Energy 228 (2021) 120486

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Features and evolution of global energy trade network based on domestic value-added decomposition of export

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ARTICLE INFO

Article history:
Received 18 August 2019
Received in revised form
18 March 2021
Accepted 25 March 2021
Available online 30 March 2021

Keywords:
Global energy trade
Complex network
Global value chains
Domestic value-added
Multiple regression quadratic assignment procedure

ABSTRACT

With the extension and expansion of the global value chain of energy, the traditional trade accounting method is no longer able to reflect the intrinsic value flow and country gains of energy trade, which render it necessary to further analyze the value added of energy trade from the perspective of global value chain (GVC). Against this backdrop, we construct the Global Energy Trade Domestic Value-added (DVA) network and three sub-networks of it by means of the new trade accounting system, and shed light on the topological features and major driving factors of those networks, and get the following results. First, at the macro level, the growing DVA networks exhibit vivid core-periphery structure, display “small world” characteristics in the early stage but have the average path lengths increased later. At the medium level, the DVA networks are split into 3 communities, and the community structure of the trade for intermediate energy products remains constant, but the trade for final energy products is volatile. At the micro level, advanced and emerging economies stay at the core of global energy trade and play key intermediary roles. The USA and Germany are key players in the downstream and intermediate part of the GVC of the energy sector, while China is the core economy that imports intermediate energy products to manufacture final products for domestic consumption. Finally, economic and population resultant forces, historical links, bilateral trade agreements, especially common language and common currency are important driving factors of DVA network and its sub-networks.

1. Introduction

Energy is a nation’s strategic resource and plays a pivotal role in economic development and national security [1,2]. What’s more, the acquisition and consumption of energy is of vital importance to nations’ role in the global value chain (GVC) [1]. With deep adjustment of GVC, the pattern of value realization of global energy is also undergoing profound changes. According to the bp Statistical Review of World Energy in 2020, China was the biggest individual driver of primary energy growth, accounting for more than three quarters of net global growth in 2019. India and Indonesia were the next largest contributors, while the US and Germany posted the largest declines in energy terms [3]. Contrary to the dramatic change in global energy demand, the distribution of energy resources remains highly uneven. For example, oil resources are still highly concentrated in the Middle East, natural gas in Middle East and Europe, coal in Europe, America and Asia-Pacific. This inevitably leads to significant cross-border energy flows, promoting global energy trading market changes to adjust to GVC adjustment. Therefore a thorough understanding of the pattern and evolution of the global energy trade market, particularly the actual consumption and value transfer of energy in its global flow, is of vital importance to the current world economic development and national security [1,2].

The rise of the GVC has become the most important feature of international trade in the 21st century [4,5], and international energy trade flows show a huge structural transformation accordingly. The increasingly refined international division of labor in the development, production, research, processing and marketing of energy resources has led to the continuous extension of the value chain of energy production, causing the trade of intermediate energy products to dominate the international energy trade [1]. This inevitably posits a severe challenge to the current model construction and computation method over global energy trade relations based on traditional energy trade data, which ignores the

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https://doi.org/10.1016/j.energy.2021.120486
0360-5442/

fact that due to the complexity of the specialization of labor in energy goods production, trade data obtained via traditional accounting methods may be highly inaccurate and fails to reveal the reality international trade based on GVC [6,7]. In other words, international specialization of labor in energy goods production has become so commonplace that the old trade accounting system is no longer suitable to measure the value-added process of energy in the GVC. Since total energy trade volume based on traditional methods fails to tell the true story about value added flow and country gains inside global energy trade, it is necessary to re-examine the value added of energy trade from the perspective of GVC.

Fortunately, researchers have developed a new trade accounting system from the GVC perspective via the input-output table to shed new light on the development of international trade, as well as a complete set of accounting rules for the national accounts system based on added value. They provide useful information on how to define and measure the transnational division of labor and the analytical results of double-counting comprehensive statistical indicators, and can effectively reveal the structure of transnational division of labor hidden behind official trade statistics [5,7–9]. However, their realm of study is focused on manufacturing [4] and other industries rather than international energy trade. Despite that there are literature studying the embodied energy flow in international trade [15–17], their major focus is to examine the energy consumption and flows of products in the production links in international specialization of production, without showing the actual flow and distribution of value added of energy products. In other words, energy value added trade focuses on the amount of value added in every production link of energy products, in contrast with embodied energy flow focusing on the amount of energy consumption. Therefore, there is still lack of study on the pattern of international energy trade relations based on the new trade accounting system from the perspective of GVC.

Meanwhile, the rise of the "new science of network" and its application in international economic issues provide a more scientific research method for understanding the global trading system [10–12]. As the international energy trade relations naturally form a network in which economies are taken as nodes and energy trade relations as edges [3], complex network analytical tools are applied to illustrating the fundamental characteristics of global energy trade [13–15] and trade for particular types of fossil fuels like oil [16–19], natural gas and coal [20,21] utilizing bilateral trade data from gross trade accounting method. Among them, Zhu & Zhuang [14] studies the spatial-temporal evolution of the production, consumption and transportation of global energy products using social network methods, concluding that the global energy market has formed a "core, semi-periphery, periphery" hierarchy. Kitamura & Managi [16] studies the trade relationship in the global crude oil market, and finds out that the global oil trade network can be split into 5 groups: crude oil exporters, large European importers, large Asian importers, the USA and other countries. Zhong et al. [15] analyzes the pattern and features of evolution of the international fossil fuel trade and discovers that the fossil fuel trade relationship is a scale free network which obeys power law distribution. Gao et al. [21] believes that the global fossil fuel trade network has multiple tiers, and so studies the topological characteristics and stability of the global fossil fuel trade network using multi-tiered network tools. The above research shows that the energy trade network does exhibit complex network features. The global division of labor organization structure is essentially a network of international relations, and GVC is also a kind of network chain structure in essence. Therefore, network analytical methods can shed greater light on the pattern of global energy trade, particularly the study of the division of labor in the GVC.

Existing research do not accurately depict the global energy trade pattern from the global value chain perspective, nor do they systematically analyze the pattern evolution of global energy added value trade from the perspective of network. To fill in these research gaps, this paper recalibrates the global energy trade flow within the new trade accounting system from the GVC perspective. Specifically, we construct the Global Energy Trade Domestic Value-added (DVA) network and its three sub-networks, analyze their topological characteristics at the macro, medium and micro level, and empirically test the influential factors on these networks based on the Multiple Regression Quadratic Assignment Procedure (MRQAP). In doing this we try to figure out what is the general pattern of the flow of value-added and distribution of country gains in the international energy trade, and the influential factors of its evolution. Therefore, our study makes the following contributions to the literature. First, we measure and calculate global energy trade using the new trade accounting methods based on value-added data for the first time ever, with the purpose of avoiding the double counting problem inherent in the traditional trade accounting method, in order to reveal the real situation of global energy trade as well as actual gains from trade of economies, against the backdrop of the global value chain. Second, we construct the DVA overall network and sub-networks using complex network tools and uncover their topological characteristics and evolution at the macro, medium and micro level. Finally, we reveal the major influential factors on DVA network and its sub-networks using MRQAP.

The rest of the paper is organized as follows. Section 2 introduces the methodology and data sources. Section 3 shows the empirical results for the network analysis. Section 4 is the conclusion and policy implication.

2. Methods and data

2.1. Methods

2.1.1. The new trade accounting system of global energy trade

According to Wang et al. [9], in the new trade accounting system, global energy trade flow from the GVC standpoint also consists of 4 parts: Domestic Value Added (DVA), Returned Domestic Value (RDV), Foreign Value Added (FVA) and Pure Double Counted Item (PDC). The formula is as follows [7,9].

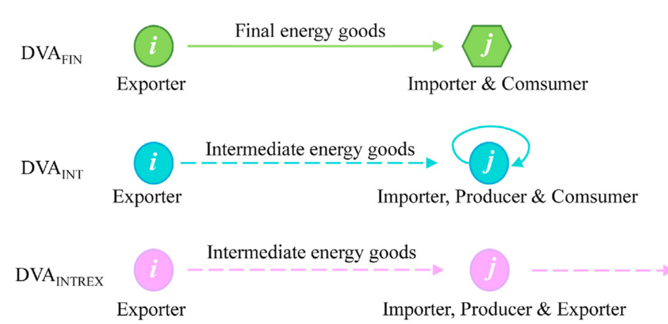


Fig. 1. Sketch of the economic implication of the directed edge $i \rightarrow j$ in the DVA sub-networks. Note: Solid and dotted lines represent trade relationships regarding final and intermediate energy products respectively.

$$
\begin{aligned}
E^{ij} = A^{ij}X^j + Y^{ij} = & \underbrace{\left(V^iB^{ii}\right)^T \# Y^{ij}}_{DVA_{FIN}} + \underbrace{\left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jj}Y^{jj}\right)}_{DVA_{INT}} \\
& + \underbrace{\left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jk}Y^{kk}\right) + \left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jj}Y^{jk}\right) + \left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jk}Y^{kj}\right)}_{DVA_{INTREX}} \\
& + \underbrace{\left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jj}Y^{jk}\right) + \left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{jk}Y^{ki}\right) + \left(V^iL^{ii}\right)^T \# \left(A^{ij}B^{ji}Y^{ii}\right)}_{RDV} \\
& + \underbrace{\left(\begin{array}{c} \left(V^jB^{ji}\right)^T \# Y^{ij} + \left(V^jB^{ji}\right)^T \# \left(A^{ij}B^{jj}Y^{jj}\right) \\ + \left(V^kB^{ki}\right)^T \# Y^{ij} + \left(V^kB^{ki}\right)^T \# \left(A^{ij}B^{jj}Y^{jj}\right) \end{array} \right)}_{FVA} \\
& + \underbrace{\left(\begin{array}{c} \left(V^iL^{ii}\right)^T \# \left[A^{ij}B^{ji}\left(Y^{ij} + Y^{ik}\right)\right] + \left[V^i\left(B^{ii} - L^{ii}\right)\right]^T \# \left(A^{ij}X^j\right) \\ + \left(V^jB^{ji}\right)^T \# \left(A^{ij}B^{jj}E^{j^*}\right) + \left(V^kB^{ki}\right)^T \# \left(A^{ij}B^{jj}E^{j^*}\right) \end{array} \right)}_{PDC}
\end{aligned} \tag{1}
$$

where $\#$ means dot product of the block matrix; E^{ij} is the export volume of the energy sector from economy i to j; i represents the exporting economy, j is the importing economy, while k in the formula means economies other than i and j; X^i is the energy output of economy i; V^i is the value-added of economy i; Y^{ij} is economy i's energy sector products absorbed into j's final products; Z^{ij} is economy i's energy sector products absorbed into j's intermediate products; A^{ij} is economy i's direct consumption coefficient against j; B is the Leontief inverse matrix $B = (I-A)^{-1}$, that is $\begin{bmatrix} B^{ii} & B^{ij} \\ B^{ji} & B^{jj} \end{bmatrix} = \begin{bmatrix} I-A^{ii} & -A^{ij} \\ -A^{ji} & I-A^{jj} \end{bmatrix}^{-1}$; and L^{ii} is the local Leontief inverse matrix $L^{ii} = (I-A^{ii})^{-1}$[22].

As formula (1) shows, RDV is the value-added of products first exported and then reimported by the home country, and thus is counted towards an economy's GDP rather than export. FVA measures the value-added of exported goods reaped by the foreign country rather than the home country, i.e. the energy exporter by itself. PDC is the double counted term of the value-added of the economy's energy trade. In comparison, DVA is the most important source of value-added and profit for an economy's energy export. Furthermore, DVA is further decomposed into DVA_{FIN}, DVA_{INT} and DVA_{INTREX}. DVA_{FIN} is domestic value added for final export. DVA_{INT} is exported intermediate product absorbed by direct importers, and DVA_{INTREX} is exported intermediate product produced by direct importers yet absorbed into third party exports. DVA is the most appropriate object of study for analyzing the new pattern of global energy trade market based on the flow of global energy trade value-added in the GVC perspective. In contrast to embodied energy trade in various industries which focuses on embodied energy consumption in production and processing [23–25], global energy trade domestic value-added studied in this paper primarily focuses on value-added reaped from the global trade of intermediate and final energy products in the energy sector. For this reason we construct the global energy trade network based on DVA only in this paper.

2.1.2. Construction of the DVA network and sub-networks

We construct the global energy trade network based on the DVA part of formula (1). The adjacency matrix element of this networkw_{ij}, is the weight of the edge between node i and j, representing the flow of energy export value added from economy i and j. DVA network's nodes represent the economies; edges represent bilateral energy trade relationships pointing from exporters to importers, weighted by the volume of domestic value-added. According to the flow process of products in each link of the value chain, production value activities can be divided into "upstream link" and "downstream link", the former of which includes the material supply, R&D and the production operation, while the latter includes storage and transportation of final products, marketing and after-sale services, etc. In accordance with formula (1), each relationship in the DVA network can be further decomposed into three parts, including DVA_{FIN}, DVA_{INT} and DVA_{INTREX}, so that we can study the network in more details and construct the three sub-networks of DVA. The DVA_{FIN} network represents the downstream link of the global energy value chain, whose edges point from final energy goods producers (exporters) to final energy goods consumers (importers), weighted by the trading volume of final products. The DVA_{INT} network represents the trade for intermediate energy products in the intermediate stage of GVCs, whose edges point from intermediate energy producers (exporters) to importers which use the imported intermediate energy products to manufacture final products for domestic consumption. In this way importing economies are engaged in the production operation (upstream link) and sales as well as after-sale of final products (downstream link). DVA_{INTREX} network represents the trade for intermediate energy products in GVC upstream, whose edges point from intermediate energy producers (exporters) to another intermediate energy producer (importers) which use imported intermediate energy products to manufacture more advanced intermediate products and then export to other economies. Fig. 1 is a sketch of the edge relationship between node i and j for the three sub-networks of DVA_{FIN}, DVA_{INT} and DVA_{INTREX}, while the weight of each edge of the DVA network is the sum of the weights of each sub-network.

Furthermore, the network that we have constructed via the abovementioned method is a complete network. As the structure and dynamics of complete networks are very complicated, and it is difficult to recognize the key nodes and edges (relations) in the network, we apply the threshold method to the DVA complete network shown in Fig. 1. Specifically, we retain only those bilateral energy trade relationships such that the DVA figure of the bilateral energy trade outnumbers the corresponding threshold value, and extract from the complete network the more important trade relationships, which carry a larger volume of trade. In this way we construct the energy trade network necessary for the topological analysis later, so as to shed more light on the key topological characteristics of the global energy trade network.

2.1.3. Network indices

(1) Macro-Level Indices

Macro-level indices depict the general topological characteristics of the network, which include the following: node number, edge number, density, average path length and clustering coefficient. Among them, node number (N) measures the size of the DVA network represented by the number of trading economies. Edge number (M) is the number of bilateral directed trade relationships among the nodes.

Network density (D) depicts the closeness of node relationship in the network [26], and is positively correlated with the number of node relationships in the DVA network. For directed network, the formula is:

$$D=\frac{M}{N(N-1)} \tag{2}$$

Average path length (APL) is the average distance between two nodes [27], and negatively correlated with the accessibility of one economy to establish trade relationship with its peers. Let d_{ij} be the distance between node i and j in the network, then the formula for APL is:

$$APL=\frac{1}{\frac{1}{2}N(N+1)}\sum_{i\geq j}d_{ij} \tag{3}$$

Clustering coefficient equals to the existing triangular relationships divided by all potential triangular relationships in the network, showing how closely one node is linked with its neighbors, and is positively correlated with the trade agglomerative effect of the DVA network. Let Tbe the clustering coefficient of the network, according to Wasserman & Faust [28], the formula is:

$$T=\frac{\sum_{i=1}^{N}\sum_{j\neq i,k\neq i,j\neq k}a_{ij}a_{ik}a_{jk}}{\sum_{i=1}^{N}\sum_{j\neq i,k\neq i,j\neq k}a_{ij}a_{ik}} \tag{4}$$

where a_{ij} represents the elements in the unweighted adjacency matrix corresponding to the network, $a_{ij}=1$ represents the existence of a directed edge pointing from node i to j, and 0 otherwise. Same is true fora_{ik} and a_{jk}.

Small world networks are characterized by high network clustering and short average path length [29]. Therefore, we can discover the small world characteristics of the global energy trade network by means of the clustering coefficient and average path length of the complex network. According to Watts & Strogatz [29], the testing method is to compare the aforementioned indices of the real network with that of the random networks. If the average path length of the real network is significantly lower than, while the clustering coefficient is significantly higher than the average value of random networks, then the real network would exhibit “small world” characteristics. Using the ER random network production method [30,31], we produce as the contrast group 1000 random networks with the same number of nodes and edges as the real network.

(2) Medium-Level Indices

Medium-level deals with analyzing the structural communities of the DVA network and its sub-networks, and evaluating the quality and stability of community partitioning. Researchers have employed various community detection methods to partition the complex network, including the random walktrap community detection method [32], the fast greedy modularity optimization algorithm community detection method [33], spin-glass community detection method [34], infomap community detection method [35], and so on. In comparison, the spin-glass community detection method[1] produces the optimal results of node community partitioning, under a given number of community divisions. Therefore, community partitioning is done via the spin-glass community detection method [34], while the indices of modularity and Normalized Mutual Information (NMI) evaluate the quality and stability of community division of networks respectively.

Modularity evaluates the quality of the community division of networks, which measures the internal features within a community compared to that between communities [33]. For the DVA network, it can be calculated by

$$Q_w=\frac{1}{\sum_{ij}w_{ij}}\sum_{ij}\left(w_{ij}-\frac{s_is_j}{\sum_{ij}w_{ij}}\right)\delta(C_i,C_j) \tag{5}$$

where s_i is the strength to node i, which is the value added of the energy trade of economy i for the year. w_{ij} is the weight of the edge between node i and j, representing the flow of export value added from economy i to j. $\delta(C_i,C_j)=1$ if node i and j belong to the same community, 0 otherwise.

NMI measures the community stability level in various years, calculated by Ref. [36]:

$$NMI_{(t,t+1)}=\frac{\sum_{h=1}^{k^t}\sum_{l=1}^{k^{t+1}}n_{h,l}\log\left(\frac{n.n_{h,l}}{n_h^t n_t^{t+1}}\right)}{\sqrt{\left(\sum_{h=1}^{k^t}n_h^t\log\frac{n_h^t}{n}\right)\left(\sum_{l=1}^{k^{t+1}}n_l^{t+1}\log\frac{n_l^{t+1}}{n}\right)}} \tag{6}$$

where ${n^t}_h$, n_l^{t+1} and $n_{h,l}$ refer to the number of economies in community h for the year t, in community l for the year $t+1$, and in both community h for the year t and community l for the year $t+1$ respectively, n is the number of economies in the network for the year t.

(3) Micro-Level Indices

Micro-level indices are concerned with the position of the nodes in the network, which include degree centrality, betweenness centrality and closeness centrality. Node degree centrality (ND) is the most important index evaluating a node's position in the

[1] The principle of this method is to regard the relation network as a random network field, in which node connections are analogous to the magnetic and anti-magnetic interactions in physics. These two interactions form an energy function. We can view the internal communities within the network as the state of the spin system, if the energy function reaches a minimum value. This process is similar to the hierarchical clustering algorithm.

network. In the DVA network, an economy's out-degree centrality is the number of export relations with its peers, while the in-degree centrality is the number of import relations. In addition, node centrality of an economy refers to the number of all of its import and export relations. It is calculated by Ref. [37]:

$$ND_i^{out} = \sum_{j=1}^{N} a_{ij}, ND_i^{in} = \sum_{j=1}^{N} a_{ji}, ND_i = ND_i^{out} + ND_i^{in} \tag{7}$$

where $a_{ij} = 1$ if economy i maintains energy trade relations with j, 0 otherwise.

Node strength (NS) describes the closeness of node relationships. In weighted directed networks, the out-strength of a node is the sum of the weights of the edges pointing out from it, while in-strength is the sum of the weights of the edges pointing towards it. It is calculated by Ref. [37]:

$$NS_i^{out} = \sum_{j=1}^{N} w_{ij}, NS_i^{in} = \sum_{j=1}^{N} w_{ji}, NS_i = NS_i^{out} + NS_i^{in} \tag{8}$$

Betweenness centrality in the DVA network represents an economy's ability to control energy trade among its peers, calculated by Ref. [37]:

$$B_C(v_i) = \frac{2\sum_{j}^{N}\sum_{k}^{N} g_{jk}(i) \Big/ g_{jk}}{N^2 - 3N + 2} \tag{9}$$

where g_{jk} is the number of paths between node j and k, $g_{jk}(i)$ is the number of g_{jk} attached to node i.

Closeness centrality measures the degree to which the node resides at the center of the network, showing whether the node is close to all other nodes in the network, calculated by Ref. [37]:

$$C_C(v_i) = \frac{N-1}{\sum_{j=1, j\neq i}^{N} d_{ij}} \tag{10}$$

Despite that the above-mentioned centrality measures help us analyze the role of nodes in the network, and community analysis helps us find node groups with intimate internal node relationships and loose ties with the outside world, none of them reveals the "core-semi periphery-periphery" hierarchy of the whole network. For this problem, we partition the DVA network using the K-core algorithm [26,38], which runs as follows. First, delete all nodes with degree below k in the original network to form a new network. Then, repeat the first step, until no nodes can be deleted and the final network remaining is a K-core [26], which is the largest subset of the nodes, in which every node is linked with at least k other nodes. In this way K-core calibrates the degree of all nodes in the entire subset of nodes, which enables us to partition the network into core, semi-periphery and periphery nodes and therefore shed light on the overall hierarchical structure of the DVA network.

2.1.4. MRQAP regression model

Considering the intercorrelation effect among relational variables modeling network data, parameter estimated based on traditional ordinary regression models, assuming mutual independence among the variables [39] would lead to upward bias in the standard deviation of the parameter estimations and render the significance testing meaningless. One solution to this problem is the Multiple Regression Quadratic Assignment Procedure (MRQAP), a nonparametric estimation method not requiring the mutual independence assumption, and thus produces more robust results than the traditional parametric method in analyzing variable relationships [39,40]. MRQAP permits not only the inclusion of dependent and independent variables in the form of network data, but also the analysis of models where the independent variables measure the similarities and differences among the units which form the nodes. So it is best suited for our analysis in this paper to analyze the influential factors on the formation and evolution of DVA and sub-networks.

MRQAP can also be used to calculate regression coefficients like other regression models through the following procedures [26,40,41]. First, transform the independent and dependent variable matrices into long vectors and calculate the regression coefficients using the OLS method. Second, randomly permutate the rows and columns of the dependent variable matrix repeatedly before carrying out the OLS regression, and record the coefficient value and goodness-of-fit data for each round of computation. Finally, rank in ascending order all the recorded coefficient values and goodness-of-fit data to form the reference distribution, and compare the initial estimated statistical value with the value in the reference distribution to get the standard error of the estimates. If less than 5% or 1% of the estimated coefficient values obtained in the permutated regression procedure are higher than the observed coefficient values, then the coefficient values are significant at 5% or 1% level respectively (single-tailed testing). In this way MRQAP is able to control the autocorrelation effect caused by lack of variable independence which leads to the underestimation of standard errors.

We utilize the gravity equations in Kitamura and Managi [16], Babri et al. [42] and Feng et al. [43] in constructing the MRQAP regression model to analyze the influential factors affecting global energy trade. Regarding the influential factors of global energy trade, researchers agree that the major impact factors of bilateral energy trade relationships include the following: economic scale, population size, geographical distance, common language, adjacency of borders, common currency, historical ties (colonial relationship), FTA, OPEC membership, etc. [16,42–44]. For example, Kitamura and Managi [16] applies the gravity model and OLS regression method to studying the influential factors of energy trade using the bilateral trade data of 185 economies in 2014. The result shows that GDP, historical ties, bilateral trade agreement and OPEC membership boost the development of bilateral energy trade relationships significantly, while geographical distance is a major dragging factor. Helpman et al. [44] argues using the heterogeneous trade model that economic scale and population size heavily influence trade development. It also shows by the panel data model that common currency, historical ties and FTA trade agreements promote bilateral trade, while geographical distance may hinder trade development. Based on that, we establish a gravity model to calibrate the magnitude of the influential effects of these factors.

$$\log W^t = F\begin{pmatrix} \log GDPS^t, \log GDPD^t, \log PopS^t, \log PopD^t, \log Dist, \\ Comlang, History, Comcur, Contig, FTA^t, OPEC^t \end{pmatrix} \tag{11}$$

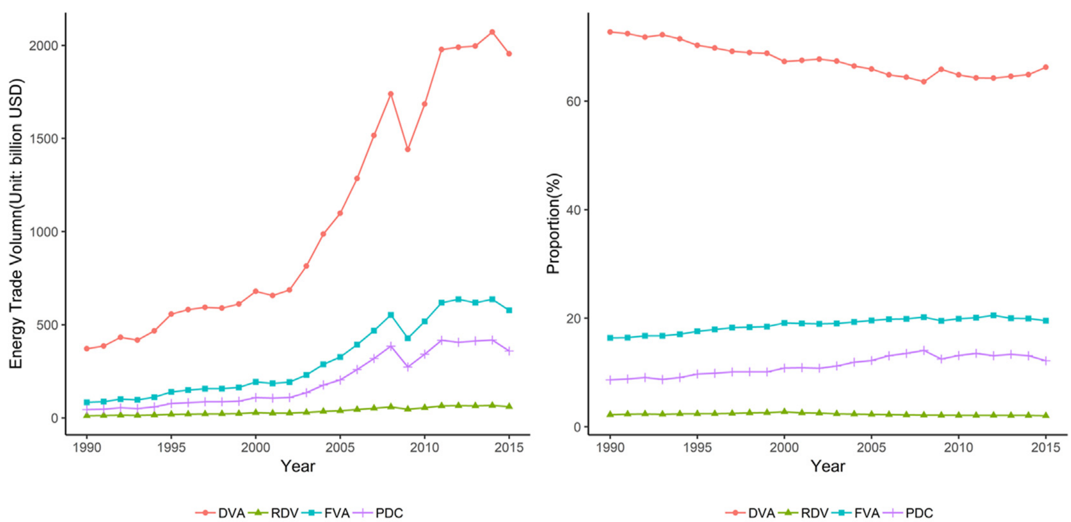
All variables in (11) are relational data represented by $N \times N$ matrices, variable explanation and data source are shown in Table 1.

2.2. Data sources

We employ trade data from the Eora 26 MRIO table in the Eora database (the Eora global supply chain database), providing input-output data from 26 industries in 189 economies during 1990–2015 period. Data compiled from the Eora MRIO database mainly come from the UN System of National Accounts (SNA), UN

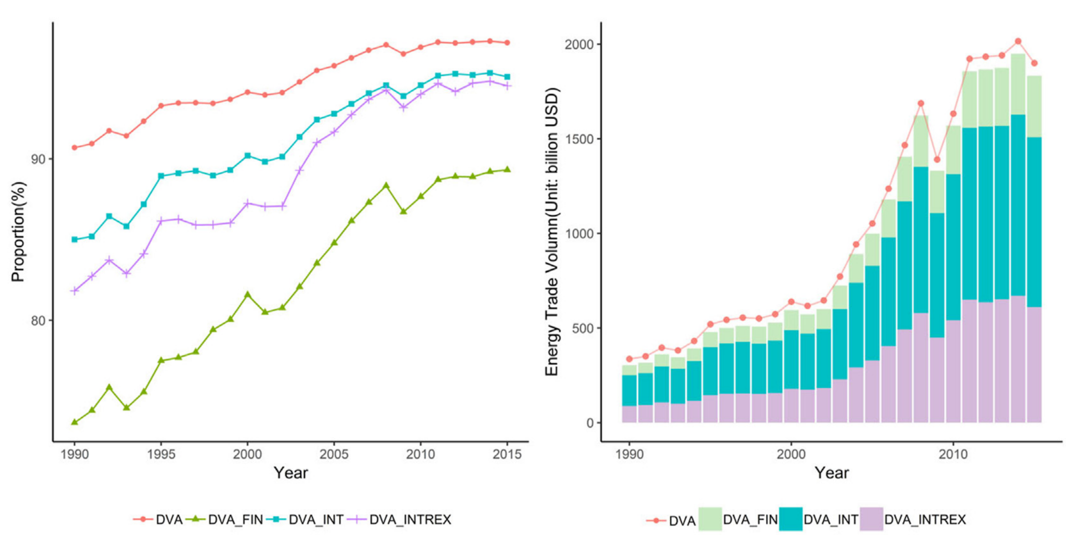
Table 1
Variable explanation and data sources.

Variable	Meaning	Measurement	Data source
W^t	Energy trade network	Weighted adjacency matrices of DVA and DVA sub-networks.	Eora database
$GDPS^t$	Economic resultant force	The economic resultant force matrix of the economy pair's GDP for the year t, the sum of the GDP of the economy pair.	CEPII Database
$GDPD^t$	Economic distance	The economic distance matrix of GDP for the year t, the absolute value of the GDP difference of the members within the economy pair.	
$POPS^t$	Population resultant force	The population resultant force matrix of the economy pair's total population for the year t.	
$POPD^t$	Population distance	The distance matrix of the economy pair's population for the year t.	
Dist	Geological distance	Distance between the economies' capital cities.	
Comlang	Common language	1 if at least 9% of the two economies' population share the same language, 0 otherwise.	
History	Historical-tie	1 if two economies have colonial connections, 0 otherwise.	
Comcur	Common currency	1 if both economies use the same currency, 0 otherwise.	
Contig	Contiguity	1 if both economies share a borderline, 0 otherwise.	
FTA^t	Free trade agreement	1 if both economies are engaged in a trade agreement for the year t, 0 otherwise.	
$OPEC^t$	OPEC	1 if the trading partner is an OPEC economy, 0 otherwise.	www.opec.org



(a) (b)

Fig. 2. Decomposition result of global energy trade value-added (1990–2015).



(a) (b)

Fig. 3. The proportion and transaction volume of the threshold value networks. Note: (a) shows the proportion of the total weight of the threshold value network in that of the complete network during 1990–2015 (threshold value: $50 million). (b) Shows the total volume change of DVA threshold value network and its sub-networks.

COMTRADE, Eurostat, IDE/JETRO and input-output tables compiled by national statistical agencies [45,46]. Two out of the 26 industries in the Eora database are from the energy sector, which include (1) Petroleum, Chemical and Non-Metallic Mineral Products, and (2) Electricity, Gas and Water. In this paper we sum them up into the energy sector. Therefore, the E^{ij} in formula (1) is the sum of the exports of 2 energy industries from economy i to j, Y^{ij} is the amount of economy i's energy sector products that are absorbed into the total final products of the 26 industries of economy j, and Z^{ij} is the amount of economy i's energy sector products that are absorbed into the total intermediate products of the 26 industries of economy j. In conclusion, based on the input-output relationship of "economy i energy sector → aggregate of 26 industries of economy j", we analyze the pattern of value-added flow and gains from trade among the world economies using the new trade accounting system from the GVC perspective.

3. Empirical results

3.1. Value decomposition of global energy trade flow

As mentioned in 2.1.1, we decompose the global energy trade flow into four parts: Domestic Value Added (DVA), Returned Domestic Value (RDV), Foreign Value Added (FVA) and Pure Double Counted Item (PDC). Fig. 2 shows the value-added flow and proportion composition during the 1990–2015 period. We can see that DVA occupies over 60% of the value-added of global energy trade export, so DVA is the most important source of value-added and profit for an economy's energy export. This justifies once again our effort to construct the energy value-added network based on DVA for analyzing the pattern of global energy trade value-added.

Having calculated DVA, we further decompose it into DVA_{FIN}, DVA_{INT} and DVA_{INTREX} in accordance with formula (1) so that we can construct the DVA network and three sub-networks of the world economies. For better analysis of the network topological structure, we follow the practice of Amador & Cabral [11] to extract the core structure of the network by the threshold value method, and we set the threshold value for the edge weight to be \$50,000,000. Under this threshold value, as Fig. 3(a) shows, the proportion of DVA network and its sub-networks are higher than 70%, and the proportion of weighted network in the complete network constantly rises. By 2015 the proportion of DVA, DVA_{FIN} and DVA_{INT} exceeded 95%, DVA_{INTREX} 89%. Also Fig. 3(b) shows that the trend of change of the 3 segmented threshold networks is consistent with that in the overall network, and satisfies the equation $DVA = DVA_{FIN} + DVA_{INT} + DVA_{INTREX}$. Therefore, the threshold network pretty well illustrates the core structure of the complete network with good representativeness.

3.2. Global characteristics-macro level

Having constructed the DVA network and its sub-networks, we illustrate in Fig. 4 the graphs of the DVA network between 1990 and 2015, partitioned using the K-cores algorithm [26,38]. According to Fig. 4, the network exhibits vivid core-periphery structure, as both the DVA network and its sub-networks can be segmented into three layers, i.e. core, semi-peripheral and peripheral layer, based on the K-cores value of the nodes. This result is consistent with Zhu & Zhuang [14]. Furthermore, a comparison of the structure of each network between 1990 and 2015 shows an upsurge in the number of core nodes and their relationships during the period. We also find that the US firmed occupied the central position in both DVA_{FIN} and DVA_{INT} network, while Germany stood at the center of DVA_{INTREX}. Therefore the US played a pivotal role at GVC downstream of the energy sector and was a major importer and consumer of energy product. Germany, on the other hand, was a core player in the GVC upstream and a principal participant in the production and trade of intermediate energy products.

The topological characteristics of the DVA network are listed in Table 2. First, while the network density stabled at around 0.1 over the years, the network was constantly getter larger and more sophisticated, with the number of nodes and edges increasing from 93 to 828 in 1990 to 146 and 2111 in 2015 respectively, which shows that at the specified threshold value, the expanding network kept attracting new economies. Specifically, the trajectory of the growth of the DVA network depicts an inverted U shape. During the 1990s when the level of economic globalization was still modest, the network was growing slowly, with an annual increase of 36.9 DVA relationships. Then, starting in 2000, fueled by the acceleration of economic globalization and international division of labor, the growth of the network gained momentum achieving an annual increase of 3.4 economies and 76 DVA relationships. This trend, however, was dampened after 2010 by trade protectionism and anti-globalization sentiment in the aftermath of the 2008 global economic crisis, resulting in the annual growth of DVA relationships dropping to 30.8 between 2010 and 2015.

Second, the breadth and depth of trading relationships in the DVA network, indicated by node degree and strength respectively [47], was constantly rising. Average network degree increased from 17.806 to 28.918 between 1990 and 2015, meaning that every country has 29 energy trading partners on average in 2015. During the same period, average network strength increased from 7.239 billion USD to 26.022 billion USD. On the demand side of the energy trade, the maximum in-degree of the DVA network grew steadily from 45 to 73 between 1990 and 2015, while the maximum in-strength rose from 48.238 to 246.457 during that period. This shows that on the demand side, the depth of energy trade increased much more than the breadth of it. In comparison, the maximum out-degree of the network increased from 64 to 86, with maximum out strength increased from 56.979 to 190.307 in the same period. On the supply side of the energy trade, trade depths showed the trend of upward spiral, while the trade breadth was growing steadily, but strength growth on the supply side was lower than that on the demand side.

Table 3 shows the topological properties of DVA sub-networks. While all sub-networks grew constantly with ever closer node relationships, there are differences among them. First, DVA_{INT} has the largest network size, implying that trade for intermediate goods is most important in global energy trade, the largest share of which is importing intermediate products for final goods production and consumption in the domestic market. Second, DVA_{FIN} has the fastest growth rate, which means that importing final energy products directly for domestic consumption is gaining popularity. Third, DVA_{INTREX} has the largest network density, and kept growing without interruption. This coincides with the fact that the trade for intermediate energy products is booming, triggered by the increasing sophistication of international division of labor. Finally, the average degree and strength of DVA_{INT} and DVA_{INTREX} far exceeds that of DVA_{FIN}, implying that both the breadth and depth of the intermediate energy goods market are much greater than that of the final energy goods market. Therefore, the value-added trade accounting method, which considers both intermediate and final product markets, more accurately reflects the reality of global energy trade than traditional trade accounting methods, which once again provides good justification for examining the energy trade network using the new trade accounting system in Wang et al. [9].

Fig. 5 shows the clustering coefficients and average path lengths of the DVA network and its sub-networks, and compares them with the clustering coefficient and average path length of 1000 random networks with the same number of nodes and edges, from which

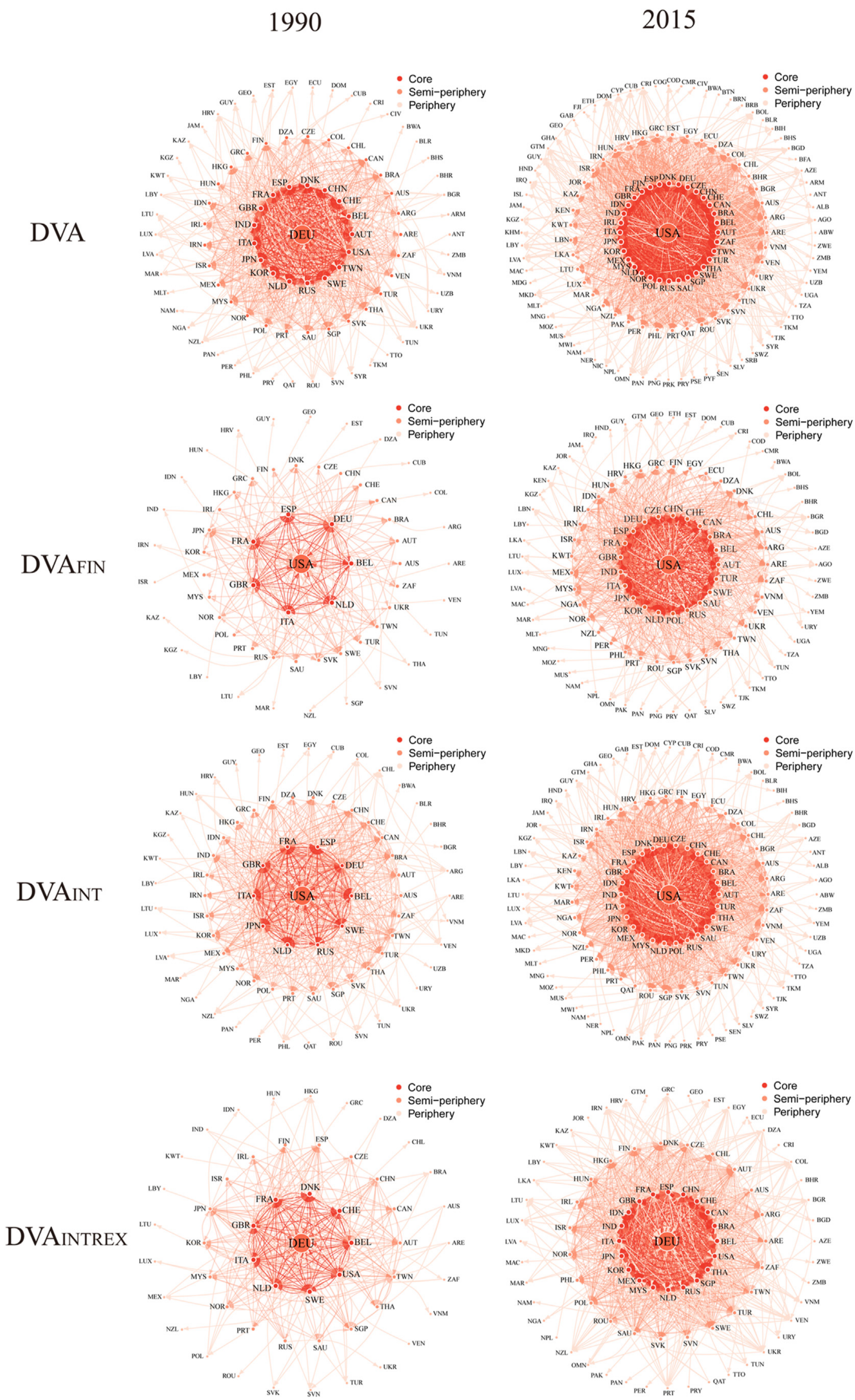


Fig. 4. Graph of the DVA network and three sub-networks. Note: darker color of the nodes corresponds to larger K-cores value, implying more pivotal position of the node. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

we can determine whether the networks exhibit obvious “small world” characteristics. As Fig. 5 shows, networks in each year have clustering coefficients greater than the maximum clustering coefficients of the corresponding random network, implying significant trade clustering effect in the global energy market. Regarding average path lengths, they are shorter than that of the corresponding random network in DVA_{FIN} and DVA_{INT}, a small-world network characteristics which means that economies are more closely linked in the GVC downstream of the energy sector [48]. For $DVA_{INTREX,}$ however, it was a small-world network like the other two during 1990–1995 due to relatively short average path length, but this index gradually got larger in the subsequent years and exceeded the maximum average path length of the random network after 2006. As the DVA_{INTREX} network represents the trade for intermediate energy products in GVC upstream, this implies the increasing sophistication of the international division of production in the energy sector and the elongation of the production links, resulting in larger distance between economies than the random network. All in all, with the advance of globalization, trade of intermediate energy goods gradually came to prominence and began to exert ever greater influence onto the DVA network and its subnetworks, in particular the DVA_{INTREX} network.

3.3. Community analysis-medium level

At the medium level, we partition the economies in the DVA network into communities based on the frequency level of international energy trade relationships. Using the spin glass community detection method [34] we partition the DVA network and subnetworks between 1990 and 2015 into the communities shown in Fig. 6, and study the evolution and stability level of the DVA network communities using modularity and NMI illustrated in Fig. 7(a) and Fig. 7(b) respectively.

According to Fig. 6, DVA, DVA_{INT} and DVA_{FIN} can be classified into three communities, with the USA, Germany and China as the respective representative country. In DVA, community 1 contains 34 economies, mostly in North & South America and a few in Africa, like US, Canada, Brazil, etc. Community 2 contains 51 economies from the Asia-Pacific and Sub-Saharan Africa, like China, India, South Africa, Australia, etc. Community 3 contains 61 economies from Europe, Central Asia and Africa, like Germany, Russia, Kazakhstan, Libya, etc. The spatial distribution of communities in DVA_{INT} and DVA_{FIN} are much the same as that of DVA, with minor differences in the membership of some African economies. The community partitioning of $DVA_{INTREX,}$ on the other hand, is strikingly different from that of the other three. In $DVA_{INTREX,}$ community 1 contains 32 economies from Europe and North Africa, like Germany and Libya. Community 2 contains 37 economies including Asian economies (China, India, etc), North American economies (US, Canada, Mexico) and economies from South America and Africa. Community 3 contains 19 economies including South American economies (Brazil, Argentina, etc), Eastern European economies (Russia, Ukraine, etc) and economies from Asia and Africa. Furthermore, the majority of the economies in the same community share common borders with one another, justifying the importance of geographical distance in the global value chain organization for energy trade.

We analyze the quality of community partitioning and trend of evolution, based on community modularity in the network. According to Fig. 7(a), the modularity of DVA network and subnetworks stabilizes in the 0.15–0.23 range. Fig. 7(b) further implies that community partitioning of DVA_{FIN} fluctuates over the years, resulting in the instability of the DVA overall network. This means that under the GVC perspective, the community structure of the trade for intermediate energy products remains relatively stable, which is not the case with that of the trade for final energy products. It also means that the international trade for final energy products is more vulnerable to external shocks like economic crisis. In comparison, the system of international division of labor based on the trade for intermediate energy products helps increase the interdependence and complementarities among economics so that the trade relationships will be more stable.

Table 2
Fundamental topological characteristics of DVA network.

Index	1990	1995	2000	2005	2010	2015
No. Nodes	93	100	108	130	142	146
No. Edges	828	1085	1197	1556	1957	2111
Density	0.097	0.110	0.104	0.093	0.098	0.100
Mean ND	17.806	21.700	22.167	23.938	27.563	28.918
Max. ND_{in}	45	57	66	66	71	73
Max. ND_{out}	64	69	65	75	84	86
Mean NS	7.239	10.394	11.834	16.188	22.997	26.022
Max. NS_{in}	48.238	76.910	125.267	187.518	225.255	246.457
Max. NS_{out}	56.979	85.851	87.464	129.959	187.819	190.307

Note: ND is the node degree centrality, Mean ND is the average value of node degree centrality of all nodes. Max. ND_{in} is the maximum value of in-degree centrality. Max. ND_{out} is the maximum value of out-degree centrality. NS is the node strength and its unit of measurement is $billion. Mean NS is the average value of the strength of all nodes. Max. NS_{in} is the maximum value of in-strength. Max. NS_{out} is the maximum of out-strength.

Table 3
Fundamental global topological characteristics of DVA Sub-networks.

Index	DVA_{FIN}		DVA_{INT}		DVA_{INTREX}	
	1990	2015	1990	2015	1990	2015
No. Nodes	60	116	78	130	53	88
No. Edges	228	961	543	1513	318	1191
Density	0.064	0.072	0.090	0.090	0.115	0.156
Mean ND	7.600	16.569	13.923	23.277	12.000	27.068
Max. ND_{in}	28	53	38	65	33	49
Max. ND_{out}	33	64	56	74	39	56
Mean NS	1.772	5.605	4.170	13.817	3.324	13.878
Max. NS_{in}	16.734	78.235	27.058	145.548	17.661	93.250
Max. NS_{out}	9.808	38.647	28.661	96.373	16.963	66.384

3.4. Economy roles-micro level

We study the network structure at the micro level to understand the roles individual economies play in the DVA network. Table 4 shows that, so far as the in-degree of DVA network is concerned, the top 5 ranked economies listed in the network include both developed and emerging economies. Among them, the USA is ranked first in DVA, DVA_{FIN} and DVA_{INT}, implying that the USA is the most important importer and consumer of final energy products, residing in GVC downstream. Germany (DEU) is ranked first regarding the in-degree of DVA_{INTREX}, followed by Italy (ITA), France (FRA), the Netherland (NLD) and UK(GBR). Therefore, Germany stays in the intermediate stage of the GVC and is a major producer of intermediate energy products in the international energy production system.

In terms of out-degree ranking, Germany ranks No.1 in DVA, DVA_{FIN} and $DVA_{INTREX.}$ Therefore Germany is the most important exporter in global energy trade, which is in line with Germany's position and role in the energy trade network, as mentioned above. In addition, China (CHN), as an emerging economy, ranks No.1 in DVA_{INT}, staying in the intermediate stage of the energy industry's value chain. In contrast with Germany, the major form of China's energy trade is using imported intermediate energy products to manufacture final products for domestic consumption.

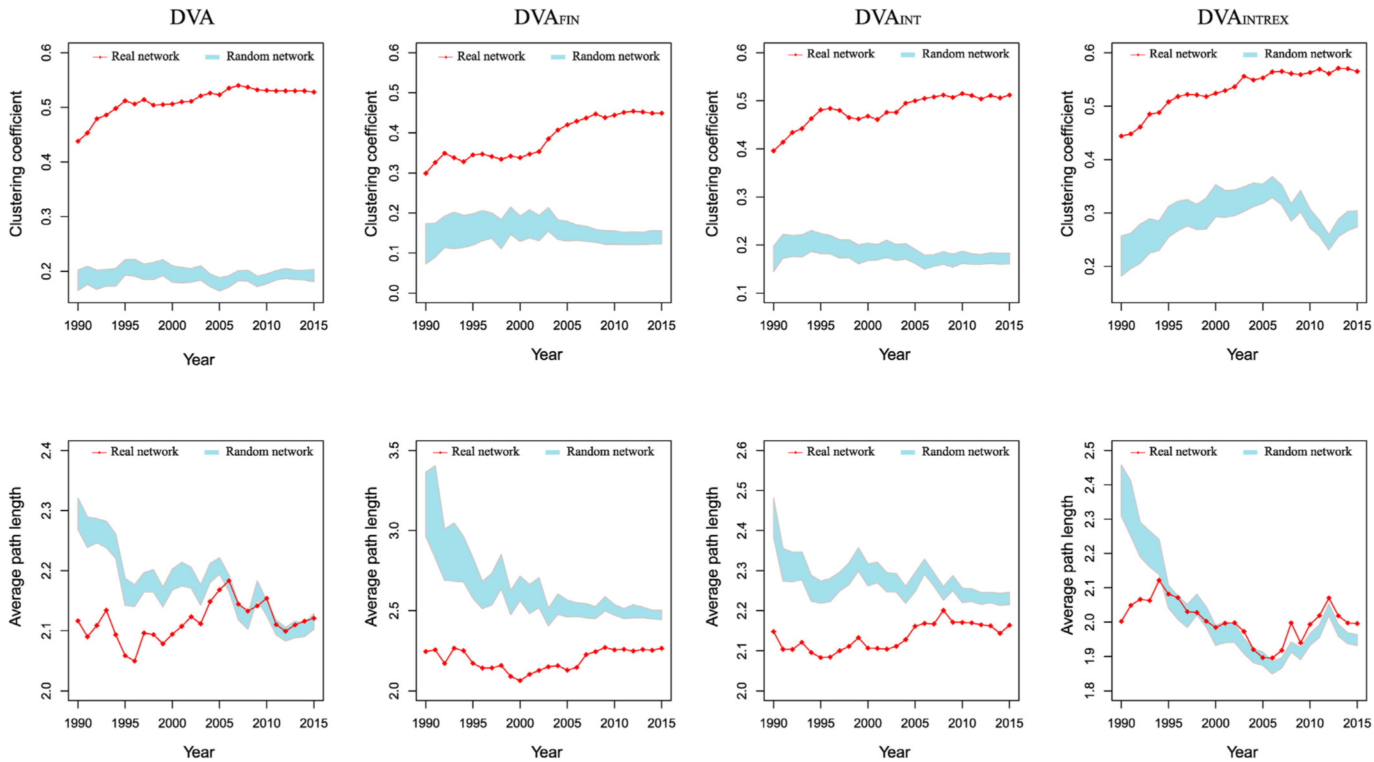


Fig. 5. The clustering coefficients and average path length of the DVA Network and its sub-networks. Note: the red line in the graph is clustering coefficient or average path length of the real network. Blue shaded area is the region encircled by the maximum and minimum value of the corresponding indices of 1000 random networks. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

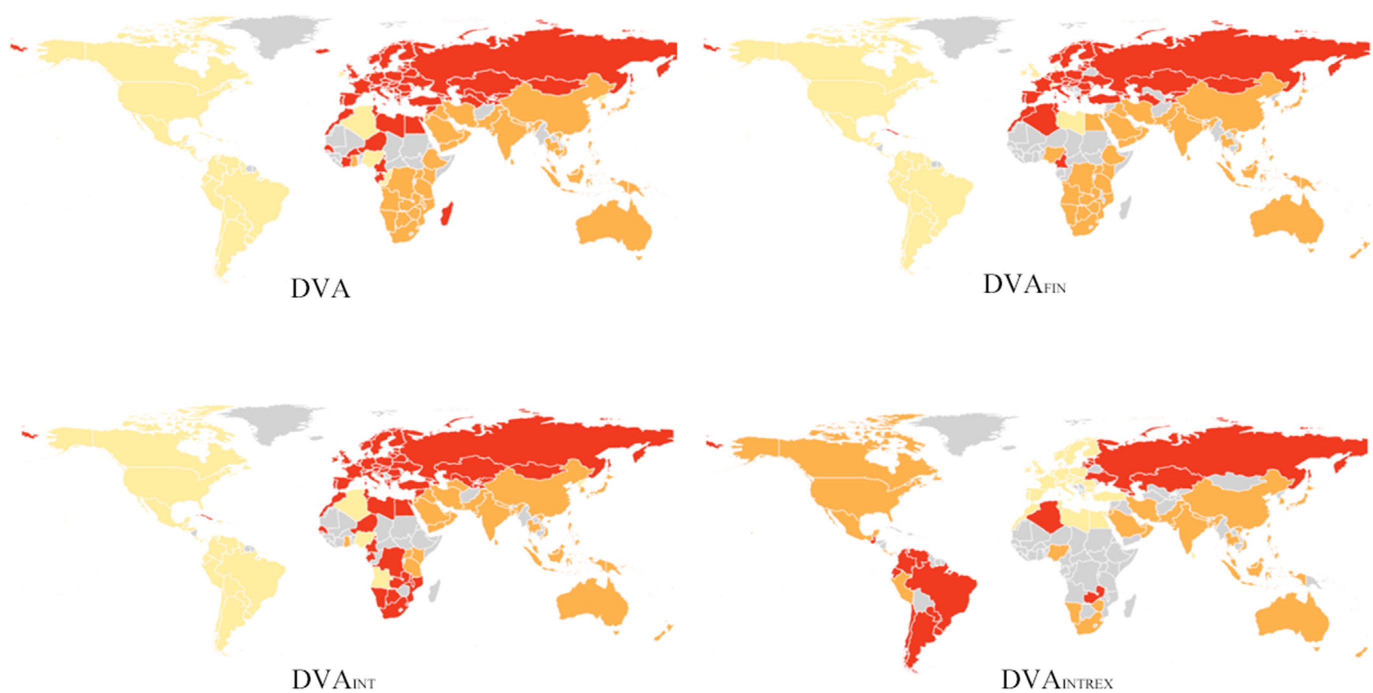
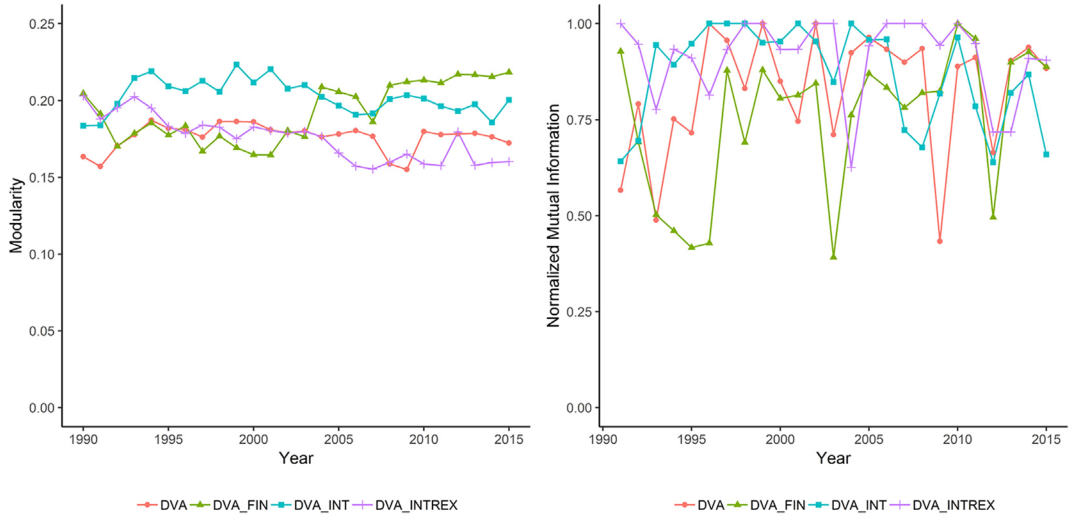


Fig. 6. Spatial distribution of communities in DVA network and its sub-networks in 2015. Note: same color in the same map implies same community membership, grey color means not considered in this study. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Furthermore, by comparing the in-degree and out-degree of the top 5 economies in the network, we find that network out-degrees significantly outnumber in-degrees in both DVA and the sub-networks. This implies that trade in DVA and its sub-networks are unbalanced, as the world economies share a common tendency of securing final or intermediate energy products from a narrow range of markets. meanwhile selling domestically produced final and intermediate energy products to a broad range of markets.



(a) (b)

Fig. 7. Change in the modularity and NMI of communities in DVA network and its sub-networks.

Table 4
The top 5 node centrality of DVA network and its sub-networks in 1990 and 2015.

Category	in-degree		out-degree		betweeness		closeness	
	1990	2015	1990	2015	1990	2015	1990	2015
DVA	USA (45)	USA (73)	DEU (64)	DEU (86)	USA (0.095)	IND(0.072)	LBY(0.141)	DEU (0.120)
	DEU (39)	CHN(55)	ITA(56)	CHN(85)	ITA(0.093)	USA (0.066)	DEU (0.138)	CHN(0.120)
	FRA(37)	ITA(55)	USA (52)	GBR (80)	FRA(0.085)	ZAF (0.049)	ANT (0.137)	ANT (0.119)
	JPN(36)	DEU (54)	FRA(49)	ITA(77)	BEL (0.068)	BRA(0.048)	ITA(0.137)	BTN (0.119)
	GBR (34)	FRA(53)	GBR (45)	FRA(75)	RUS(0.067)	ESP(0.047)	USA (0.136)	NER(0.119)
DVA_{FIN}	USA (28)	USA (53)	DEU (33)	DEU (64)	USA (0.222)	USA (0.124)	CHN(0.112)	BHR (0.185)
	DEU (18)	GBR (40)	USA (24)	USA (57)	GBR (0.103)	ITA(0.059)	IRL (0.112)	DEU (0.185)
	FRA(16)	DEU (38)	FRA(23)	FRA(52)	ITA(0.092)	NLD (0.057)	DEU (0.107)	USA (0.182)
	GBR (14)	FRA(29)	GBR (19)	ITA(52)	RUS(0.092)	GBR (0.055)	HUN(0.107)	LBY(0.182)
	JPN(11)	CHN(27)	ITA(18)	CHN(51)	FRA(0.083)	DEU (0.052)	ISR(0.107)	FRA(0.181)
DVA_{INT}	USA (38)	USA (65)	DEU (56)	CHN(74)	USA (0.134)	USA (0.075)	DEU (0.122)	BHR (0.108)
	JPN(33)	CHN(53)	ITA(42)	DEU (72)	ITA(0.120)	RUS(0.064)	LBY(0.122)	LBY(0.107)
	DEU (28)	ITA(47)	USA (41)	USA (66)	DEU (0.106)	IND(0.059)	ITA(0.12)	ANT (0.107)
	ITA(27)	BRA(46)	FRA(37)	ITA(64)	RUS(0.087)	CHN(0.056)	USA (0.119)	CHN(0.107)
	FRA(25)	IND(45)	GBR (37)	FRA(60)	BEL (0.067)	ITA(0.055)	FRA(0.119)	ABW(0.107)
DVA_{INTREX}	DEU (33)	DEU (49)	DEU (39)	DEU (56)	DEU (0.276)	ITA(0.088)	AUS(0.12)	AZE (0.107)
	NLD (22)	ITA(48)	USA (25)	CHN(55)	USA (0.109)	IND(0.087)	IND(0.112)	KWT (0.101)
	BEL (20)	FRA(46)	FRA(22)	ITA(50)	TWN(0.077)	USA (0.072)	DEU (0.11)	LBY(0.099)
	FRA(20)	NLD (46)	ITA(21)	USA (49)	FRA(0.062)	ESP(0.060)	DZA (0.109)	QAT (0.099)
	GBR (17)	GBR (43)	GBR (19)	FRA(47)	ITA(0.06)	CHN(0.054)	VEN (0.108)	BHR (0.098)

Note: in-degree, out-degree, betweeness and closeness stand for in-degree centrality, out-degree centrality, betweenness centrality and closeness centrality respectively. The node centrality data of the corresponding economy are in the brackets.

Finally, we evaluate the intermediary roles that nodes play in the network and closeness of the nodes by means of intermediary centrality and closeness centrality. Regarding intermediary centrality, Table 4 shows the economies that play fundamental intermediary roles in the DVA network. In particular, India is ranked first in the DVA network, acting as a most important hub, followed by the USA and South Africa. In contrast, the USA is the most important hub in the trade network for final energy products in GVC downstream, evidenced by its top ranking in DVA_{FIN} and DVA_{INT} network, while Italy is the most important hub in the trade for intermediate energy products in the intermediate stage of the GVC.

As for closeness centrality, which evaluates a country's trade accessibility in the network, top 5 economies include advanced economies like Germany, USA and Italy, China, as well as energy rich economies like Bahrain (BHR), Qatar (QAT) and Azerbaijan (AZE). In particular, Germany and China are ranked No.1 and No.2 in the DVA network, and therefore keep much closer energy trade relationships with other economies. Bahrain and Azerbaijan are ranked No.1 in the sub-networks due to their rich endowment in energy resources like oil and natural gas and keep close trade relations with other economies.

3.5. Empirical analysis of impact factors

Based on the method introduced in 2.1.4 and formula (10), we use MRQAP for analyzing the factors influencing the formation and evolution of DVA and its sub-networks. Considering that the MRQAP method is mainly based on cross-relational data, by comparing the MRQAP regression analysis results of DVA and its sub-networks between 1990 and 2015, we find that the impact of the explanatory variables on DVA are much the same all over the years. For this reason, we first present the MRQAP regression analysis results of DVA for the year 1990, 1995, 2000, 2005, 2010 and 2015 in Table 5 in order to study the influential factors on DVA

Table 5
MRQAP regression results of the DVA networks during 1990–2015.

Variable	1990	1995	2000	2005	2010	2015
log *GDPS*	0.746***	1.174***	1.139***	1.376***	1.695***	1.961***
log *GDPD*	−0.293***	−0.574***	−0.522***	−0.633***	−0.773***	−0.846***
log *PopS*	0.184***	0.283***	0.292***	0.388***	0.457***	0.367***
log *PopD*	−0.133***	−0.163***	−0.140***	−0.153***	−0.180***	−0.147***
log *Dist*	−0.323***	−0.304***	−0.191***	−0.264***	−0.517***	−0.676***
Comlang	0.051	0.302***	0.054	0.175	0.422***	0.514***
History	2.493***	2.241***	2.873***	4.187***	4.788***	5.203***
Comcur	−1.154***	−1.694***	4.228***	4.011***	3.587***	3.436***
Contig	2.811***	3.124***	2.590***	3.686***	5.200***	5.074***
FTA	8.176***	4.308***	3.695***	3.254***	2.672***	2.391***
Opec	−0.527***	−0.359***	−0.468***	−0.506***	−0.846***	−0.950***
Constant	−8.302***	−12.461***	−13.980***	−17.051***	−19.908***	−23.456***
Adjusted R^2	0.1872	0.1872	0.1942	0.2181	0.2402	0.2544
F-statistic	602.4***	609.6***	660.5***	764.2***	846.5***	820.2***
Observation	28730	29070	30102	30102	29412	26406

Note: ***, ** and * indicate significance levels at 1%, 5% and 10% respectively.

and explain the robustness of the regression results. Then we explain the influential effects on DVA_{FIN}, DVA_{INT} and DVA_{INTREX}.

First, regarding economic and population factors, economic resultant forces of the two economies positively influence DVA networks, while the disparity in their economic scales is a significantly negative influential factor. Furthermore, the absolute value of the influential effects increases with time. Therefore, economic scale is a key influential factor for global energy trade, and that smaller difference in the economic scale between the two economies promotes bilateral energy trade, and this phenomenon is more obvious with time. The same is true for population size as well.

Second, regarding humane and geological factors, physical distance is a significant negative factor for DVA, while positive factors include common language, common border and historical tie. As European economies occupy important places in the network, the euro put in use in 1999 changed the influence of the common currency on DVA from negative to positive [49]. In addition, bilateral free trade agreement is a significant positive factor for DVA, but the effects gradually diminished with time, which means that the effects of bilateral trade agreements stimulating energy trade development will gradually be overshadowed by international division of labor and subsequent global economic integration in the energy market.

Third, trading partnership with OPEC countries is a significant negative factor on DVA, and this dragging effect increases over time, implying that energy trade is increasingly dominated by non-OPEC economies. This is consistent with the domination of the trade for intermediate energy products in energy trade. Against this backdrop, non-OPEC economies are able to exert a much larger influence on DVA for being both producers and consumers of final energy products, in contrast with the OPEC economies that are mostly engaged with processing and exporting raw materials, and so get trapped in the preliminary stage of the GVC upstream. This shows that the trade for intermediate energy products plays an increasingly important role in the international energy market. The coordinated development of global energy sector should pay attention not only to the trade flow of final energy products under the traditional accounting method, but also to the value added of global energy flows and the international division of production.

Table 6 shows the influential factors on DVA_{FIN}, DVA_{INT} and DVA_{INTREX} for 1990 and 2015. The regression results are similar to the DVA networks, that the positive factors include combined forces of economic scale and population, historical linkage, common currency and existence of bilateral trade agreement, while the negative factors include disparity in economic scale, geographical distance, and trade partnership with OPEC countries. It should be noted that although common language has significant positive effect on DVA_{FIN} and DVA_{INT}, this is not the case with DVA_{INTREX}. It is obvious that product sales and marketing activities in GVC downstream have greater preference over common language. To the contrary, common currency influences DVA_{INTREX} more

Table 6
MRQAP regression result of the DVA Sub-networks for the year 1990 and 2015.

Variable	DVA_{FIN}		DVA_{INT}		DVA_{INTREX}	
	1990	2015	1990	2015	1990	2015
log *GDPS*	0.190***	0.916***	0.473***	1.367***	0.290***	1.286***
log *GDPD*	−0.064***	−0.375***	−0.179***	−0.570***	−0.114***	−0.555***
log *PopS*	0.048**	0.210***	0.156***	0.384***	0.051	0.225***
log *PopD*	−0.028	−0.055	−0.086***	−0.115***	−0.038*	−0.137***
log *Dist*	−0.074***	−0.328***	−0.179***	−0.433***	−0.153***	−0.462***
Comlang	0.018	0.358***	0.060	0.396***	−0.019	0.027
History	1.257***	3.247***	1.782***	4.160***	0.489***	2.333***
Comcur	−0.936***	2.493***	−1.088***	2.758***	−0.879***	3.969***
Contig	1.615***	4.073***	2.168***	4.994***	1.356***	2.942***
FTA	4.265***	1.109***	6.527***	1.708***	6.229***	1.478***
Opec	−0.222***	−0.424***	−0.357***	−0.696***	−0.313***	−0.955***
Constant	−2.471***	−11.627***	−5.777***	−17.612***	−2.971***	−15.122***
Adjusted R^2	0.1146	0.1612	0.151	0.2097	0.149	0.1809
F-statistic	339.1***	462.4***	466***	637.8***	456.3***	531.2***
Observation	28730	26406	28730	26406	28730	26406

Note: ***, ** and * indicate significance levels at 1%, 5% and 10% respectively.

significantly than DVA_{FIN} and $DVA_{INT,}$ so the intermediate stage of the GVC prefer common currency more than others. The reason is that common currency is an important lubricant to international trade, indispensable for firms engaged in the production processes outside the home economy. In contrast, firms in DVA_{FIN} and DVA_{INT} are mostly involved in domestic production and marketing. With little or low demand for foreign currency, they have low preferences in common currency. Finally, trading partnership with OPEC economies has significant negative impact on DVA sub-networks, greatest in DVA_{INTREX}, which implies that it is non-OPEC economies that participate in the intermediate stage of GVC.

4. Conclusion and policy implication

4.1. Conclusion

Using global input-output data during 1990–2015, this study reassesses and explains the global energy trade flow based on the new trade accounting system, and sheds light on the topological characteristics and major influential factors of the DVA network and its three sub-networks under international division of labor.

At the macro level, the DVA network and its sub-networks exhibit core-periphery structure, and can be segmented into core, semi-peripheral and peripheral layers. The breadth and depth of trading relationships in those networks were growing during the time, but both DVA_{INT} and DVA_{INTREX} far exceeds that of DVA_{FIN}. The DVA_{FIN} and DVA_{INT} networks carry the characteristics of small world network while DVA_{INTREX} network not displays the characteristics after 2006. Also trade for intermediate energy products is gaining popularity in the global market and has taken the largest share in the international energy trade, triggering the increasing sophistication of the international division of production in the energy sector and the elongation of the production links.

At the medium level, DVA, DVA_{FIN} and DVA_{INT} can be partitioned into three communities represented by the USA, Germany and China respectively. DVA_{INTREX}, being the dominating trade network in GVC upstream, is different from others as far as community partition is concerned. Furthermore, the structure of the network communities of the trade for intermediate energy products is relatively stable, in contrast with that of the trade for final energy products. So different from final energy products is more vulnerable to external shocks, the trade of intermediate energy products can help to increase the interdependence and complementarities among economics, then to promote the global energy system more stable.

At the micro-level, both advanced and emerging economies stay at the core of global energy trade and act as important intermediaries. Specifically, the USA is most important in terms of importing and final consumption of energy products, located in GVC downstream. Germany is the most vital importer of intermediate energy products and exporter of final energy products, staying in the middle of the GVC. China is the most important country staying in the intermediate stage of the energy industry's value chain, taking the form of using imported intermediate energy products to manufacture final products for domestic consumption. In addition, India is a significant hub in DVA network, while USA and Italy are important hubs in the trade for final and intermediate energy products respectively.

Finally, we find that the most essential factors influencing the growth of DVA network include economic scale, population, historical link, common language, common currency, and bilateral trade agreements, among which common language is more influential to energy trade in GVC downstream, while common currency is more influential to energy trade in GVC upstream. Non-OPEC economies are able to exert a much larger influence on DVA for being both producers and consumers of final energy products, while the OPEC economies mainly get trapped in the preliminary stage of the GVC upstream.

4.2. Policy implication

In accordance with the above research results, we draw to the following policy implications. First, focusing on the value added of energy is very important for the coordination and regulation of global energy trade, which is crucial for promoting the healthy development of global energy value chain. The deepening division of labor in the global economy and the resources allocation on a global scale contributed to the booming of global energy trade. This greatly stimulated the extension and expansion of the global energy value chain and boosted the global trade of final and intermediate energy products. In particular, our findings reveal a greater breadth and depth of trading in the intermediate energy product market than that of the final energy product market. The increasing sophistication of international division of labor in production has turned economies around the world into links in the global value chain of the energy industry, participating in production, processing and marketing of energy products. While the trade for intermediate energy products remains stable, it is not the case with the trade for final energy products. Actually, OPEC countries, as exporters of crude oil, are in the preliminary stage of the GVC upstream and mainly influence the production and output of raw materials. The influence of OPEC, however, is diminishing due to the sophistication of the division of labor in energy goods production and the subsequent lengthening of the value chain in the energy sector. This means that global energy coordination should not only look at the trade flow of final energy products, but also at the trade flow of intermediate energy products, especially the value added and contribution of energy flow to the global division of production.

Second, trade facilitation and regional trade liberalization, represented by the common currency, will show a further and deeper impact on the pattern of global energy trade. Its influence on global energy trade has changed as the emergence of Euro challenged the position of the US dollar as the settlement currency of oil trade [49]. Common currency exerts heavy influence on domestic value-added of global energy trade, as evidenced by the US dollar and the emergence of the eurozone, which are the key factors for USA and Germany to act as important intermediaries in the global energy market. Therefore, it is expected that the process of the internationalization of other currencies like RMB has the potential of reshaping the existing pattern of global energy trade. As emerging economies like China, India and Russia becoming indispensable players in the global energy market, they will play much bigger roles in the division of labor in the global value chain of energy and the coordination of international energy relations.

The contribution of this paper is to re-measure the added value of global energy trade with the new trade accounting system from the perspective of GVC, construct the Domestic Value-added (DVA) network of global energy trade and its three sub-networks, and then analyze the structural features and evolution of the DVA networks of global energy trade. However, there is still large room for improvement not only in analytical methods, but also in data processing. First, in addition to DVA, according to the energy trade decomposition accounting framework in WWZ (2013) [9], trade value added also includes Returned Domestic Value (RDV), Foreign Value Added (FVA) and Pure Double Counted Item (PDC). In particular, FVA is also an important index calibrating the engagement of a country's industry in global division of labor. Therefore, further comparison of FVA and DVA networks may yield more interesting results. Second, empirically testing the influential factors on DVA networks based on MRQAP fails to consider the endogenous self-organization effect of the network, which may be important for network formation. Therefore, further empirical tests can be considered based on the newly developed exponential random graph model (ERGM). Third, we studied global energy trade flow using Eora 26 database, in which the energy industry is relatively rough and general. So future studies may extend to the value-added trade pattern of segmented energy products like crude oil, electricity, etc. Moreover, we can compare the results of Eora26 database with other world input output tables (e.g., WIOT, GTAP and EXIOBASE et al.) in order to verify the robustness of the results. Finally, in the future we can study how the differences in the resource endowment of the economies affect international division of labor, which in turn influence the economies' gain from energy trade. This will give us some new insights about the topological structure of value-added trade networks.

Credit author statement

Gang Wu: Conceptualization, Methodology, Organization and direction, Manuscript revision, Yue Pu: Data processing, Empirical analysis, Visualization, Writing – original draft preparation, Tianran Shu: Validation, Writing – review & editing, Manuscript revision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study is sponsored by the National Natural Science Foundation of China (72003152; 71832012: 71503213) and the Fundamental Research Funds for the Central Universities (JBK2102054). The authors are grateful to anonymous referees and editors.

Appendix

Table A1
The 189 economy names and their abbreviations in this paper.

Economy name	ISO3	Economy name	ISO3
Afghanistan	AFG	Lesotho	LSO
Albania	ALB	Liberia	LBR
Algeria	DZA	Libya	LBY
Andorra	AND	Liechtenstein	LIE
Angola	AGO	Lithuania	LTU
Antigua	ATG	Luxembourg	LUX
Argentina	ARG	Macao SAR	MAC
Armenia	ARM	Madagascar	MDG
Aruba	ABW	Malawi	MWI
Australia	AUS	Malaysia	MYS
Austria	AUT	Maldives	MDV
Azerbaijan	AZE	Mali	MLI
Bahamas	BHS	Malta	MLT
Bahrain	BHR	Mauritania	MRT
Bangladesh	BGD	Mauritius	MUS
Barbados	BRB	Mexico	MEX
Belarus	BLR	Monaco, China	MCO
Belgium	BEL	Mongolia	MNG
Belize	BLZ	Montenegro	MNE
Benin	BEN	Morocco	MAR
Bermuda	BMU	Mozambique	MOZ
Bhutan	BTN	Myanmar	MMR

Table A1 (*continued*)

Economy name	ISO3	Economy name	ISO3
Bolivia	BOL	Namibia	NAM
Bosnia and Herzegovina	BIH	Nepal	NPL
Botswana	BWA	Netherlands	NLD
Brazil	BRA	Netherlands Antilles	ANT
British Virgin Islands	VGB	New Caledonia	NCL
Brunei	BRN	New Zealand	NZL
Bulgaria	BGR	Nicaragua	NIC
Burkina Faso	BFA	Niger	NER
Burundi	BDI	Nigeria	NGA
Cambodia	KHM	Norway	NOR
Cameroon	CMR	Gaza Strip	PSE
Canada	CAN	Oman	OMN
Cape Verde	CPV	Pakistan	PAK
Cayman Islands	CYM	Panama	PAN
Central African Republic	CAF	Papua New Guinea	PNG
Chad	TCD	Paraguay	PRY
Chile	CHL	Peru	PER
China	CHN	Philippines	PHL
Colombia	COL	Poland	POL
Congo	COG	Portugal	PRT
Costa Rica	CRI	Qatar	QAT
Croatia	HRV	South Korea	KOR
Cuba	CUB	Moldova	MDA
Cyprus	CYP	Romania	ROU
Czech Republic	CZE	Russia	RUS
Cote dIvoire	CIV	Rwanda	RWA
North Korea	PRK	Samoa	WSM
DR Congo	COD	San Marino	SMR
Denmark	DNK	Sao Tome and Principe	STP
Djibouti	DJI	Saudi Arabia	SAU
Dominican Republic	DOM	Senegal	SEN
Ecuador	ECU	Serbia	SRB
Egypt	EGY	Seychelles	SYC
El Salvador	SLV	Sierra Leone	SLE
Eritrea	ERI	Singapore	SGP
Estonia	EST	Slovakia	SVK
Ethiopia	ETH	Slovenia	SVN
Fiji	FJI	Somalia	SOM
Finland	FIN	South Africa	ZAF
France	FRA	South Sudan	SDS
French Polynesia	PYF	Spain	ESP
Gabon	GAB	Sri Lanka	LKA
Gambia	GMB	Sudan	SUD
Georgia	GEO	Suriname	SUR
Germany	DEU	Swaziland	SWZ
Ghana	GHA	Sweden	SWE
Greece	GRC	Switzerland	CHE
Greenland	GRL	Syria	SYR
Guatemala	GTM	Taiwan, China	TWN
Guinea	GIN	Tajikistan	TJK
Guyana	GUY	Thailand	THA
Haiti	HTI	TFYR Macedonia	MKD
Honduras	HND	Togo	TGO
Hong Kong, China	HKG	Trinidad and Tobago	TTO
Hungary	HUN	Tunisia	TUN
Iceland	ISL	Turkey	TUR
India	IND	Turkmenistan	TKM
Indonesia	IDN	Former USSR	USR
Iran	IRN	Uganda	UGA
Iraq	IRQ	Ukraine	UKR
Ireland	IRL	UAE	ARE
Israel	ISR	UK	GBR
Italy	ITA	Tanzania	TZA
Jamaica	JAM	USA	USA
Japan	JPN	Uruguay	URY
Jordan	JOR	Uzbekistan	UZB
Kazakhstan	KAZ	Vanuatu	VUT
Kenya	KEN	Venezuela	VEN
Kuwait	KWT	Viet Nam	VNM
Kyrgyzstan	KGZ	Yemen	YEM
Laos	LAO	Zambia	ZMB
Latvia	LVA	Zimbabwe	ZWE
Lebanon	LBN		

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