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The evolution of oil trade: A complex network approach

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Abstract

Trade in oil has undergone significant changes in the last 20 years: technical progress has allowed the exploitation of new and previously untapped fields; the emergence of new large oil importers, such as China, has shifted the traditional patterns of demand and supply, while the desire to diversify energy sources has favored the emergence of new suppliers. This paper compares the topological properties of the network of crude oil trade over the period 1995–2014. The analysis covers both aggregate measures (such as network density and centralization) and node-specific indicators (e.g. centrality) that allow to uncover the rise (demise) of new (old) important players. Accounting for the position of each country within the network provides valuable information above and beyond traditional measures such as market shares. To investigate whether oil trade has experienced a process of globalization or, rather, regionalization, we look at the community structure of the network: the number of communities increases in the aftermath of the global financial crisis, but then goes back to its historical values. Something similar happens to the average geographic distance within each community, showing that along a regional component there are also strategic/political considerations at play. Econometric analysis suggests that high oil prices increase the likelihood that high-production-cost exporters play a more central role in the network, thus reducing the power of traditional suppliers.

Keywords: *oil, communities, globalization, regionalization, networks*

1 Introduction

Trade in oil has undergone significant changes in the last 20 years due to the evolution of technological, economic, and geo-political factors. Advances in drilling

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techniques have made it possible to exploit new and previously untapped fields. Moreover, the emergence of new large energy importers, such as China, contributed to push up demand and prices in the early 2000s, thereby shifting also the traditional patterns of trade. The desire of importing countries to diversify their supply has favored the emergence of new producers, while an ongoing shift in consumption toward cleaner sources of energy—albeit still marginal at a global level—has started a long-term process that eventually might challenge the established role of traditional oil exporters.

Crude oil is one of the most actively and internationally traded commodity. At least 50 countries produce significant volumes of crude oil and two thirds of the total production is exported across the globe (Smith, 2009). Global oil trade has grown rapidly in recent decades due to the uneven distribution of oil resources and the fast increase in demand in developed and emerging economies: oil imports grew 74% from 1990 to 2011 (Zhang *et al*., 2014) and account for more than 60% of total oil consumption.

This paper investigates the evolution of international trade in oil through the lenses of network analysis, in particular by comparing the topological properties of the network of crude oil trade over the period 1995–2014. More specifically, the analysis covers both aggregate measures (such as network density and centralization) and node-specific indicators (e.g. centrality) that allow to uncover the rise (demise) of new (old) important players. The paper shows that accounting for the position of each country within the network provides valuable information above and beyond traditional measures of trade as, for instance, market shares or total exports.

The paper further documents the evolution of oil trade by looking at the community structure in the network. This allows us to investigate whether oil trade has experienced a process of globalization or, rather, one of regionalization; moreover, it allows to detect whether the emergence of new important exporters has resulted in a more multipolar system. The analysis reveals that the number of communities increases over time, in favor of a pattern of regionalization of oil trade: to dig deeper into this issue, the analysis focuses on the average geographic distance within each community, so as to see whether these groups have mainly a regional nature or, rather, they are driven by strategic/political considerations. It turns out that both factors are at play.

The paper closes with a series of econometric exercises performed with a view to looking at the relationship between the degree of network centralization and a number of economic determinants, among which the price of oil. In particular, the paper tests the hypothesis that a high oil price increases the likelihood that high-production-cost oil exporters play a more central role in the network, thus reducing the power of "core" traditional (e.g. OPEC) exporters and making the international oil market less concentrated than in the past. The paper offers evidence suggesting that this is indeed the case.

2 A glance at the existing literature

While the application of network analysis to international trade flows has a long tradition in the literature (see for instance Snyder & Kick, 1979; Smith & White,

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1992; Garlaschelli & Loffredo, 2005; Fagiolo *et al*., 2008; De Benedictis & Tajoli, 2010), only a few studies investigated the specific features of trade in oil.

Ji *et al*. (2014) analyze the binary network comprising 79 large oil trading countries, which account for around 80% of total trade volume, in 2010. This work shows that the node-degree distribution follows a power-law, suggesting that the majority of exporters serve few destinations while only a fraction of them sell oil to several importing countries. Using the community detection method proposed by Leicht & Newman (2008), the authors identify the existence of three main trading blocs: South America–West Africa–North America, the former Soviet Union–North Africa–Europe, and Middle East–Asia–Pacific. The analysis also suggests that the emergence of a small number of large players makes the oil trade network fragile, i.e. vulnerable to specific disruptions hitting major exporters, such as Saudi Arabia and Russia.[1]

Zhong *et al*. (2014) examine the evolution of the community structure of the oil network over time. The main differences with respect to Ji *et al*. (2014) lie in the adoption of a different methodology for the detection of the communities (Zhong *et al*., 2014 employ the optimal modularity algorithm developed by Blondel *et al*., 2008), in the investigation of both the binary and the weighted versions of the network, and in the more comprehensive coverage of 179 countries over the period 2002–2011. Moreover, the focus of Zhong *et al*. (2014) is not on crude oil as in Ji *et al*. (2014), but on a different oil-related product called "Light Petroleum distillates" (6-digit HS code 271019). In line with Ji *et al*. (2014), Zhong *et al*. (2014) find evidence that the binary network can be partitioned into four communities; however, they show that in the weighted version of the network the number of communities varies over time from three to seven. They find that the community structure was affected by the Iraq War in 2003, and by the 2008–2009 financial crisis, when several countries moved in and out of their communities before going back to their previous positions after a few years.

Another recent paper by Zhang *et al*. (2014) takes the viewpoint of the importing countries and investigates competition among them in three years, namely 2004, 2008, and 2011. The authors build a network where two countries are linked if they import oil from the same source and show that this "oil-trading competition network" has become denser over time, since more importers try to diversify their energy sources, and resources have become more concentrated due to higher internal consumption in some producing countries and the exhaustion of accumulated reserves. Europe appears as competing with both North American and Asian countries, whose role as importers has grown over the last few years. Zhang *et al*. (2014) find evidence that the network of oil trade exhibits small-world features, i.e. higher clustering and smaller shortest distance than a random network, due to the fact that the number of oil importers is much larger than the number of exporters.

While both Zhang *et al*. (2014) and Ji *et al*. (2014) address the entire network of oil trade and its constituting communities, they do not undertake any node-level analysis despite this representing a complementary piece of evidence necessary to

[1] Systemic vulnerability in the context of oil trade is probably more complex to model relative to the diffusion of an epidemic or to a cascading failure in an energy grid. In fact, oil can easily be imported from alternative routes, there are reserves and stocks, and the price response of a disruption would probably affect demand. Therefore, the usual metrics employed to assess network fragility might not be adequate to measure fragility in the context of oil trade.

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understand the features of the oil trade network. In this work, we address this issue and use the main findings of the analysis to interpret the role of new and old important players in the network and the features of the main communities. The paper offers three contributions to the existing literature: (i) it extends the analysis to 2014, thus moving away from the immediate post-crisis years and looking to a period marked by important events such as the Arab spring or the embargo imposed on Iran; (ii) it performs a detailed node-level analysis that looks at the behavior of some key players in the network, in addition to looking at systemic network measures; (iii) it combines network analysis with an econometric exercise to investigate the globalization vs. regionalization hypotheses.

3 Evolution of the oil trade network

3.1 Data

We use bilateral trade data taken from the BACI dataset maintained by CEPII (Gaulier & Zignago, 2010) covering the years 1995–2014. This database builds on the information contained in the UN-Comtrade archive and applies a series of strategies to impute missing data, ensure consistency, and clean possible mistakes. In the empirical work we focus on international trade in crude oil, identified by the code 270900 in the 6-digit Harmonized System classification, and use information on quantities (tons).[2]

In the end, the number of countries/nodes in the network ranges between 138 (in 1995) and 165 (in 2010).[3] In the rest of this section, we shall report results for a few selected years, namely 1995, 2000, 2005, 2010, and 2014: since the topological properties of the network change rather slowly (see for instance Fagiolo *et al*., 2009, for evidence on total trade), the choice of the specific years to display has no bearing on the overall picture that emerges from the analysis.

3.2 Basic network statistics

The crude oil network is very sparse, as one would expect for a graph where only a few nodes can actually produce the commodity that flows across the network. Between 1995 and 2014, the density of the network ranges between 3.7% and 4.3%. Over time one can observe an increase in the number of both nodes and links, at least until 2011 when they stabilize. The increase in the number of nodes is mainly due to one-off geo-political factors, such as the breakdown of the Soviet Union and Yugoslavia, which gave rise to several independent countries; the rise in the number of links reflects instead a generalized increase in international trade, facilitated by a reduction in trade costs and an increase in energy demand by developing countries such as China and India. Even focusing on the period 2000–2014, when the number

[2] The possible presence of black market oil trading, especially in regions at war, is not incorporated in the data. This might result in an underestimation of the role played by countries involved in conflicts, as black market trade does not enter official statistics. We thank an anonymous referee for pointing this out to us.

[3] From the original data we remove aggregate regions or unspecified destinations, such as "special categories," "other Europe," and the like.

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Table 1. Basic network indicators, selected years.

	1995	2000	2005	2010	2014
Nodes	138	161	166	165	160
Links	765	940	1,049	1,099	1,105
Density	0.041	0.037	0.038	0.041	0.043
Average degree	5.543	5.839	6.391	6.661	6.906
Centralization	0.488	0.445	0.438	0.393	0.453

of nodes remains roughly constant (see Table 1), density increases from 3.7% in 2000 to 4.3% in 2014.

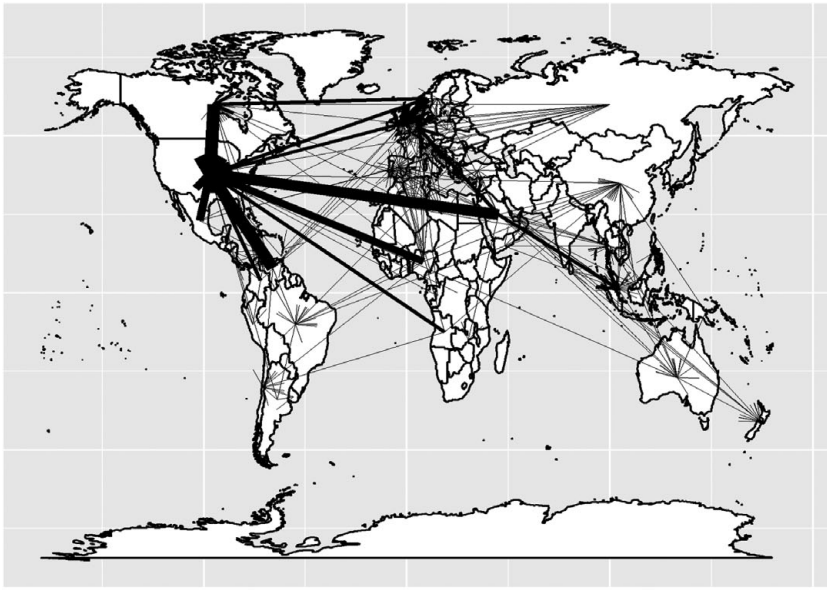
While these figures inform about the average connectivity in the network, heterogeneity at the level of the individual nodes is very high. To grasp it, one can either look at the distribution of node degree (as we shall do below) or calculate a measure of degree centralization to capture similarity among nodes (following Freeman, 1979). Degree centralization looks at the differences between the degree of the most connected country/node and that of all other players; accordingly, it is calculated as the ratio of the sum of these differences (computed on the actual network) to the maximum possible sum of differences (obtained in a "star" graph with the same number of nodes). Degree centralization can take values between 0 and 1: a value of 1 is achieved in a star graph where one node represents a single central hub, while a value of 0 occurs in case of a complete network (where all nodes have the same number of connections). In Table 1, we show that centralization falls over time, from 0.488 to 0.393 between 1995 and 2010, suggesting that the oil trade network has become more balanced in this period. In the following years (2010–2014) however, centralization has edged up, back to values observed in the early 2000s.

Figure 1 provides a snapshot of the evolution of the oil trade network in 1995, 2005, and 2014. In order to make the maps readable, the figures only report flows above the median value for each year. The maps confirm that, over time, the network has become denser and slightly more homogeneous. China emerges as an important new oil importer, attracting flows mainly from Africa (and to a lesser extent from Russia and the Gulf). On the contrary, European countries lose relevance both as exporters (due to the depletion of resources) and as importers, as suggested by Zhang *et al.* (2014).

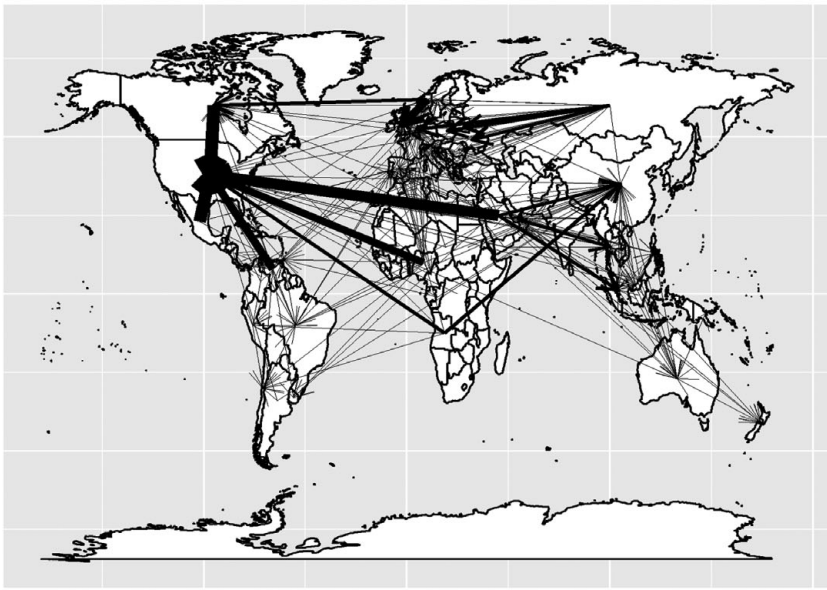
To further analyze the evolution of connectivity, we can look at the distribution of node (in- and out-) degree. In 1995, more than 60% of the exporting countries served less than four destinations, while only 6% served more than 20 countries. Similarly, on the import side, more than 60% of the countries bought oil from less than 4 producers and only 7% from more than 20. The situation is quite similar in 2014, although slightly more balanced: the fraction of export (import) countries shipping to (sourcing from) less than 4 partners is down to 55% (58%), while the share of highly diversified players with more than 20 partners has in both cases (import and export) reached 10%. Overall, the distributions of inward and outward node degree remain stable over the 20-year span under investigation.

The moderate fall in the degree of heterogeneity in connectivity is reflected in lower values of skewness of node in-degree, which moves from 2.9 in 1995 and 2.4 in

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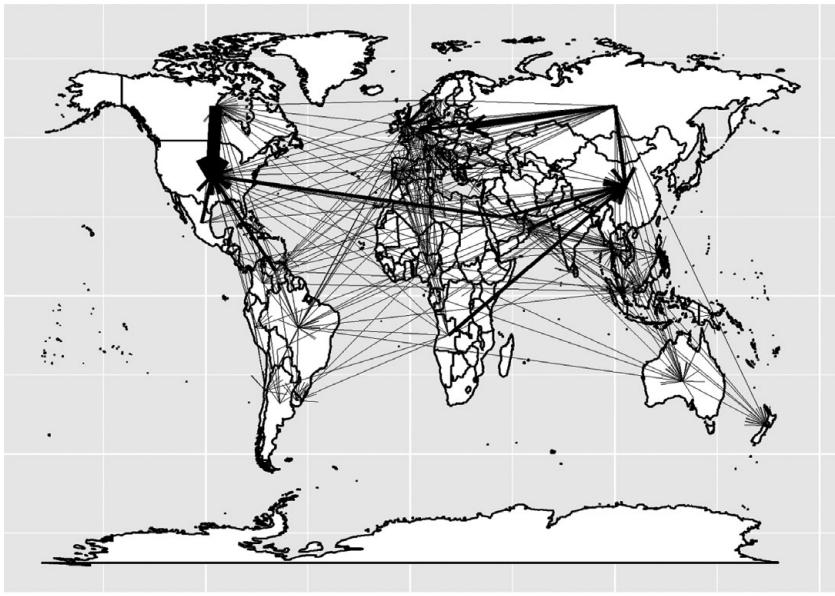
(a) 1995



(b) 2005

Fig. 1. The oil trade network in 1995 (a), 2005 (b), and 2014 (c). Line thickness represents link weight relative to the maximum value for the year. Only the top 50% of links is displayed.

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(c) 2014

Fig. 1. Continued

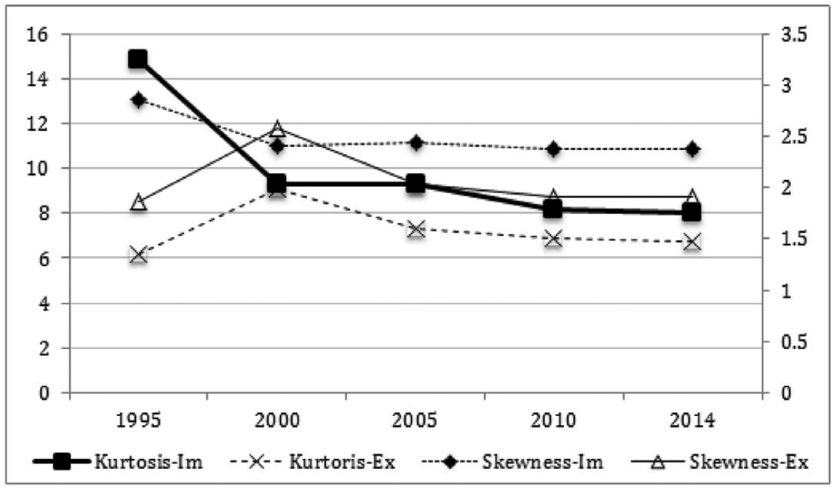
2014. The corresponding values for out-degree tend to be smaller and flat (ranging between 1.8 and 2.6), apart from a spike in 2000. The importance of heavy tails in the distribution can be detected by looking at kurtosis: for both in- and out-degree kurtosis is on a declining trend at least since 2000, although it remains well above the value associated with the normal distribution (i.e. 3). As observed for skewness, values for the out-degree distribution tend to be smaller and more stable.

It is worth noting that the distribution of out-degree appears significantly affected by the geo-political turmoil of the early 1990s, which results in 23 new countries joining the network. As it is clear from Figure 2, this leads to a sharp increase in the heterogeneity of the export network, documented by the rise in both skewness and kurtosis. Conversely, the import network becomes less heterogeneous. Starting from the year 2000, both the import and the export networks become less heterogeneous in terms of the connectivity of the individual countries.

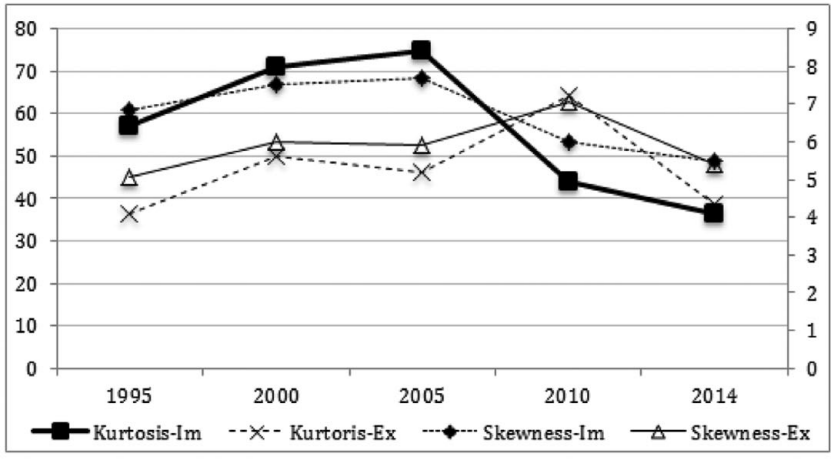
This finding is no longer valid if one looks at the *weighted* version of the network that considers trade volumes besides binary measures of connectivity. The weighted import network appears more heterogeneous than the export one, at least until the financial crisis of 2008–2009, with values of skewness and kurtosis on the import side always larger than their export counterparts. After 2010 the values tend to converge and by 2014 they are virtually the same for imports and exports. The difference in the behavior of the binary and weighted networks suggests that the financial crisis affected the overall quantities exchanged across the globe and modified the strength of the individual bilateral links, while it impacted to a lower extent on the extensive margin of crude oil trade (picked up by the binary version of the network.)

Assortative mixing, which captures the tendency of highly connected nodes to link with players featuring a similar degree of connectivity, appears rather weak in the crude oil network. Unlike total trade, for which the literature finds a strong

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(a) Binary network



(b) Weighted network

Fig. 2. Skewness and kurtosis in binary (top) and weighted (bottom) import and export networks. Values for skewness refer to the right-hand scale. (a) Binary network. (b) Weighted network.

disassortative pattern (in the binary network), oil trade is only weakly disassortative: this feature is stable over the entire time span and does not depend on the way we measure assortativity, either the correlation between average nearest neighbor degree (ANND) and node degree (k), or degree-degree correlation. Interestingly, the dissortative pattern for nodes with middle-high degree ($k > 10$) is stronger (ANND-degree correlation equals −0.67) whereas the dissortative pattern seems to disappear in poorly connected countries (ANND-degree correlation is almost 0 for countries with $k \leqslant 10$). When considering link weights, the dissortative pattern becomes even weaker than in the binary network. Indeed, strength–strength correlation is half of the corresponding degree–degree correlation in all years considered.

For what concerns clustering, the binary network displays values that remain close to 0.2 in all years (see Table 2). However, this value is approximately three

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Table 2. Clustering coefficient: comparison between actual and random networks.

	1995	2000	2005	2010	2014
			Binary network		
Random network	0.081	0.073	0.077	0.081	0.086
Oil data	0.213	0.251	0.245	0.267	0.276
			Weighted network		
Random network	0.034	0.031	0.032	0.034	0.036
Weighted random*	0.002	0.001	0.001	0.001	0.001
Oil data	0.001	0.001	0.002	0.001	0.001

Average clustering coefficient of the 1,000 random networks for each year mentioned above.
*Empirical degree sequence, but reshuffled weights. Average clustering coefficient of 1,000 replications.

times larger than the corresponding figure obtained by randomly assigning the same number of links to existing nodes (we take the average of 1,000 replications). Therefore, the neighbors of a country are, on average, more likely to have trading relationships to each other, and the clustering we observe in the data cannot be a simple statistical fluke. In other words, "regional trading" seems more important than expected in the crude oil network, although the term "regional" does not necessarily have a geographic meaning here, but rather a topological one.

When we incorporate link weights into the analysis, the picture changes: average clustering is very low (around 0.001) and the comparison with random networks is sensitive to the way we build the random benchmark. In fact, a naïve random network where we simultaneously reshuffle both the link sequence and link weights yields a much higher clustering than what we find in the data (0.031–0.034 for the random network vs. 0.001–0.002 for the actual data). However, since the distribution of node degree does not follow a uniform-distribution, another (more meaningful) way to randomize the network is to reshuffle weights across the existing links (Opsahl *et al.*, 2008). To do this, we create 1,000 random networks with the same (binary) structure as the empirical graph and randomly assign weights. Results, reported in the last row of Table 2, show that the clustering in the crude oil network is roughly in line with the random benchmark. Interestingly, we find that a significant fraction of countries (34%–37%) is more clustered than expected, suggesting that a group of countries does form an intensive-clustered hub.

3.3 Community structure

To address more directly the question of globalization vs. regionalization of oil trade, we investigate the presence of a community structure in the data. A community is a set of nodes that are densely connected internally while presenting a sparser connectivity with the rest of the network. Several methods exist to detect communities, based on different ways "densely connected groups" are defined and identified: we follow Zhong *et al.* (2014) and apply the optimal modularity algorithm developed by Blondel *et al.* (2008). This methodology provides a complete partition of the

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Table 3. Community structure: number of communities, modularity, and average distance (km) within communities.

	Binary network			Weighted network		
Year	#Comm.	Modularity	Avg. distance	#Comm.*	Modularity	Avg. distance*
1995	4	0.324	5,009	5 (4)	0.384	5,069 (6,212)
2000	4	0.349	4,791	5 (4)	0.429	4,354 (5,380)
2005	5	0.345	3,231	5 (5)	0.438	5,780 (5,780)
2010	4	0.338	5,227	7 (6)	0.411	5,320 (6,080)
2014	5	0.283	4,583	5 (5)	0.408	5,074 (5,074)

* Numbers in parentheses report results excluding communities with only two members.

network and also yields a modularity index that measures the quality of a particular division of the network into communities.

In the binary network, the number of communities is four in 1995, 2000, and 2010, and five in 2005 and 2014. The average bilateral distance within each community decreases significantly in the first 10 years, from 5,009 km in 1995 to 3,231 km in 2005, then it jumps to 5,227 km in 2010 only to go back to 4,583 km by the end of the sample period.

A similar pattern is found also in the weighted network, where the number of communities is slightly larger and moves from five in 1995–2005 to seven in 2010, back to five in 2014.[4] We observe that in 1995, 2000, and 2010, one of the communities has only two members; Table 3 also reports information excluding this pair. At first sight, the increase in the number of communities may suggest a regionalization of oil trade, where countries progressively intensify trade relations with a limited number of partners. However, when we look at the average distance within each partition of the network, we observe that a larger number of communities does not always correspond to a smaller average distance within them (as one would expect if regionalization was under way). Moreover, between 1995 and 2010, the number of countries in each partition becomes less homogeneous: in 2010 we observe the presence of a single dominant (and global) partition comprising 55 countries, while the second and third largest communities only count, respectively, 36 and 28 members. Such a large difference in community size is much less important in previous years. By 2014, however, we are back to more homogeneity: the two largest communities count 49 and 41 members, the next two count, respectively, 28 and 26.

Considering that, over time, the density of the network has increased and its centralization has decreased (see Section 3.2) we interpret our results in terms of a globalization of the oil market, partly due to the emergence of China, India and other important players.[5] This phenomenon is particularly evident in the aftermath of the crisis, when energy demand from OECD countries experienced a significant drop and the relative importance of emerging economies grew stronger. In fact,

[4] The countries belonging to each (weighted) community are listed in Table A1 in the Appendix.

[5] Although their approach differs from ours (they analyze a competitive network among importers, whereas we focus on oil exporters), Zhang *et al.* (2014) reach similar conclusions. Indeed, they find that the emergence of the Asia-Pacific region as a large importer broke the competition pattern dominated by North America and Europe.

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while at the beginning of the sample China belongs to an Asian/Far East partition of the network, over time it attracts trade flows mainly from African countries and, by 2010, it has basically set up its own community consisting mainly of African producers, such as Angola, Congo, and Sudan.

We not only determine the number and composition of communities, but, by looking at the value of modularity, we also determine how well the resulting partition actually describes the data: higher values of modularity imply a more precise partition of the data, whereas low modularity suggests that the boundaries across different communities are less clear-cut. Table 3 shows that in all the years the weighted network features a higher value of modularity than the binary one. This means that the extra information provided by link weights is important to better determine the community structure of the crude oil network. In both the binary and weighted cases, modularity follows an inverted-U shape, suggesting first a fragmentation of the graph (in the late 1990s), followed by a globalization of oil trade that blurs the partition of the network. Hence, even if the average distance within each community goes down, the partition of the network is less clear cut, indicating that in the last few years both regionalization and globalization forces were at work.

3.4 Major players in the network

We further investigate the role played by specific countries and the evolution of their neighborhood by looking at the top importing and exporting countries, using both traditional measures such as market shares, and network-based indicators.

The aggregate share of the top-10 oil exporters has remained roughly constant over the 20-year span under investigation, passing from around 68% of global exports in 1995 to 67% in 2014 (with a drop to 64% in 2010). Saudi Arabia remains the largest exporter over time, Russia moves from 6th to 2nd position, and is followed in 2014 by Canada, the United Arab Emirates and Nigeria (see Table 4). Two big changes in export shares stand out: first, Norway—which ranked second in 1995 with a global export share of 9%—is barely among the top-10 exporters 20 years later, and its market share has fallen to 3%; second, sanctions against Iran (adopted in June 2011 and lifted only in 2016 as a result of a deal on the country's nuclear program) have resulted in the Middle Eastern country—the 3rd largest exporter between 1995 and 2010 with a share of 7%—to disappear from the list of the top exporters by 2014. On the import side, one can observe more evident changes in the country rankings. China and India, for instance, became the 2nd and 3rd largest importers by 2014, respectively, whereas they were not among the top-10 importers in the mid-1990s.

The importance of individual countries in a network can be evaluated, as done above, by looking at the relative size of their trade flows, i.e. their shares in global trade. Alternatively, one can look at the entire network so as to take into account the importance of any trade partners of a given country in the assessment of its own centrality. This is done, for instance, by using the HITS algorithm developed by Kleinberg (1999). The algorithm yields hub-and-authority scores both in the binary and in the weighted networks, and captures the interdependence of the nodes. Interestingly, the results generate a country ranking, in terms of centrality, that differs from the one we obtain looking exclusively at trade shares.

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Table 4. Top-10 oil exporters and importers in 1995, 2005, and 2014, with share of world crude oil export/import.

Exporters						
	1995		2005		2014	
Rank	Country	Share	Country	Share	Country	Share
1	Saudi Arabia	18%	Saudi Arabia	18%	Saudi Arabia	17%
2	Norway	8%	Russia	11%	Russia	11%
3	Iran	6%	Norway	6%	Canada	6%
4	UAE	6%	Iran	6%	UAE	6%
5	Russia	6%	UAE	6%	Iraq	6%
6	Nigeria	5%	Nigeria	5%	Nigeria	5%
7	United Kingdom	5%	Mexico	4%	Kuwait	4%
8	Venezuela	5%	Venezuela	4%	Venezuela	4%
9	Mexico	4%	Canada	4%	Angola	4%
10	Canada	4%	Lybia	3%	Norway	3%
Importers						
	1995		2005		2014	
Rank	Country	Share	Country	Share	Country	Share
1	United States	25%	United States	24%	United States	18%
2	Japan	15%	Japan	10%	China	15%
3	Germany	6%	China	6%	India	9%
4	Rep. of Korea	6%	Rep. of Korea	5%	Japan	8%
5	France	5%	Italy	5%	Rep. of Korea	6%
6	Italy	5%	Germany	5%	Netherlands	5%
7	Netherlands	4%	Netherlands	4%	Germany	3%
8	Singapore	4%	France	4%	Italy	3%
9	Spain	3%	Spain	3%	Spain	3%
10	United Kingdom	3%	Canada	3%	France	2%

The rationale behind the HITS algorithm is to use the information on the import–export patterns in the entire crude oil network to infer which countries play a leading role. Authorities (i.e. countries that import from many producers) represent leading importers; hubs instead (i.e. countries that sell oil to many destinations) are leading exporters. We would like to check whether authorities are countries simply importing the largest amounts of oil, or rather those importing from a (possibly overlapping) set of leading producers. Symmetrically, the algorithm defines "oil hubs" as nodes that export preferentially to leading importers, in a mutual reinforcing relationship.

Focusing first on the case of the export network, we reproduce in Figure 3 (left panel) a scatterplot where the values of the weighted HITS-hub measure (on the vertical axis) are plotted against the share of exports (on the horizontal axis). We see that several countries are quite far from the 45-degree line, suggesting that the market shares and the hub scores—two measures of centrality or relevance—do not always coincide. Hence, once the entire structure of the network is taken into account, it is not only the overall volume of trade that matters in the assessment of the importance of a country.

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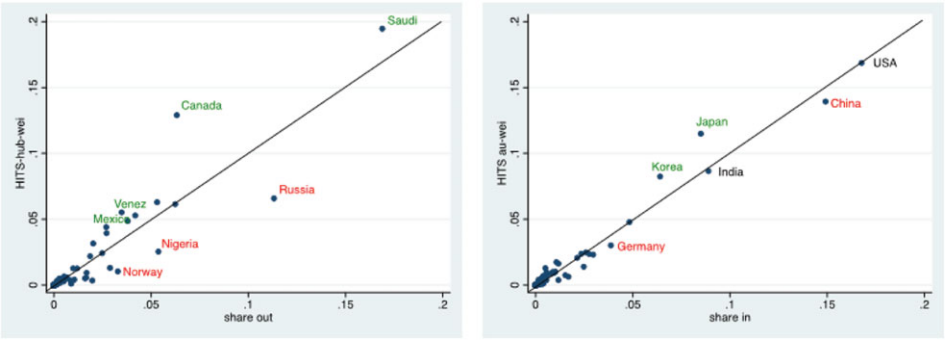


Fig. 3. Scatterplot of HITS-hub (left) and HITS-authority (right) against market share in 2014. (Color online)

The most striking deviations from the 45-degree line (in absolute terms) are associated with Canada and Russia. We consider the case of Canada to illustrate how one can read and interpret Figure 3. While the country's share of export is 6%, roughly 1/3 of the Saudi share, its HITS-hub score is 0.13 (the second largest value in the whole network) and only 30% lower than the score of Saudi Arabia. This result suggests that Canada is more influential than its export values would indicate. The preferential commercial ties between Canada and the United States, which was the largest importer of oil, helps explaining this relevance. This holds true for Mexico and (to a lesser extent) Venezuela.

Russia is another interesting case to look at. While its volume of export grows 2.5 times in the last 20 years, and its market share surges from 5% to above 11% its hub score (0.07) still lags behind that of Saudi Arabia (0.20) and Canada (0.13), although the latter country has a market share that is only half the Russian one. Again, this is explained by the geography of Russian exports: in 1995, Russia exported to 32 countries, and almost all of them were European destinations; by 2014, it served 49 markets, including Asian and American countries, but Europe still accounted for 60% of its exports. Hence, its position within the network is less prominent than what its market share would suggest. Among the other countries that lie below the 45-degree line in the figure, one can spot Iran, the United Arab Emirates, and Norway. These countries export preferentially toward European economies, whose positions in the ranking of the importers are relatively low.

Saudi Arabia remains the most influential exporter (in terms of HITS-hub score) throughout the period we analyze: however, Saudi export patterns have changed, adapting to the new geography of world demand. In fact, while in 1995 Saudi Arabia exported to Asia around 40% of its total export, 35% to Europe and 25% to the United States, 20 years later, Asia has become more and more important for Saudi Arabia, counting for more than 60% of its total crude oil exports. Particularly important is the emergence of China as trading partner. China imported only around 0.1% of total Saudi Arabia's exports in 1995, but its share increased to 14.5% in 2014, becoming the third biggest destination market (following Japan and the United States) for Saudi oil.

Europe and the United Arab Emirates lose importance over time: two European countries appear among the top-10 important exporters in 1995, just one in 2014.

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More precisely, the United Kingdom and Norway occupy, respectively, the 2nd and 7th positions in 1995, while they fall to the 10th and 18th places in 2014. As to Norway, the volume of its exports drops by 50% over the 20 years under investigation, its weighted HITS-hub value drops from 0.046 to 0.010 and its ranking falls. The situation is similar in case of the United Kingdom, whose absolute volume of trade goes down alongside its HITS-hub ranking falls. The main explanation for this gradual demise of the United Kingdom and Norway lies in the fact that the two countries still export preferentially to other European economies, whose relevance in the network declines over time.

On the import side (see the right panel of Figure 3) there is much more concordance between the share of world import of a country and its weighted authority score. Most countries lie near the diagonal and only a handful of them (such as Japan and Korea) exhibit visible deviations. Japan, for instance, has the same import share as India, but features a much larger HITS-authority score. The reason is that Japan imports 16.5% of total Saudi Arabia's exports, while India only 10%.

4 Econometric analysis

The analysis of the entire network is a fundamental step in understanding the features of this globalized market. Additional insights can be drawn from the analysis of node-specific indicators (e.g. out-degree and centrality) since they can shed light on the features that characterize the most important players. To do so, we build an unbalanced panel covering up to 90 countries for the years 1995, 2000, 2005, 2010, and 2014: we include a series of network-based node-specific measures and an array of variables capable of influencing the performance of the individual countries.[6]

For the sake of brevity, we propose a general representation of the functional form to estimate

$$Y_{it} = \alpha + \boldsymbol{\beta} \boldsymbol{X_{it}} + \epsilon_{it} \tag{1}$$

where Y_{it} stands for a node-specific network measure and $\boldsymbol{X_{it}}$ is the matrix of explanatory variables. We shall describe the individual covariates in each exercise.

The first exercise we perform regards the binary network of crude oil trade. More precisely, it is directed to identify the main determinants of node-level outward degree (i.e., the number of destination markets) whose distribution has been discussed before.

The explanatory factors we include in $\boldsymbol{X_{it}}$ are chosen according to economic theory. The variable GDP, measuring the size of the domestic economy, is introduced to capture the possibility that largest and more advanced countries can serve a greater number of foreign markets. REM is a multilateral measure of distance, capturing country remoteness as defined in Fagiolo (2010) and accounting for trade and transaction costs; this variable is calculated as the weighted average of the distances of a country to all other countries, with weights equal to the country share of world GDP. STA is a proxy of internal political instability which potentially affects the

[6] Although the empirical analysis in this section focuses on circa 90 countries, the node-level network measures are built on the entire dataset (covering 194 countries) illustrated above.

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ability of an exporting country to serve many partners (data taken from Kaufmann *et al*., 2010). RTA is total number of preferential trade agreements, covering any sector or group of sectors and not just the oil sector, and it captures the country's general trade connectivity.[7] PR and RES measure the daily overall production of oil and the available reserves (data taken from the U.S. Energy Information Administration), which are associated with the exchange of crude oil produced domestically. As the price of crude oil experienced remarkable changes over the decades considered, we finally insert the international price of oil (PO, data come from the U.S. Energy Information Administration and refer to the Brent spot price; the average annual price is obtained from monthly figures) among the explanatory variables: the hypothesis to test is that higher oil prices may allow oil exporters to serve a larger number of foreign markets.

The above-mentioned price effect may in fact be differentiated across producers according to their oil production costs. Countries with very high costs of production can find it prohibitive to extract and sell oil when the international price is low, whereas countries enjoying low production costs (such as the Gulf countries) may suffer less the variation in the international price of crude oil. The hypothesis to test is that when the oil price is high the likelihood that high-production-cost exporters play a more central role in the network is also higher. We therefore include in the estimation an interaction term $PO\text{-}HC$ whereby the international price of oil is multiplied by a dummy taking value 1 if oil production involves high costs, and zero otherwise.[8] A positive and significant coefficient would support the idea that the higher the oil price, the lower the relative power of "core" traditional (e.g. OPEC) exporters and the less concentrated the international oil market.

To capture the impact of the oil price on the role played by oil exporters in the network, we also develop an alternative specification. Rather than including PO and $PO\text{–}HC$ as before, we calculate the national oil rent per barrel ($OIL\ RENT$) with a view to capturing the ability of a country to draw returns from its oil production.[9] Notably, $OIL\ RENT$ is affected by variations in the cost of production across countries and over time, whereas $PO\text{–}HC$ exploits exclusively the cross-sectional variation in production costs.

For each specification we propose both an OLS random effects estimation[10] and an instrumental variable (IV) approach so as to account for the possible simultaneity between oil price and number of exporting relationship.[11] As external instruments, we use two variables correlated with the evolution of oil price but not with

[7] Data are calculated from the dataset collected by De Sousa (2012).

[8] The countries characterized by low production costs (below 20 U.S. dollars (USD) per barrel) are Saudi Arabia, Iraq, United Arab Emirates, Algeria, Iran, Qatar, Oman, Kazakhstan, Venezuela, Ecuador. All the remaining producers are classified as high-cost countries.

[9] This variable is built as follows. The World Bank publishes in the World Development Indicators the ratio of total oil rents over national GDP. Multiplying this ratio for the GDP and dividing it for the oil production reported by U.S. Energy Information Administration (see "International energy statistics for crude oil"), we obtain a proxy of oil rent per barrel. It is worth noticing that this variable has missing values for countries that do not produce oil.

[10] The Hausmann test statistics fail to reject that the coefficients from random and fixed effects estimates are statistically different one from another.

[11] We would like to thank an anonymous reviewer for suggesting this extension. The stability of the results confirms the weak relationship between the country-invariant oil price and the country-varying value of out-degree.

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Table 5. Socio-economic determinants of node out-degree.

	OLS	IV	OLS	IV	OLS
GDP	0.469	0.511	0.433	0.463	0.599*
	(0.141)	(0.126)	(0.176)	(0.168)	(0.06)
REM	−5.609	−5.465	−6.019*	−5.951*	−5.386
	(0.101)	(0.121)	(0.08)	(0.094)	(0.123)
STA	0.602	0.585	0.68	0.678	0.689
	(0.205)	(0.225)	(0.153)	(0.16)	(0.163)
PTA	0.019	0.0227	0.0146	0.0171	0.0265
	(0.376)	(0.305)	(0.499)	(0.441)	(0.161)
PR	1.710***	1.712***	1.700***	1.704***	1.580***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RES	2.778***	2.786***	3.047***	3.077***	2.776***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PO	0.0148	0.0114	−0.0162	−0.0225	
	(0.188)	(0.361)	(0.448)	(0.317)	
PO–HC			0.0361*	0.0401*	
			(0.085)	(0.065)	
OIL RENT					4.055**
					(0.048)
Obs	344	344	344	344	299
Countries	85	85	85	85	75

Dependent variable: out-degree. *p*-values in parentheses. Significance levels: *10%; **5%; ***1%. Instruments: 6-month ahead World Economic Climate index by Ifo and the nominal price of natural gas.

country-specific oil export patterns: the 6-month ahead World Economic Climate index by Ifo (which is expected to capture expectations for the business cycle and, accordingly, the global demand of oil) and the nominal price of natural gas (highly correlated with the oil price but independent from annual, country-varying patterns of oil exports).

The results are reported in Table 5. The sample includes circa 90 countries and covers five non-consecutive years: 1995, 2000, 2005, 2010, and 2014. The price of crude oil (PO) is not significantly associated with the node-level out-degree while, as expected, its interaction term $PO–HC$ is positive and significantly different from zero. This suggests that the oil price affects the position of high-cost producers in the network. This is confirmed by the last specification, including $OILRENT$ that subsumes oil price variation over time, as well as cross-sectional and longitudinal variation in production costs for all the oil producers. When this variable enters in place of PO and $PO–HC$, its estimated coefficient is positive and significant.

Several explanatory variables enter with the expected sign and are significant. The overall production of oil (PR) and the size of the reserves (RES) are positively related to the number of foreign buyers. Country remoteness (REM) is negatively associated with local centrality, as captured by out-degree.

Other explanatory variables enter with the expected sign but the coefficients are statistically insignificant. This is the case of internal stability (STA – positive), domestic GDP (GDP – positive), and preferential trade agreements (PTA – positive).

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Table 6. Socio-economic determinants of nodedegree: Robustness check.

	OLS	IV	OLS	IV	OLS
DEG	0.554*	0.622*	0.522*	0.579*	0.788***
	(0.068)	(0.052)	(0.087)	(0.072)	(0.006)
REM	−6.013*	−6.004*	−6.277*	−6.318*	−5.958*
	(0.062)	(0.07)	(0.053)	(0.059)	(0.072)
STA	0.71	0.687	0.778*	0.770*	0.702
	(0.119)	(0.137)	(0.087)	(0.094)	(0.128)
PR	1.704***	1.697***	1.681***	1.673***	1.461***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RES	2.500***	2.488***	2.932***	2.989***	2.618***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OP	0.0195**	0.0162*	−0.0262	−0.0368*	
	(0.029)	(0.091)	(0.168)	(0.065)	
OP–HC			0.0517***	0.0604***	
			(0.006)	(0.002)	
OIL RENT					5.413***
					(0.004)
Obs	392	392	392	392	336
Countries	92	92	92	92	80

Dependent variable: out-degree. p-values in parentheses. Significance levels: *10%; **5%; ***1%. Instruments: 6-month ahead World Economic Climate index by Ifo and the nominal price of natural gas.

Coefficients' insignificance should be interpreted with care. As a matter of fact, as trade theory suggests, PTA is affected by GDP, REM, and STA; similarly, $OIL\ RENT$ may depend on PR and may in turn affect the GDP of oil-dependent countries. The correlation of these explanatory variables may negatively affect the significance of individual coefficients despite the ability of the estimated models to account for more than 60% of the variation in out-degree. As can be seen in Table 6, the exclusion of PTA from the estimation increases the significance of the remaining variables.

Internal political stability may not be the only way to operationalize the hypothesis that non-economic factors may impact on oil trade patterns. As a robustness check, we thus repeat the exercise by substituting the variable STA with either the strength of political rights (measured by Freedom House), i.e. $FH\ POL\ R$, or the adjusted index of democracy (from Polity IV), i.e. $DEMOC$. Table 7 reports regression results for these alternative specifications. While the variable capturing the strength of political rights does not appear to be significant, the extent to which the local institutions are democratic is positively and significantly associated with the number of trade partners. Democratic countries appear to manage to reach out for new destinations with greater facility than autocracies probably because they face lower restrictions from foreign democratic partners or because they can purposefully look for greater differentiation. The other main results of interest are somehow robust across the specifications, although one must note some differences in terms of significance. This can be due either to the change in sample (i.e. size reduction) due to data availability or to the limited stability of the estimates.

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Table 7. Node-level out-degree. Robustness checks.

	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	OLS
GDP	0.152	0.199	0.146	0.181	0.356	0.409	0.351	0.396	0.471	0.556*
	(0.696)	(0.628)	(0.709)	(0.66)	(0.294)	(0.25)	(0.302)	(0.269)	(0.232)	(0.097)
REM	−8.021**	−7.892**	−8.296**	−8.274**	−6.676*	−6.476*	−6.944**	−6.826*	−7.478*	−6.002*
	(0.038)	(0.048)	(0.033)	(0.04)	(0.057)	(0.073)	(0.049)	(0.061)	(0.059)	(0.089)
DEMOC	0.198**	0.195**	0.180*	0.174*					0.163*	
	(0.03)	(0.035)	(0.05)	(0.063)					(0.1)	
FH POL R					−0.405	−0.386	−0.38	−0.362		−0.304
					(0.13)	(0.156)	(0.157)	(0.185)		(0.25)
PTA	0.0235	0.027	0.02	0.0218	0.0162	0.0202	0.0131	0.0158	0.0291	0.0255
	(0.307)	(0.253)	(0.385)	(0.356)	(0.455)	(0.367)	(0.548)	(0.479)	(0.16)	(0.178)
PR	1.939***	1.938***	1.918***	1.918***	1.844***	1.837***	1.820***	1.815***	1.754***	1.664***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RES	2.925***	2.925***	3.151***	3.194***	2.775***	2.784***	3.004***	3.039***	2.742***	2.724***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OP	0.0142	0.0109	−0.0127	−0.0216	0.0165	0.0128	−0.0112	−0.0183		
	(0.252)	(0.429)	(0.576)	(0.368)	(0.149)	(0.312)	(0.607)	(0.427)		
OP–HC			0.0312	0.0386*			0.0314	0.0359*		
			(0.156)	(0.091)			(0.134)	(0.098)		
OIL RENT									3.488	3.939*
									(0.115)	(0.055)
Obs	302	302	302	302	344	344	344	344	260	299
Country	75	75	75	75	85	85	85	85	65	75

Dependent variable: out-degree. *p*-values in parentheses. Significance levels: *10%; **5%; ***1%. Instruments: 6-month ahead World Economic Climate index by Ifo and the nominal price of natural gas.

As said, the importance of an exporter in the network can be assessed in alternative ways with respect to the node outward degree: we therefore supplement our econometric investigation by looking at socio-economic correlates of the HITS-hub score. As explained before, the HITS-hub score captures the interdependence of the nodes and allows to order the exporters in a way that follows, but does not coincide with, the ranking obtained by looking exclusively at export shares (as shown in Figure 3). While narrative evidence has been provided to explain possible reasons why countries such as Canada, Mexico, and Venezuela are off the diagonal of the scatterplot, we investigate here a series of variables which may systematically influence the gap between HITS-hub values and export shares.

The functional form we estimate takes again the form of Equation (1) where Y, this time, is the node-level HITS-hub score. As before, the covariates in X are chosen following economic logic. Unsurprisingly, the first variable we include is $SHARE$, that is the country' share in global exports: all the remaining covariates are basically meant to explain the gap between HITS-hub values and global export shares. We insert world GDP growth ($WGDPG$) to evaluate whether economic momentum may affect the role of certain countries beyond what is already reflected in a higher level of the oil price. The nominal exchange rate between the USD and the euro (the ECU before the year 2000) is included to take into consideration the fact that oil is priced in USD and that many exporters of oil are net buyers of euro-denominated merchandises and services: the USD/euro exchange rate is known to affect oil production and, possibly, trade. Following the very logic underpinning the HITS algorithm, we include the distance from the largest destination market, that is the United States ($DistUS$). Political stability (STA) is included as it was significant in some of the previous regressions and may affect the actual array of destinations a country serves. The covariates include also the domestic production of oil and the level of the reserves (respectively, PR and RES) as it makes a big difference whether a country is exporting its own crude oil or it is simply carrying along the commodity extracted elsewhere.

The international price of oil PO and the interaction for high-cost countries $PO–HC$ are included as one would expect that the higher the oil price, the greater the importance of the countries able to produce it only at high costs. The same effect is alternatively captured by the variable $OIL\ RENT$, introduced beforehand. In this specification we do not adopt an IV approach, as there is no reason to expect oil price to be endogenous. Since HITS-hub takes into account the position of all countries in the network, and not all countries can see their score move simultaneously in the same direction, then it is very unlikely that hub scores can affect the price of oil (which is common to all countries).

The estimated coefficients of $SHARE$, $DistUS$, and RES, reported in Table 8, are similar across the two specifications and highly significant. In sum, a country exhibits a larger HITS-hub score the larger its share of global export, the less distant it is from the United States, and the larger its reserves are. This evidence strengthens the intuitive interpretation offered in Section 3.4, discussing Canada and other outliers in Figure 3. The nominal exchange rate between the USD and the euro is also significant, though barely: when the dollar appreciates with respect to the euro, oil producers tend to increase their centrality beyond what suggested by the mere market share. A possible explanation is that a stronger USD makes oil cheaper for

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Table 8. Socio-economic determinants of node HITS-hub values.

SHARE	0.319***	0.280***
	(0)	(0)
WGDPG	−0.048	−0.022
	(0.574)	(0.741)
USD/EU	0.652*	0.420*
	(0.067)	(0.098)
DistUS	−0.534***	−0.740***
	(0.028)	(0)
STA	0.101	0.112
	(0.263)	(0.127)
PR	0.079	0.05
	(0.2)	(0.299)
RES	0.845***	0.629***
	(0)	(0)
PO	−0.006***	
	(0)	
PO–HC	−0.008**	
	(0.048)	
OIL RENT		−1.040***
		(0)
R^2	0.667	0.621
Obs	405	336
Countries	92	80

Dependent variable: hub score; *p*-values in parentheses. Significance levels: *10%; **5%; ***1%.

the United States, further increasing its demand and, as a result, strengthening the position of its main suppliers.

We also find that the higher the oil price, the lower the country's HITS-hub score: this probably happens because once the price increases, more countries become ready to produce and export. This effect is stronger for the countries with low production costs and thus it confirms that oil price increases tend to reduce the centrality of traditional low-cost exporters, since more countries find profitable to produce and export. Similar results hold for the specification where $OIL\ RENT$ enters in place of PO and $PO–HC$.

5 Conclusions

The paper analyzes the evolution of international trade crude oil, one of the most important commodities exchanged in world markets. We find that oil trade has undergone significant structural changes in the last 20 years, which have led to a reduced role for traditional (i.e. OPEC) producing countries, and the emergence of new important importers, most notably China.

Our results show that network analysis can contribute to our understanding of the evolution of oil trade, since the position of different countries within the network is not always strictly related to classical measures such as export or import shares.

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This is particularly relevant in the case of a strategic commodity as oil, since a central position in the network conveys geo-political clout to countries.

From 1995 to 2014, the international oil market has experienced first a phase of regionalization, whereby regional clusters have emerged and the network could be split into more or less homogeneous partitions, then a process of globalization that has seen the emergence of new important players and an increase in the average distance of trade flows. This second phase has peaked in the immediate aftermath of the recent financial crisis, when emerging markets have played a more prominent role in the world economy.

The econometric analysis allows us to dig deeper in the determinants of such structural changes, and it suggests that low oil prices reinforce the position of low-cost producers. This finding appears in line with recent events: OPEC members, in particular Saudi Arabia, have kept production high in order to push new (high-cost) producers out of business.[12]

Future developments are difficult to predict as regulatory changes (for instance regulation concerning hydraulic fracturing), political choices (a possible lift of the U.S. export ban) or geo-political events (e.g. economic sanctions) may alter the relationship between oil prices and countries' position. Nevertheless, combining network analysis with more standard econometric tools can help us gaining a better understanding of the forces that shape the structure of oil trade.

Conflicts of interest

The authors have nothing to disclose.

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[12] Only at end of 2016, the main oil producers agreed on production cuts to prop up prices.

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Appendix

Table A1. Communities in weighted network.

1995					
Angola	0	Australia	1	Iraq	2
Antigua	0	Brunei Dar.	1	Jordan	2
Argentina	0	Myanmar	1		
Bangladesh	0	Sri Lanka	1	Algeria	4
Barbados	0	China	1	Bahamas	4
Bolivia	0	Congo	1	Belgium	4
Brazil	0	Ecuador	1	Bulgaria	4
Chad	0	Hong Kong	1	Belarus	4
Chile	0	Indonesia	1	Canada	4
Colombia	0	Japan	1	Croatia	4
DR Congo	0	Korea, DPR	1	Cyprus	4
Costa Rica	0	Korea, Rep.	1	Czech Republic	4
Benin	0	Malaysia	1	Denmark	4
El Salvador	0	Malta	1	Estonia	4
Eq. Guinea	0	Taiwan	1	Fiji	4
Ethiopia	0	Oman	1	Finland	4
Gabon	0	New Zealand	1	France	4
Guatemala	0	Pakistan	1	French Polynesia	4

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Table A1. Continued

1995

Guinea	0	Panama	1	Gambia	4
Honduras	0	Papua New Guinea	1	Germany	4
Ivory Coast	0	Philippines	1	Hungary	4
Kuwait	0	Guinea-Bissau	1	Ireland	4
Malawi	0	Qatar	1	Kazakstan	4
Morocco	0	Vietnam	1	Kyrgyzstan	4
Net. Antilles	0	Sudan	1	Latvia	4
Aruba	0	Thailand	1	Liberia	4
Nicaragua	0	UAE	1	Lithuania	4
Nigeria	0	Uganda	1	Mauritania	4
Paraguay	0	Yemen	1	Moldova	4
Peru	0			Netherlands	4
Portugal	0	Austria	3	Norway	4
Anguilla	0	Cameroon	3	Poland	4
Saudi Arabia	0	Cuba	3	Russia	4
India	0	Dominican Rep.	3	St. Lucia	4
Singapore	0	Greece	3	Slovakia	4
Zimbabwe	0	Iran	3	Slovenia	4
Suriname	0	Israel	3	Sweden	4
Togo	0	Italy	3	Syria	4
Trinidad	0	Jamaica	3	Macedonia	4
United States	0	Kenya	3	United Kingdom	4
Uruguay	0	Libya	3	Uzbekistan	4
Venezuela	0	Madagascar	3		
Zambia	0	Mexico	3		
		Mongolia	3		
		Mozambique	3		
		Niger	3		
		Roumania	3		
		South Africa	3		
		Spain	3		
		Switzerland	3		
		Tunisia	3		
		Turkey	3		
		Turkmenistan	3		
		Ukraine	3		
		Egypt	3		
		Tanzania	3		

2005

Angola	0	Azerbaijan	2	Albania	3
Argentina	0	Austria	2	Algeria	3
Chile	0	Belgium	2	Bahamas	3
China	0	Bosnia Herz.	2	Bahrain	3
Congo	0	British V. Isl.	2	Bangladesh	3
Korea, Rep.	0	Bulgaria	2	Barbados	3
Mongolia	0	Belarus	2	Bermuda	3

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Table A1. Continued

2005					
Paraguay	0	Central African Rep.	2	Bolivia	3
Sudan	0	DR Congo	2	Brazil	3
Yemen	0	Croatia	2	Brunei Dar.	3
		Cyprus	2	Cameroon	3
Costa Rica	1	Czech Republic	2	Canada	3
Cuba	1	Denmark	2	Chad	3
El Salvador	1	Estonia	2	Colombia	3
Jamaica	1	Sandwich Isl.	2	Dominican Rep.	3
Net. Antilles	1	Finland	2	Ecuador	3
Nicaragua	1	France	2	Eq. Guinea	3
St. Lucia	1	Germany	2	Ethiopia	3
St. Vincent	1	Gibraltar	2	Djibouti	3
Uruguay	1	Greece	2	Gabon	3
Venezuela	1	Greenland	2	Georgia	3
		Hong Kong	2	Gambia	3
Australia	4	Hungary	2	Ghana	3
Myanmar	4	Ireland	2	Guatemala	3
Burundi	4	Israel	2	Guinea	3
Sri Lanka	4	Italy	2	Guyana	3
Cook Isl.	4	Kazakstan	2	Honduras	3
Fiji	4	Kyrgyzstan	2	Iceland	3
Iran	4	Lebanon	2	Indonesia	3
Japan	4	Latvia	2	Iraq	3
Kenya	4	Libya	2	Ivory Coast	3
Kuwait	4	Lithuania	2	Jordan	3
Malaysia	4	Malawi	2	Korea, Rep.	3
Maldives	4	Malta	2	Liberia	3
Mauritania	4	Mauritius	2	Mali	3
Taiwan	4	Moldova	2	Mexico	3
Mozambique	4	Netherlands	2	Morocco	3
Oman	4	Niger	2	Nepal	3
New Zealand	4	Norway	2	Aruba	3
Pakistan	4	Poland	2	Nigeria	3
Papua New Guinea	4	Roumania	2	Panama	3
Philippines	4	Russia	2	Peru	3
East Timor	4	Serbia	2	Portugal	3
Qatar	4	Slovakia	2	Guinea-Bissau	3
Seychelles	4	Sweden	2	Saudi Arabia	3
Singapore	4	Switzerland	2	Senegal	3
Vietnam	4	Syria	2	Sierra Leone	3
South Africa	4	Tunisia	2	India	3
Zimbabwe	4	Turkey	2	Slovenia	3
Thailand	4	Turkmenistan	2	Somalia	3
UAE	4	Ukraine	2	Spain	3
Uganda	4	Macedonia	2	Tajikistan	3
Tanzania	4	United Kingdom	2	Togo	3
Wallis & Futuna	4	Burkina Faso	2	Trinidad	3
Samoa	4	Uzbekistan	2	Egypt	3
		Yugoslavia	2	USA	3
		Zambia	2		

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Table A1. Continued

2014							
Argentina	0	Algeria	2	Andorra	3	Albania	4
Bahamas	0	Azerbaijan	2	Australia	3	Brazil	4
Barbados	0	Austria	2	Bahrain	3	Cameroon	4
Bolivia	0	Belgium-Luxembourg	2	Bangladesh	3	Chile	4
Belize	0	Bermuda	2	Solomon Isds	3	Cuba	4
Canada	0	Bosnia Herzegovina	2	Brunei Darussalam	3	Cyprus	4
Chad	0	Bulgaria	2	Myanmar	3	Benin	4
Colombia	0	Belarus	2	Cambodia	3	Estonia	4
Dominican Rep.	0	Croatia	2	Sri Lanka	3	Gambia	4
Ecuador	0	Czech Republic	2	Fiji	3	Ghana	4
Guatemala	0	Denmark	2	Gabon	3	Cte d'Ivoire	4
Honduras	0	Ethiopia	2	Guinea	3	Latvia	4
Hong Kong	0	Finland	2	Indonesia	3	Malawi	4
Jamaica	0	France	2	Iran	3	Malta	4
Mauritania	0	Georgia	2	Japan	3	Mozambique	4
Mexico	0	Germany	2	Jordan	3	Bonaire	4
Montserrat	0	Gibraltar	2	Rep. of Korea	3	Nigeria	4
Curaao	0	Greece	2	Kuwait	3	Paraguay	4
Aruba	0	Hungary	2	Malaysia	3	Saint Helena	4
Nicaragua	0	Iceland	2	Maldives	3	Saint Lucia	4
Panama	0	Ireland	2	Mauritius	3	Senegal	4
Peru	0	Israel	2	Morocco	3	Slovenia	4
Saint Pierre & Miquelon	0	Italy	2	New Caledonia	3	South Africa	4
Suriname	0	Kazakhstan	2	New Zealand	3	Zimbabwe	4
Trinidad and Tobago	0	Kyrgyzstan	2	Marshall Isds	3	Spain	4
Turks & Caicos Isds	0	Libya	2	Pakistan	3	Uruguay	4
USA	0	Lithuania	2	Papua New Guinea	3		
Venezuela	0	Rep. of Moldova	2	Philippines	3		
		Netherlands	2	Timor-Leste	3		
Angola	1	Niger	2	Qatar	3		
China	1	Norway	2	Saudi Arabia	3		
Congo	1	Poland	2	India	3		
Dem. Rep. of the Congo	1	Romania	2	Singapore	3		
Equatorial Guinea	1	Russian Federation	2	Viet Nam	3		
Iraq	1	Serbia	2	Syria	3		
Lebanon	1	Seychelles	2	Thailand	3		
Liberia	1	Slovakia	2	Tonga	3		
Mongolia	1	Sweden	2	United Arab Emirates	3		
Oman	1	Switzerland	2	Uganda	3		

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Table A1. Continued

2014					
Portugal	1	Togo	2	Samoa	3
Rwanda	1	Tunisia	2	Zambia	3
South Sudan	1	Turkey	2		
Sudan	1	Turkmenistan	2		
United Rep. of Tanzania	1	Ukraine	2		
Yemen	1	TFYR of Macedonia	2		
		Egypt	2		
		United Kingdom	2		
		Burkina Faso	2		
		Uzbekistan	2		

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