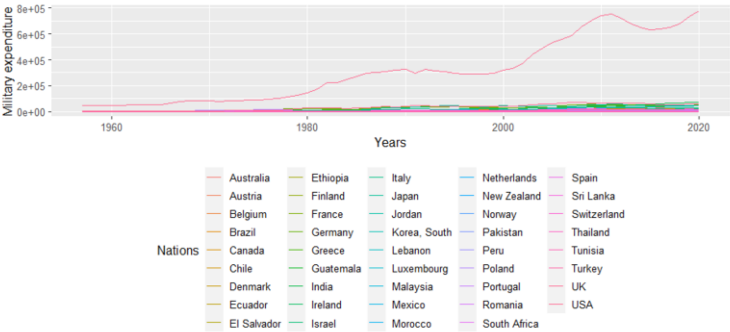

Figure 1. Historical military expenditure of 44 nations with USA

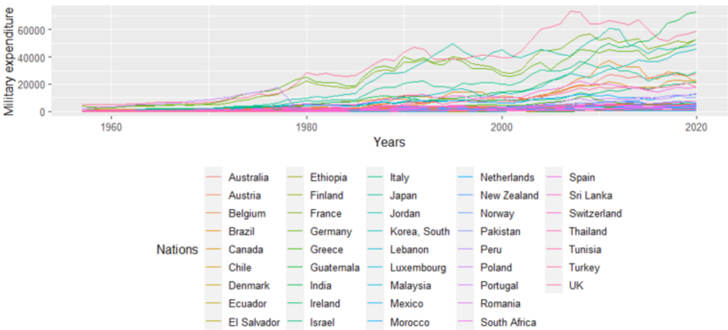

Figure 2. Historical military expenditure of remaining 43 nations without USA

3. Methodology

With the help of EMD model, we do a decomposition of the military expenditure time series into components to represent short- and long-term military expenditure value. Then, we construct the international military expenditure co-movement causality network with test of Granger causality.

EMD originates from signal processing, which is widely used in many domains since it was invented by Huang [12]. With the example of American military expenditure series, we do an introduction of EMD process.

EMD's key feature is to do a decomposition of a signal into intrinsic mode functions (IMF) of different frequencies, from high to low. Therefore, a signal is divided into some IMFs and a residual.

$$x(t) = \sum_{i=1}^{n} imf_i(t) + r(t) \tag{1}$$

From the highest-frequency component, IMFs are separated from the series one by one, through iteration process. The important step is to extract an IMF, which need to identify an oscillation embedded in a signal from local time scale. Firstly, to identify the local extrema, and generate two functions, the upper envelope and lower envelope, which are interpolated local maxima and local minima, respectively. Secondly, taking their average, and producing a lower frequency component than original signal. Thirdly, with the subtraction of the envelope mean from the series x, the highly oscillated pattern is separated. An oscillating wave is defined to be IMF, if it satisfies two requests, i.e., (1) the number of zero-crossings and number of extrema differ only by one, and (2) the local average is zero [12]. If the conditions of IMF are not satisfied after one iteration of aforementioned process, the same procedure is applied to the residue signal again until IMF's properties are satisfied. This iteration process is named sifting. So, we extract the highest-frequency IMF component.

After the shift and decomposition process, we get series of IMFs' different frequency. Then, for each nation, we divide these IMFs into 2 subgroups according to their frequency or cycle length, reconstructing fluctuation component into short and long-time scales. Specifically speaking, denoting our whole series length as T (64 years in our data), and total number of extrema as N_i for the i-th IMF. In our paper, we choose 5 years as the threshold to distinguish short-term and long-term, and short and long fluctuation components are constructed as follows.

$$I_1(t) = \sum_{T/N_i \leq 5} IMF_i(t)$$
$$I_2(t) = \sum_{5 < T/N_i} IMF_i(t) + r(t) \tag{2}$$

In figure 3, it shows the short and long-term fluctuation components constructed from time series of military expenditure of USA. IMFs with cycle less than 5 years is defined as short-term fluctuation. The remaining ones and the residual are called long-term trend.

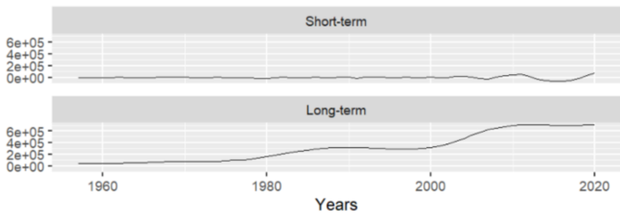

Figure 3. Reconstructed military expenditure's components of USA on short and long-time scales

4. Empirical Results

We do an analysis of EMD to time series of 44 nations' military expenditure with the division of IMFs into different groups based on their cycles. Using the method of reconstruction presented in Section 3, for each national military expenditure, we form short and long-term scale fluctuation components. Then, we pair wisely do the test of Granger causality, generating directed causality networks according to 5% statistically significant Granger causality test.

Figure 3-4 respectively show the short and long-term time scales causality network. For conciseness concerns, the larger node out-degree, the larger node size. Table 2 demonstrates in and out-degree of each nation with short and long-time scales.

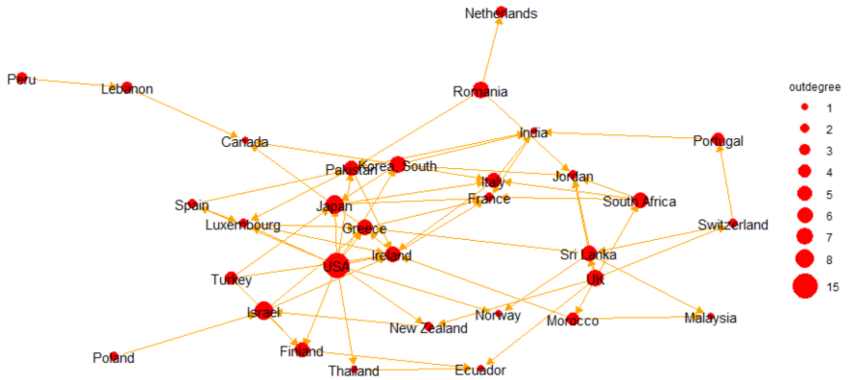

Figure 3. Short-term co-movement of international military expenditure

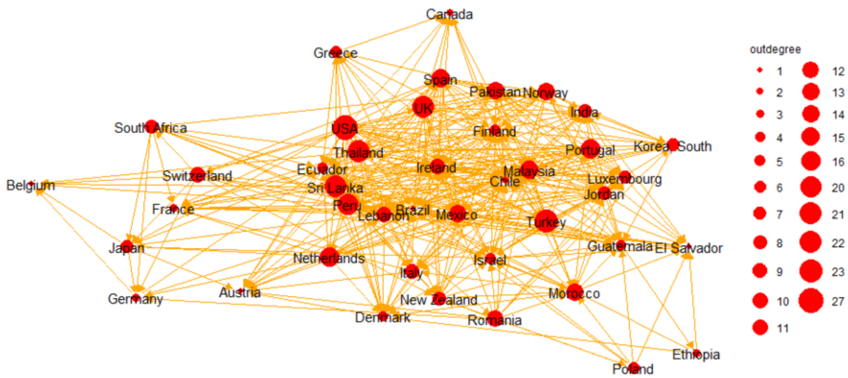

Figure 4. Long-term co-movement of international military expenditure

The in- and out-degree is an important centrality measure of network, measuring the closeness of the country among others. Specifically, the out-degree of a nation node depicts the influence power on the others, and in-degree of a nation node measures the susceptibility effected by other nations. Based on the network plots of figure 3-4 and table 2, we get the following conclusions.

First, with increase of the time scale, the node centrality increases as well. Specifically, the in- and out- degree of nations are small on the short-term scale, and these values increase in the long-term scale. We assume the signals are mixed with more noises, which have no casual relations in the short time scale. The advantage of EMD is to separate the short time scale fluctuations from long time scale.

Second, for a specific node, it is shown that, the larger out-degree, the smaller in-degree, exhibited in table 2. This finding demonstrates that if a nation has a strong effect upon others, and it would show a low probability to be influenced by other nations. The finding is in agreement with our intuition. For example, in short-term causality network of figure 3, the American military expenditure has a larger out-degree value of 15 and in-degree value of 0, which satisfies the influential power of American military.

Third, from the perspective of out-degree, nations with strong military power, such as USA and UK, have strong effect upon others, regardless of short or long-time scales. The finding is consistent with common sense. Also, we confirm that USA has the strongest influence on the other nations no matter in short or long-term scale.

Table 2. Centrality of international military expenditure among the Granger causality network with threshold of 5 years

Ranking	S_Out	S_In	Ranking	L_Out	L_In
USA	15	0	USA	27	0
Israel	8	2	Turkey	23	2
Japan	8	3	Sri Lanka	22	4
Korea,South	7	1	Thailand	22	3
Romania	7	0	UK	21	1
UK	7	0	Peru	20	6
Greece	6	5	Portugal	16	4
Ireland	6	7	Netherlands	16	3
South Africa	6	1	Spain	15	6
Sri Lanka	6	2	Malaysia	15	14
Finland	5	3	Norway	14	8
Italy	5	3	Mexico	14	8
Pakistan	5	3	Pakistan	13	8
Morocco	4	1	Morocco	13	6
Portugal	4	1	Romania	12	1
Turkey	4	0	Ireland	11	21
Lebanon	3	1	Lebanon	11	15
Netherlands	3	1	Switzerland	10	2
Peru	3	0	Italy	9	9
France	2	5	South Africa	8	2
Jordan	2	5	Jordan	8	15
Luxembourg	2	3	New Zealand	8	7
New Zealand	2	2	India	8	12
Poland	2	0	Japan	7	4
Spain	2	1	Korea, South	7	6
Switzerland	2	1	Luxembourg	7	13
Canada	1	3	Greece	6	6
Ecuador	1	3	Poland	6	1
India	1	4	Israel	5	14
Malaysia	1	2	Finland	5	19
Norway	1	2	Ecuador	5	22

Thailand	1	1	Denmark	4	13
Australia	0	7	Guatemala	4	16
Austria	0	11	France	3	10
Belgium	0	10	Ethiopia	3	1
Brazil	0	8	Germany	3	5
Chile	0	5	Canada	2	8
Denmark	0	9	Chile	2	24
El Salvador	0	3	Austria	1	13
Ethiopia	0	4	Belgium	1	6
Germany	0	5	Brazil	1	29
Guatemala	0	4	El Salvador	1	12
Mexico	0	0	Australia	0	30

Note: S_Out represents the out-degree of short-term causality network; S_In denotes the in-degree of short-term causality network; L_Out is short for the out-degree of long-term causality network; L_In represents the in-degree of long-term causality network.

5. Robustness Check

In this section, we explore the robustness of our results. In the earlier parts, the threshold of short- and long-time scale is 5 years. Considering there are different threshold to discriminate short- and long-term, here we adopt 3 years as the threshold to do robustness check. Additionally, we choose per capita military expenditures to replace the total military expenditure as a military spending measure to do another robustness check, the results are shown in table 4.

Based on the results of table 3 and 4, we find that on different time scale, the most influential nations are similar. With the increase of time scale, the nations with developed economy or powerful military force, e.g., UK and USA are the most influential nations in co-movement of military expenditure. These results are consistent with the results in Section 4, which support that our conclusions are robust.

Table 3. Centrality of national military expenditure among the Granger causality network with threshold of 3 years

Ranking	S_Out	S_In	Ranking	L_Out	L_In
USA	11	0	USA	22	0
UK	10	0	UK	20	1
Spain	9	0	Turkey	18	2
Japan	8	3	Spain	17	3
Greece	7	6	Thailand	17	3
South Africa	7	0	Sri Lanka	15	4
Italy	6	2	Netherlands	15	1
New Zealand	5	3	Peru	15	6

Finland	5	7	Portugal	15	5
Korea South	5	1	Norway	13	6
Israel	5	5	Ireland	11	14
Malaysia	4	1	Malaysia	10	8
Luxembourg	4	4	Morocco	10	8
Romania	4	0	Luxembourg	9	11
Pakistan	4	1	Romania	9	0
Jordan	4	2	Mexico	9	8
Lebanon	3	0	Pakistan	8	8
Poland	3	0	Italy	7	11
Switzerland	3	0	New Zealand	7	2
Netherlands	2	0	Lebanon	7	15
Peru	2	1	Finland	6	7
Portugal	2	0	Greece	5	6
Norway	2	1	Jordan	5	10
India	2	6	Poland	5	1
Ecuador	2	5	France	5	9
Morocco	1	0	Japan	4	4
France	1	6	South Africa	4	2
Denmark	1	4	Korea South	4	3
Canada	1	4	Switzerland	4	1
Sri Lanka	0	0	Denmark	4	4
Ireland	0	0	India	3	12
Turkey	0	0	Ecuador	2	21
Thailand	0	0	Canada	2	6
Mexico	0	1	Germany	2	4
Germany	0	4	Guatemala	2	15
Guatemala	0	4	Israel	1	7
Austria	0	6	Austria	1	11
Belgium	0	13	Belgium	1	2
Brazil	0	4	Brazil	1	20
Ethiopia	0	3	Ethiopia	1	1
Australia	0	9	Australia	0	23
Chile	0	8	Chile	0	19
El Salvador	0	9	El Salvador	0	12

Note: S_Out represents the out-degree of short-term causality network; S_In denotes the in-degree of short-term causality network; L_Out is short for the out-degree of long-term causality network; L_In represents the in-degree of long-term causality network.

Table 4. Centrality of per capita military expenditures among the Granger causality network with threshold of 5 years

Ranking	S_Out	S_In	Ranking	L_Out	L_In
USA	12	0	USA	28	0
UK	10	0	Turkey	26	3
Romania	9	2	Thailand	25	2
Ireland	8	7	UK	23	1
Israel	8	1	Spain	23	6
Turkey	7	0	Sri Lanka	20	4
Malaysia	7	2	Pakistan	20	9
Mexico	7	2	Portugal	19	8
South Africa	6	1	Peru	18	6
Norway	6	3	Romania	17	1
Portugal	5	0	Switzerland	17	2
Sri Lanka	5	2	Malaysia	16	13
Finland	5	4	Mexico	15	12
New Zealand	4	2	Norway	14	9
Morocco	4	2	New Zealand	14	5
Luxembourg	4	3	South Africa	13	2
Peru	4	0	Morocco	13	10
Lebanon	3	2	Lebanon	13	13
Jordan	3	3	Netherlands	13	7
Korea,South	3	5	Jordan	13	15
Greece	2	10	Korea, South	13	15
Pakistan	2	4	Italy	12	23
Switzerland	2	2	Japan	12	17
India	2	1	Luxembourg	11	9
Ecuador	2	5	Greece	11	13
Thailand	1	0	India	11	14
Spain	1	1	Poland	10	2
Netherlands	1	6	Ireland	9	21
Italy	1	2	Israel	8	16
Japan	1	6	Ecuador	7	21
Poland	1	0	France	6	20
France	1	7	Finland	5	18
Guatemala	1	3	Denmark	4	12
Canada	1	9	Guatemala	4	13
Denmark	0	5	Ethiopia	4	12
Ethiopia	0	5	Germany	3	8

Germany	0	3	Canada	3	23
Chile	0	5	Chile	2	22
El Salvador	0	2	El Salvador	2	12
Austria	0	5	Austria	1	10
Brazil	0	9	Brazil	1	28
Australia	0	3	Australia	0	27
Belgium	0	9	Belgium	0	18

Note: S_Out represents the out-degree of short-term causality network; S_In denotes the in-degree of short-term causality network; L_Out is short for the out-degree of long-term causality network; L_In represents the in-degree of long-term causality network.

6. Conclusions

With the help of empirical mode decomposition method, we decompose the time series of national military expenditure in fluctuations with different time-scales. Then, we develop networks of different time-scales with test of Granger causality. We explore the co-movement effect with different time scales between the national military expenditure via investigating nodes centrality in the networks and get the conclusions. First, in component of short-term, the fluctuation is mixed with more noise and less causality. Second, the co-movement path among nations is clear directed, and influencers and affectees are distinctive. The nations with strong economy and military power are the most influential nations in military expenditure co-movement. Last, our paper provides a network method with EMD model and Granger causality to study the co-movement path between global military expenditure from short- and long-term time-scale.

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