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How crude oil prices shape the global division of labor

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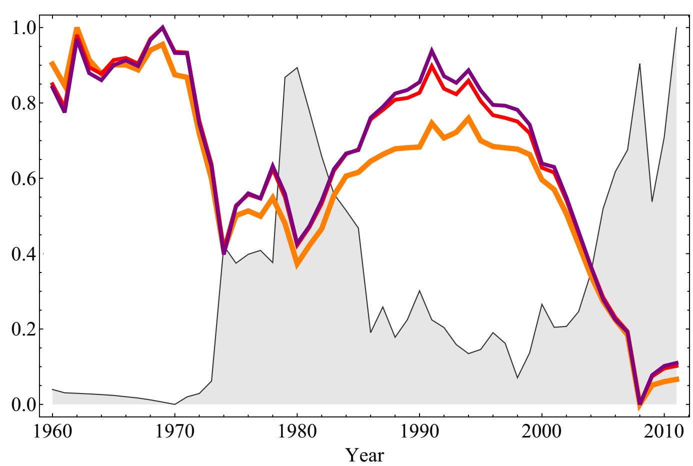
HIGHLIGHTS

- A network analysis of trade investigates the global value chains in the long run.
- The share of cyclic value shows a correlation with oil price of 85%.
- The null model proves that this is not explained by first order properties of network.
- Results show the link between crude oil price and the international division of labor.
- Transport costs had an underestimated impact on the structure of production globally.

GRAPHICAL ABSTRACT



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ABSTRACT

Our work sheds new light on the role of oil prices in shaping the world economy by investigating flows of goods and services through global value chains between 1960 and 2011, by means of Markov Chain and network analysis. We show that over that time period the international division of labor and trade patterns are tightly linked to the price of oil. We observe a remarkably high negative correlation (−0.85) between the oil price and the share of cyclical value, i.e. the share of value embodied in raw materials and intermediate products that are conserved across direct and indirect relationships. We demonstrate that this correlation does not depend on the balance of payments nor on the nominal value of trade or trade agreements; it is instead linked to the way Global Value Chains (GVCs) shape global trade. The cycling indexes show two majors structural breaks in terms of distance and length of GVCs, hinting at two phases of the recent globalization dynamics, sustained by two major transport modes. Our study suggests that transport played an important structural role in shaping GVCs, unveiling the deep, long-term impact of energy costs on the structure and connectivity of the global economy. In more theoretical term, our results indicate that the production structure could be approached as an energy system, forged by the efficiency in the transport sector. Understanding the role of oil in a globalized economy is of paramount importance for decoupling of economic growth from energy growth and transitioning toward a de-carbonized economy.

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1. Introduction

In the aftermath of the oil crisis of the early 1970s, the relationship between oil prices and economic growth became a focal point of the scientific discourse and public debate. In 1983, James Hamilton published an influential article showing that an oil price increase had preceded all but one recession in the United States since the end of World II [1]. Since then, a large number of empirical studies have looked into the connection between oil prices and real economic growth and frequently found a significant negative correlation [2,3]. The importance of this link between oil price and economic growth was less clear after the second oil shock [4–7]. Recent studies, with more refined statistical tools and price specifications, have restored the link between the oil price and economic growth [8–12]. There is now a general consensus that this connection did not cease but has become more complex in terms of direction (anticyclical and procyclical), typology of shocks (demand or supply) and lag patterns [4,9,11,13,14]. This line of research tried to explain this tight relationship, given that the cost of energy is only a small part of GDP [13] but satisfactory explanations have remained elusive [2,4,13,15]. Interestingly, this research exploring the link between the oil price and economic indicators seems to have entirely ignored the transport sector, which is heavily reliant on refined crude oil products, and its role in shaping the global division of labor. In the post-war period, world trade grew at a faster pace than world GDP [16]. According to recent studies on globalization, the remarkably high rate was propelled by a dramatic decline in international transport costs [16–19]. Perhaps, the notion that trade grew amid globalization because of transport should not come as a surprise. What is more surprising, but is closely related or even a corollary, is the fact, that intermediate and capital goods, in the last decades, grew faster than final products and now account for the largest part of trade in OECD countries [20]. While, in the aftermath of World War II international trade mainly concerned final products, the second wave of globalization (since the late 1980s) extended to intermediate products and capital goods, and the integration of factor markets as another important effect [21]. This process led to the fragmentation of production internationally [22]. Disregarding the transport sector, most of the scholars focused their attention on other factors in order to explain the fragmentation of the global value chain, like the pursuit of cheap labor or more favorable environmental legislation [21–23]. Amador and Cabral recently suggested that the strong increase of trade associated with the development of global value chains (GVCs) in the 1990s coincides with a period of low oil prices, although admitting that there is little empirical evidence linking these two factors [24]. These findings emphasizes the importance of assessing the impact of oil shocks upon an internationally integrated system rather than indivual countries. Furthermore, the new issues posed by climate change demand a deeper understanding of the nexus between energy consumption and the global economic structure. Our study addresses the connection between oil price and the global economy, by means of network theory and Markov chain theory, with the aim of understanding how the GVCs expanded and shrank following price changes in crude oil, between 1960 and 2011. Departing from a recent stream of research that investigated the structure of production with models and metrics based on Markov chain theory, on a disaggregated level (single sector or product) and limited time scale, [25–27], we analyzed the cycle of value on a global scale, at an aggregate level and employing a long time perspective. In contrast to previous analyses focusing on the oil-economy nexus that progressed by refining price specifications and statistical methods, we observed the correlation of the economy with the crude oil price (Brent), but we changed the macro-economic variables under investigation. We first applied network theory to trade imbalances and bilateral trade to understand how these two global measures of trade are linked to the oil price. These two quantities are thereby used to introduce the cycling index that builds on Markov chain analysis to assess the amount of value that is conserved across direct and indirect relationships in trade. With this measure, we looked at the share of cyclical value (the share of value that returns to the starting point), along different paths in the world trade network.

2. Analysis and results

2.1. Balance of trade per country: trade (im)balance

The balance of trade is the difference in value of national exports and imports and defines the status of *surplus* or *deficit* of the commercial balance, permanent or temporary, for every country (see methods). Many have viewed the existence of large current account imbalances as a possible cause of the financial crisis [28,29]. There is growing evidence that current account (im)balances are correlated to oil prices worldwide [29]. The reason for this correlation lies in the burden placed on imports (or exports, for oil exporting countries) by energy commodities, but also in monetary policies aimed at regulating inflation (which is correlated to oil price) [29]. The analysis has been performed on a yearly basis between 1960 and 2011, on aggregate trade flows (total import/export for every country), in nominal values (all measures are normalized to world GDP), of all the reporting countries in the world. Data are taken from Gleditsch's [30] and BACI datasets [31]. The fluctuation in the balance of trade and the variation of the adjusted crude oil price are moderately, yet statistically significantly, negatively correlated: the linear correlation coefficient is -0.32 (see Table 1). It is noteworthy that in a network where flows tend to be balanced at every vertex, the matrix tends to be symmetrical (which means that entries in the upper triangular part of the matrix mirror those in the lower) [32]. In other words, symmetric weights (flows) between every pair of vertices is statistically the simplest way to balance ingoing and outgoing flows at every vertex. A local symmetry (exports equals imports) tends to produce a global symmetry (export from i to j equal export from j to i). We thus expect that the balance of bilateral trade in the world trade web (WTW) to be negatively correlated to oil prices because we observe a negative correlation of the balance of trade locally. It should be noted though, that this is just a statistical relationship, obtained by imposing the local balance as a constraint in the null model [32].

2.2. Balance of bilateral trade: trade reciprocity

A global measure for evaluating the balance of trade between every pair of countries is the weighted reciprocity [32]. Reciprocity is a first-order property, meaning that it concerns the direct relationship of nodes with the nearest topological neighbors (one link-length). Reciprocity has proven to be an helpful measure in understanding the effects of the structure on dynamic processes, explaining patterns of growth in out-of-equilibrium networks [33,34], and starting to evaluate higher order properties [35–39]. The reciprocity for weighted networks, for every year $t, r_w(t)$, is defined as follows:

$$r^w(t) = \frac{\sum_i \sum_j \min[w_{ij}(t), w_{ji}(t)]}{\sum_i \sum_j w_{ij}(t)} \tag{1}$$

where $w_{ij}(t)$ is the trade from country i to country j during the year t (the subscript t will be omitted for simplicity for the remaining). If all flows are perfectly reciprocated/balanced then $r^w = 1$. If they are

Table 1
Pearson correlation index R, 1960–2011. The linear correlation index between b_t (the balance of trade, Eq. (2)), r^w (reciprocity of trade, Eq. (1)), $\Gamma^{(S)}$ (cycling index for steps of length $S \in \{2,3,4,\infty\}$, Eq. (7)) and the crude oil price are reported, in the third row the respective p-values are shown (95% confidence). In the last row we report the linear correlation index for $\Gamma^{(S)}$ (for $S \in \{2,3,4,\infty\}$) evaluate on the expected value according to the Weighted Directed Configuration Model.

	b^t	r^w	$\Gamma^{(2)}$	$\Gamma^{(3)}$	$\Gamma^{(4)}$	$\Gamma^{(\infty)}$
R	−0.32	−0.70	−0.85	−0.83	−0.82	−0.62
$p - value$	0.02	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$
R_{WDCM}	–	–	−0.32	−0.36	−0.37	−0.35

unidirectional $r^w = 0$. The correlation of r^w with the oil price is −0.70. As the oil price increases (decreases), reciprocity decreases (increases). This result shows that changes in the international bilateral trade structure and the oil price are more closely and inversely linked than expected by observing only global volumes or distances of trade [16–18]. These results deliver two important pieces of information: (1) given that the correlation of the oil price with reciprocity is higher than the correlation with imbalance, the nexus between oil price and reciprocity (bilateral trade balance) cannot be reduced to the correlation between oil price and imbalance, despite the expected symmetrical effect (see above); (2) this tight correlation is not explainable with trade agreements, as it is ubiquitous [40], nor with a general reduction in barriers [16], as it has a discontinuous trend in time (see Fig. S3). Can we link reciprocity to some structural effect in production, like the development of GVCs? As previously stated, reciprocity is a first-order property, though, unless we assume that production chains involve only two sites in a row, GVCs should be pertinent to higher-order properties of networks. In the Supplementary Information (SI) we show (Fig. S4), with a heuristic model based on three countries, one product and two factors, how reciprocity increases when the production chain expands, involving second order properties of the network (neighbors of neighbors, or indirect relationships). With this simple model with three nodes, the shift from a single-country production chain to a multi-country production chain will always increase the reciprocity of the network, independently of the distribution and share of the total volume traded. We thus expect that shifting the production sites abroad increases the reciprocity of the network. However, to check this hypothesis we must extend the analysis to longer paths of the productive chain, involving more than three nodes (like in the heuristic model) and, most importantly, encompassing indirect relationships.

2.3. Markov chain analysis: cyclic paths of value in the world economy

The largest share of trade in the world economy involves inputs to production (raw materials, intermediate and capital goods) [20]. In the modern economy countries import these production inputs and export final products or intermediate goods that are further processed elsewhere often involving numerous production stages in many different countries. At every step in the global production chain value added is embodied [24]. We are interested in detecting the share of traded value that is conserved throughout the stages of GVCs, or the initial value at the beginning of a global production chain, like mass particles in ecological networks that are conserved throughout every stage of a food chain [41] (see methods for a detailed description of the concept). Thus, we want to assess the share of trade that is cyclical (that runs a cyclic path), along paths of a given length S, in the WTW. By means of Markov chain theory, we can statistically evaluate the probability of an "elementary" trade, i.e. the amount of value embodied in raw materials or intermediates that is conserved in a product, going from country i to country j and returning to the initial country throughout all the possible direct and indirect trade relationships [42,43]. For example, Fig. 1 illustrates all the possible cyclic paths that a particle (a unit value of trade, in our case) can follow from country i within the first 4 steps (i.e. stages of production).

In order to assess the share of cyclical value over the total value traded, we need a normalized measure, like the previous measures of imbalance and reciprocity. We indicate with the cycling index $\Gamma^{(S)}$ the share of trade that comes back to the starting country in S steps with $S = 2,\ldots,\infty$ (see methods). In Fig. 2 trends of the cyclical quantity are shown for the WTW, for $S = 2,3,4,\infty$. We observe that the percentage of cyclical value inside the network and oil price are negatively correlated, at various degrees. The lower the number of steps (i.e. the shorter the production chain) taken into account while evaluating $\Gamma^{(S)}$ the higher the negative correlation. The correlation from $\Gamma^{(2)}$ to $\Gamma^{(\infty)}$ goes from −0.85 to −0.62, exhibiting a much higher score compared to imbalance and reciprocity (see Table 1).

3. Discussion

3.1. Digging into the tight relationship between cycling and oil price

As much as it seems implausible to many scholars to explain the correlation between economic growth and oil price given that the cost of energy is only a small part of GDP [13], it is difficult to explain the tight relationship between the reciprocity and cycling with the oil price asserting that energy is dominant in trade. Although energy (oil, gas and coal) represents the largest sector in global trade, the share of energy commodities traded globally is not much different from the share of energy expenditures in the global economy. Fuels grew from 7% of world exports in 1995 to 17% in 2014 [44] (mainly because of a fivefold increase in energy prices) and consumers' global energy expenditure grew from 6% to 10% of global GDP (in 2005 prices) between 1990 and 2010 [45]. Even if we look at the oil and gas sector, according to the BACI database, its share of global trade ranged between 2% and 6% between 1998 and 2010, which is comparable to the share of the gross revenue of the entire sector over the global economy, recently estimated to be between 4.6% and 6.5% of World GDP [46]. Thus there is not any substantial reason to give stronger emphasis to the effect of oil prices on trade versus the economy on account of the relative higher share. However, it is true that both oil supply and demand in the short run are very inelastic. The interplay of in-elasticity with macroeconomic constraints outlined in the introduction can substantially modify global trade patterns. One may argue, for example, that a general increase in exports and imports driven by global GDP growth, would inevitably lead to a rise in the share of mutual trade. In this view, the correlation between cycling and oil price could be brought back to the GDP-oil price nexus. Moreover, it is also possible that oil prices inflating commodity prices and automatically increasing nominal trade flows, could explain this tight correlation. In this latter case, the relationship would boil down to the link between inflation and oil price. Thirdly, it is possible that the correlation between oil price and cycling is a multiplicative effect (re-spending effect of petrodollars) of the correlation between imbalance and oil price, linking oil producing with oil consuming

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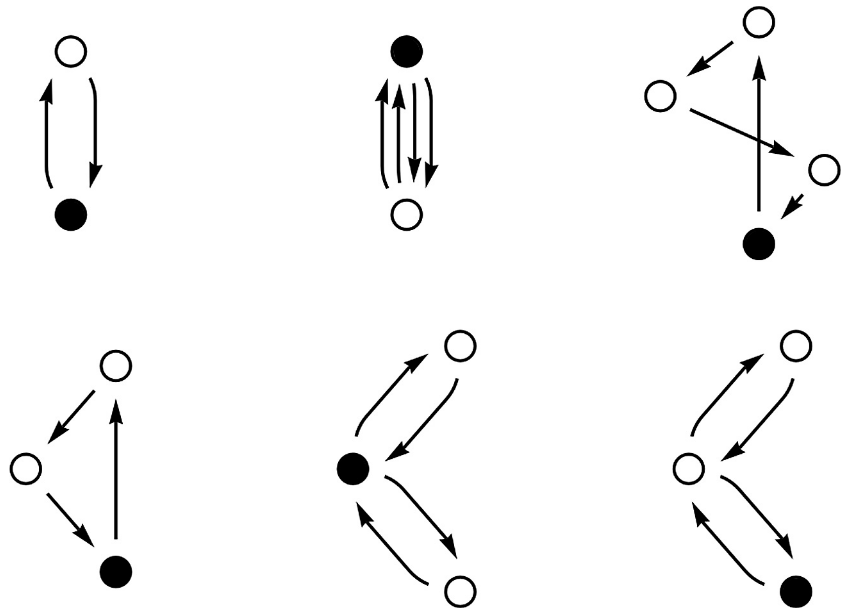

Fig. 1. Cyclic paths up to four steps. The possible cyclic paths that a trade can follow on a network within 4 steps. Node i (represented by the black dot) is the starting and ending country of each path. $\Gamma^{(S)}$ evaluates the share of the total trade that follow a cyclic path of length up to S.

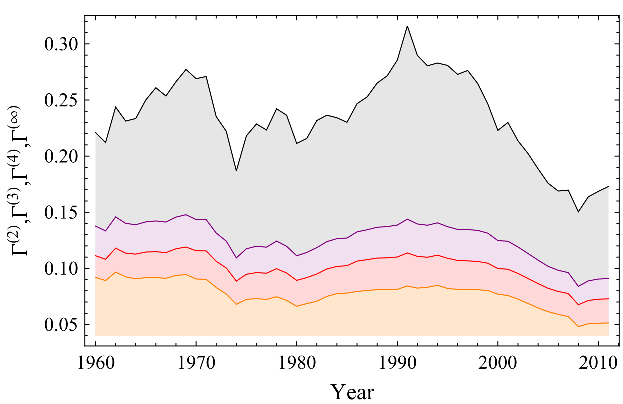

Fig. 2. Cycling indexes at different path lengths. The trend of the cyclical flow index, $\Gamma^{(S)}$, of the World Trade Web calculated in Eq. (5) from 1960 to 2011. From lighter to darker color: $\Gamma^{(2)}$ (orange line), $\Gamma^{(3)}$ (red line), $\Gamma^{(4)}$ (purple line), and $\Gamma^{(\infty)}$ (black line).

countries. This is conceivable on the notion that oil exporters tend to import goods and services from oil importers. On the other hand, to maintain a sustainable trade balance, oil importers must either export more or import less of other items with further implications for trade patterns. A fourth possible explanation relates to the link between the costs of energy for production and the embodied energy in trade [47,48]. In this context, rising energy costs could change trade patterns in relation to the energy intensity of the production process. Nevertheless, what matters though is that all the four cases concern the first order properties of the network (bilateral trade and global value of trade) and would thus not affect cycling, which is a second order property. The correlation between cycling and oil price is not related to trade patterns concerning only bilateral relationships. In other words, to understand the nexus between cycling and oil, indirect relationships matter, rather than just direct ones. We can show, using a Null Model as a benchmark that the negative correlation between the cyclical value inside of the network and oil price does not depend on first order properties (direct relationships), but depends on higher-order properties of the network (indirect relationships). The chosen null model is the Weighted Directed Configuration Model (WDCM). The WDCM is a well-known and frequently utilized null model that preserves the quantity of trade and the distribution of trade relationship of each country [32]. We performed the analysis of the null model and we evaluated the correlation of the expected cyclical value with the oil price (see methods). The correlation between the expected $\Gamma^{(S)}$'s and the oil price are lower than the observed ones but significantly stable. They range from −0.32 to −0.38. Notably by using the WDCM we preserve: (1) the nominal value of all the exports/imports sequence; (2) the global value of trade; (3) the difference between import and export (balance of payments) at every vertex. The comparison of expected correlation from the Null Model with the observed correlation assures us that the latter is not due to the global volume traded, nor to the nominal values of trading relationships or the distribution of trade imbalance: it depends on the specific architecture of trade flows globally, which can only be understood by the way GVCs unfold.

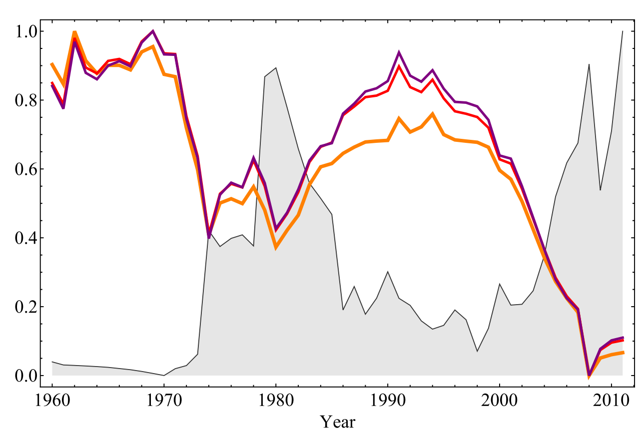

Fig. 3. Trends in the normalized values of crude oil price and cycling indexes. The normalized crude oil price(black solid line with subtended gray area) is shown. The trend of the normalized value of $\Gamma^{(2)}$ (orange line), $\Gamma^{(3)}$ (red line), $\Gamma^{(4)}$ (purple line) are also shown. The linear normalization is done based on the maximum and minimum value reached by each quantity. The final scaled values lie between 0 and 1.

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In order to understand the underlying process, it is also instructive to observe the trend of cycling indexes of different path-length over time. In Figs. 2 and 3, the 2-steps length peak of the early 1990s is lower than the one of the late 1960s, meaning that the higher orders contribution to the cycling has become more and more important, following the decreasing trend of the 1970s. If we look at the trend of the normalized values of the two, three and four steps cycling compared to oil price (Fiig. 3), it is evident that until the mid-1970s the three degree of cycling overlap, while between the first and the last oil crisis (2008) the curves of the three and four step cycling stand above that of the two step cycling. The longer-than-two step cycling also displays higher growth rates until the peak of the 1990s, suggesting that the ongoing globalization was characterized by longer paths of cycling. Longer cycles in the value chain probably underline the growing share of intermediate goods in trade and a process that led to a more interdependent global economy (see SI). To sum up: (1) the notion that reciprocity is almost twice as much as (negatively) correlated with oil price compared to imbalance suggests that this does not depend on the balance of payments or other effects on nominal value of trade; (2) the fact that cycling (second or higher order property) further increases the correlation compared to reciprocity (first order property) suggests that the correlation with oil price of both strongly depends on indirect relationships, (3) the Null Model demonstrates that almost half of the correlation of cycling with oil price holds even randomizing the import/export structure of the network, confirming that this can only be explained by looking at higher-than-one order properties of the network; (4) longer-than-two cycling's paths showed higher growth rates between late 1970s until mid 1990s.

3.2. The second wave of globalization and the role of transport

We hypothesize that the transmission mechanism behind the correlation between oil price and GVCs, statistically measured by cycling, is the transport sector. Oil prices affect transport costs, making international outsourcing more or less profitable [49,50]. If this hypothesis is correct, we expect oil prices to have an impact on cycling, by influencing the length of GVCs. We tested Granger causality, between oil price and the three network measures here considered (imbalance, reciprocity and 2-step-cycling), in both directions, with one lag specification and a significance level of 5% [51]. Only in the case of cycling can we reject the null hypothesis that oil price does not Granger cause 2-step-cycling. The Granger test, however, indicates that causation runs in both directions. Indeed, the most important information brought about the Granger causality test is that 2-step-cycling is cointegrated with oil price, meaning that these two variables follow the same trend, pointing to long-term dynamics. By enlarging the scope of the analysis from first order properties of the network to higher order properties, we obtained not only a higher correlation to oil, but also a cointegration, meaning that the analysis through the cycling quantity are able to detect and capture the global changes of the pattern of WTW. It thus seems plausible to believe that transport is the nexus between GVCs and oil price, as we expect changes in the structure of production to occur in the long-term. However, there are many other factors that influence the global division of labor that would need to be included to better explain this relationship. What seems somewhat surprising, given the declining costs of transport, is the fact that the process of international integration peaked in the 1990s and declined in the 2000s. Indeed, the second half of the 1990s witnessed the onset of the second wave of globalization [21]. This apparent contradiction is probably explained by observing single-country cycling (the portion of cycling passing through a single vertex, see Fig. 4). During the 2000s the single-cycling of fast-growing economies, like China, increased considerably, climbing the ranking of the World's economies. While the cycling index of developed economies remained constant, China showed a rapid growth in the share of cyclical value of its trade, meaning that a large part of the GVCs began passing through this country. Some economies like China attracted a significant portion of the cycling value across the World, concentrating the flows into a few hubs. The decrease in cycling globally is consistent with the emergence of hubs, which are topologically like stars (see Fig. S4). It is plausible that outsourcing initially, from the late 1980s, was propelled by road transport, over medium distances and involving many countries (inflating global cycling) whereas in the second stage, from the 1990s, was fueled by air and cargo shipping, concerning longer distances and few hubs (reducing global cycling). According to IEA, international cargo shipping, mostly in non-OECD countries, displayed the highest growth rates among the different transport modes between 1990 and 2000 [50]. It is noteworthy that the first major shift coincides with a sudden leap in efficiency in road transports triggered by the oil crisis [49], whereas the second change followed a dramatic decrease in international transports costs, both in air and cargo shipping, following the introduction of a more efficient aircraft fleet and the containers system [16]. To investigate this hypothesis, we assessed how the role of distances in shaping the cyclical value has changed over time. If we trim the network at different distance thresholds (removing all the links placed between a couple of vertices above a certain distance value) and calculate the cycling, we observe that there have been two bifurcations between short and long distance cycling in the second wave of globalization that began in the 1980s (see Fig. S6). While before the 1980, the cycling indexes trimmed at different distances were moving coherently, after the 1980s the share of short-distance cycling index (less than 2500 km) began to increase compared the share of long-distance cycling index (greater than 5000 km). After the 1990, the two trends reversed and while the short-distance cycling decreased, the long-distance cycling increased. This seems to indicate that the GVC's shifted from a regional domain (clusters of neighboring countries), with a range of distance lower than 2500 km, to a global (oversea relationships) domain with a range of distance greater than 5000 km. Interestingly, the second bifurcation coincides with the rising cycling of China and with the a dramatic increase in the efficiency of cargo-shipping [50,16].

4. Concluding remarks

Global trade, in the age of the second globalization, has entangled national economies, by interconnecting production sites internationally, in a fashion that is still underestimated [21,24] [20,23]. This historical process of vertical integration has been producing global value chains (GVCs) wherein goods traveling across countries augment their value at every stage of production [24]. The novelty of our work is that we investigated this cyclic path of value across countries by means of network theory and Markov chain theory on a global scale and a very long time scale. In this way, we show that over a longer time period the oil price has a striking correlation with the structure of trade, globally. A correlation that increases with the scope of the analysis, from first order properties of the network (one link distance), to higher order properties. The worldwide sum of country trade imbalances show a weak correlation of -0.32. The correlation increases by engulfing bilateral relationships between countries on a global scale (reciprocity, -0.70). Finally, the highest correlation, up to -0.85, is observed when we involve more complex patterns at the global level. By means of statistical mechanics of networks (exponential random graphs) we were able to demonstrate that this remarkable correlation can only be explained with higher-than-one order properties of

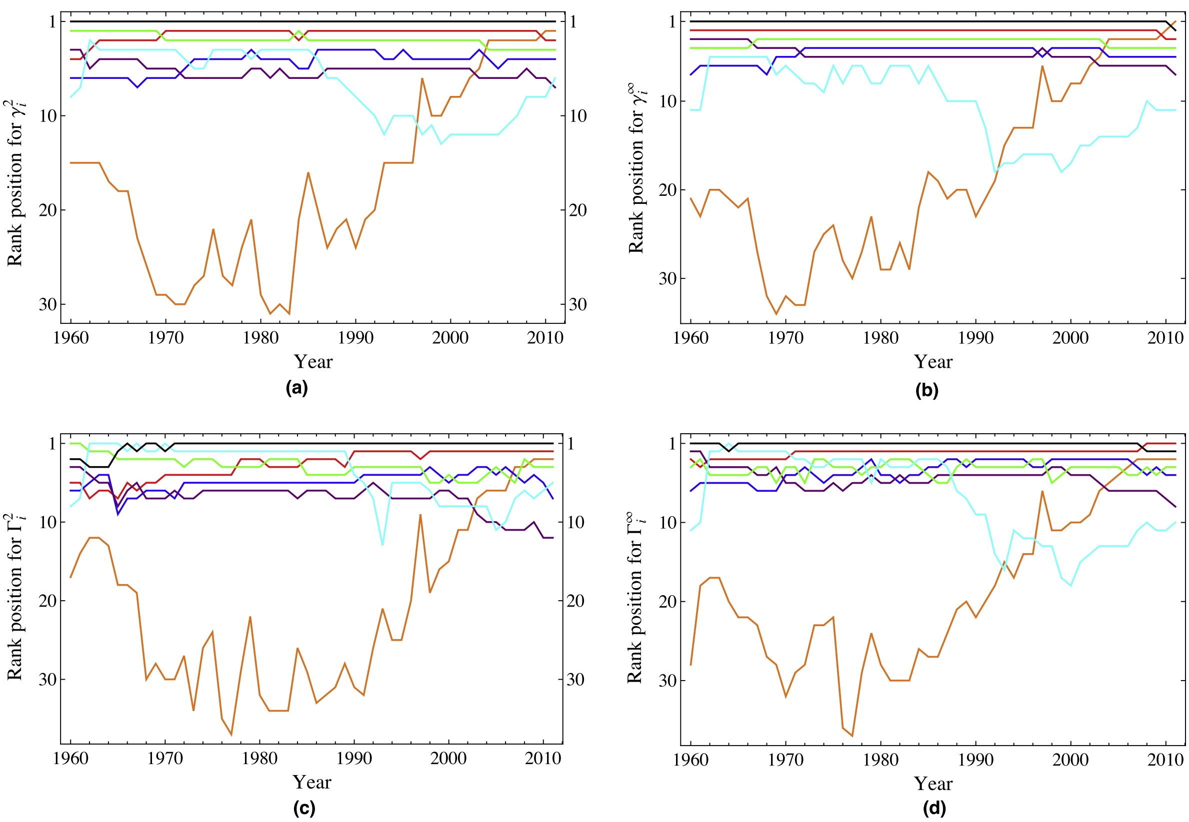

Fig. 4. The ranking position for seven countries according to the value of local cycling index. $\gamma_i^{(2)}$ (panel a) and $\gamma_i^{(\infty)}$ (panel b), $\Gamma_i^{(2)}$ (panel c) and $\Gamma_i^{(\infty)}$ (panel d). The data range covers from 1960 to 2011. The seven countries are the following: China (orange), Germany (red), France (blue), Great Britain (purple), Japan (green), Russia (cyan), USA (black). We chose these countries for their interesting patterns in order to reveal how the variables $\gamma_i^{(S)}$ and $\Gamma_i^{(S)}$ can explain structural changes in economy. Russia position is always higher in the relative than in the absolute rank, and for $S = 2$ than for $S = \infty$. Moreover we can observe a decline in both starting in late 80s and a rise since around 2000. Results seem in line with the USSR dissolution, explained by a Russian chain value made up substantially by bilateral exchanges with other former Soviet Republics. A remark on the performance of China and Germany: the former has been on the rise in the last decades and we point out the pervasiveness of its chain value in absolute value reaching the top of the rank for $\gamma_i^{(\infty)}$ in the last years of our analysis. In the same period, Germany overtakes USA share of cyclic trade ($S = \infty$), as emerges from panel d. (For interpretation of the references to colours in this figure legend, the reader is referred to the web version of this paper.)

the network, indicating that GVCs and structure of trade are intimately linked to oil price. We hypothesize that this tight relationship points to the role of transports in determining, in the long run, the extent and the way production sites connect internationally. By looking closely at the single-country cycling index (Fig. 4) and by dissecting the global cycling according to different distance thresholds (Fig. S1), we identified two structural breaks and two phases of the second wave of globalization (the *second unbundling*). The first, which started in the 1980s and peaked in the 1990s, was featured by shorter distance and increasing cycling, the second, that probably lasted until the economic crisis, was featured by longer distances, declining global cycling and increasing cycling of China (star-like structure). Our results suggest that the transmission mechanism between oil price and economic growth lays not only in the labor or retail markets (via inflation), but also, more profoundly, in the structure of production, globally. Furthermore, in a more general perspective, our results indicate that the production structure could be approached as an energy system, constrained by energy efficiency in the transport sector. This view of the economic system builds on the work of scholars like Ayres [52], for approaching growth as a product of energy efficiency, but also on fundamental advances in the study of allometric scaling, aimed at explaining the structure and size of many biological processes as the result of general features of efficient transportation networks [53]. Nevertheless, in order to establish a clear causation among factors, further research should tackle two aspects more in depth: (1) the dynamic process between input/output matrices of national economies and sectoral trade; (2) the evolution of energy efficiency and costs of transports globally and in the long run. The authors of this article believe this is crucial for understanding the role of oil in the present economic system, given that this is not yet a fungible source of energy in the transport sector, and for paving the way for a prosperous economy freed from fossil fuels. Furthermore, this study suggests that, besides the implication for the environmental and energy policy, the oil-economy nexus has an underestimated importance for the economic and social policy addressing the issue of full employment in the context of globalization and international division of labor. The structural role played by oil, via transports, in shaping production might explain why the current law energy prices are failing to ignite a recovery in the economy. Indeed, if we look at oil (or more broadly, energy) only as a functional variable of the system rather than a property affecting its structure, we fail to understand why a reversal on the price evolution does not produce a one-to-one reversal in the economical trend. Energy might represent only a marginal share in the global economy, but on the long course, as this study aims to clarify, has far deeper impact on the structure *and complexity* of our economy and society.

5. Methods

5.1. Description of the dataset

In the following sections, a brief description of the analyzed networks is given. We analyze the series of yearly bilateral data on exports and imports from the Gleditsch's database [30], from

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1960 to 1997. From 1997 to 2011, we employed international trade data provided by the BACI database. All data are in millions of current U.S.dollars and are bilaterally harmonized. Original data are provided by the United Nations Statistical Division (COMTRADE database). Gleditsch uses a complex procedure of harmonization that is extensively explained in his widely cited paper [30]. BACI is constructed using an original procedure that reconciles the declarations of the exporter and the importer. For further information see the CEPII Working Paper by Gaulier and Zignago [31]. The crude oil price data refers to the Brent and are freely available [54].

5.2. Evaluating the balance of trade

In network approach the World trade web is described by matrix W, where each node i is a country and w_{ij} is the trade from country i to country j, we can evaluate trade imbalance as follows:

$$b = \frac{\sum_i \min[s_i^{in}, s_i^{out}]}{\sum_i \sum_j w_{ij}} \tag{2}$$

where $s_i^{in} = \sum_j w_{ji}$ is the in-strength (total import) of node i and $s_i^{out} = \sum_j w_{ij}$ is the out-strength (total export) of node i. In doing so, we do not distinguish between trade surplus or deficit (positive or negative value), instead we calculate only the amount of trade that is balanced between imports and exports for every country (i.e. the minimum of total imports and exports); $b = 1$ if exports and import are equal for all the countries, $0 \geqslant b > 1$ otherwise. Eq. (2) is time dependent and evaluated for every year in the range 1960–2011.

5.3. Evaluating patterns of traded value

In order to estimate the paths of cyclic value embodied in trade, we must assess the probability of a unitary value of trade to be in a country j, starting from i, after a number of production steps. Markov chain analysis allows us to statistically determine this. The probability is calculated according to the trade relationships between country in WTW reported by [30,31].

Calculating transition probabilities. In probability theory a Markov chain is a stochastic process defined on a discrete state space satisfying the Markov property. It is a set of random variables, representing the evolution of a certain system, without memory: each actual state of the system just depends on the previous one. The changes of states are called transitions and the Markov chain can be described by a Markov matrix, M, whose elements m_{ij} represent the probabilities from a state i to a state j (transition probabilities or transition rules). Given the memory-less nature of a Markov chain it is not possible to predict the state of a system, in a given time t, but it is possible to predict its statistical properties. In this paper the transition probabilities are set according to the elements of the matrix W that describes the World Trade Web, i.e. the trade network. A link, w_{ij} , is assigned to any import/export relationship between two countries, from i to j, where w is the volume of the trade as provided by datasets [30,31]. In what follow, we explain how the transition rules are assigned. In general, given a system of N nodes and a $N \times N$ matrix representing their interactions, the matrix is said balanced if if $s_i^{out} = s_i^{in}, \forall i \in \{1, \ldots, N\}$, i.e., the sum of each column is equal to the sum of its related row. Systems described by a balanced matrix can be considered isolated: nodes perfectly balance their total in- and out-flows themselves, without needing any further exchange with the outside. However, most of the network representing real systems are not balanced. This means that $s_i^{out} \neq s_i^{in}$ for at least one i such that $i \in \{1, \ldots, N\}$. In these systems three different sets of nodes can be identified: the set of vertices with $s_i^{out} = s_i^{in}$, the set of vertices with $s_i^{out} > s_i^{in}$ and the set of vertices with $s_i^{out} < s_i^{in}$. In the first group, the total ingoing and outgoing fluxes of all nodes are balanced. In the second set, each vertex needs an extra incoming weight in order to balance in and out strengths. In this case, in order to balance the nodes in this set, we introduce an additional node/vertex, called *source* and labeled with 0, providing extra-ingoing fluxes to all nodes in the set. Similarly, a new vertex is introduced for the nodes in the third group in order to balance their in-strengths. It is called *sink* and labeled $N + 1$. The new links between this latter and the nodes in the set will have weights equal to:

$$w_{0i} = \begin{cases} s_i^{out} - s_i^{in} & \text{if } s_i^{in} < s_i^{out} \\ 0 & \text{if } s_i^{in} = s_i^{out} \\ 0 & \text{if } s_i^{in} > s_i^{out} \end{cases} \tag{3}$$

$$w_{i(N+1)} = \begin{cases} 0 & \text{if } s_i^{in} < s_i^{out} \\ 0 & \text{if } s_i^{in} = s_i^{out} \\ s_i^{in} - s_i^{out} & \text{if } s_i^{in} > s_i^{out} \end{cases} \tag{4}$$

The vertices source and sink are statistical artefacts to balance the node's strengths. An economic interpretation of those artificial links is provided in the next sub section. For each node i with $i \in \{1, \ldots, N\}$ the *total outgoing flow*, υ_i, is given by: $\upsilon_i = s_i^{out} + w_{i(N+1)}$. Now, we introduce a $N \times N$ directed and weighted matrix M, such that $m_{ij} = w_{ij}/\upsilon_i$. The elements of M, represent the one-step transition probability for a single particle (unit of value) to go from i to j. Higher powers of M express the transition probability from i to j in a given number of steps. We indicate with $U^{(S)}$, with S integer, the sum of the first S powers fuel international transport purely as a matter of macroeconomic adjustment. of M:

$$U^{(S)} \equiv (u_{ij}^{(S)})_{1 \leqslant i,j \leqslant N} \equiv \sum_{q=0}^{S} M^q = \frac{(I - M^{S+1})}{(I - M)} \tag{5}$$

Since M is a sub-stochastic matrix, the series converges for $S \to \infty$ [55]. The non-diagonal elements of $U^{(S)}$ represent the probabilities of reaching node j starting from node i within S steps [42,43]. Therefore, if we take into account all possible paths of any length between two nodes (i.e. $S = \infty$) Eq. (3) becomes $U^{(\infty)} \equiv (I - M)^{-1}$. The element $u_{ii}^{(S)}$ enables us to compute the probability to come back to the source node i within S steps. We can therefore compute the cycling index of a vertex as the fraction of trade passing through a node/country i that returns statistically (directly or indirectly) to it within S steps, formally:

$$\gamma_i^{(S)} = \frac{u_{ii} - 1}{u_{ii}} \Gamma_i^{(S)} \upsilon_i \tag{6}$$

The global cycling index of the network (i.e. the fraction of traded value that returns, directly or indirectly, to a starting node) within S steps is given by:

$$\Gamma^{(S)} = \frac{\sum_i \gamma_i}{\sum_i \upsilon_i} = \frac{\sum_i \Gamma_i^{(S)} \upsilon_i}{\sum_i \upsilon_i} \tag{7}$$

where $\gamma_i = \Gamma_i^{(S)} \upsilon_i$ represents the quantity of cyclic trade (millions of current U.S. dollars), that returns to a node/country i within S steps. The value of $\Gamma^{(S)}$ ranges between 0 and 1. The former case is observed when there is no trade that starts at some country i that comes back to it. The latter case represent a systems where all trade come back to the starting country. Note that the residual share of trade, up to 1, represent the share of trade that is acyclic, the starting country is different from the ending country. The quantity $\Gamma^{(\infty)}$ has been used in ecological studies, with the aim of evaluating the total amount of cyclical matter in ecosystems [41,56,57].

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Eqs. (5)–(7) are time dependent, and are evaluated for every year in the range 1960–2011.

5.4. Interpreting the cycling index

Ecosystems are open systems exchanging both matter and energy with a source and a sink. The above mentioned cycling index was developed to assess the share of matter that is recycled throughout food chains in an ecological network, from the primary producers (photosynthesis) to the top predators and detritus feeders. Likewise, we can think of added-value as matter in food chains and look by means of cycling how this is conserved throughout the stages of production internationally (GVCs), where the sink and the source of value are national economies. In this view, monetary flows are footprint of material flows flowing in the opposite direction [58]. Hence, considering that when we are importing/exporting goods we are also introducing/extruding mass from the system, the excess/deficit of mass must be balanced by the national economy. National economies play the role of sink and source in parallel with ecosystems because the WTW, like ecological networks, are open systems: matter is not conserved through every stage of the international production chain, whereby every country is a source of row material and a sink of waste. Here, we are not tracing mass flows, but the value embodied in traded goods and the cycling index will be used to assess the GVCs. It is worth noting that the cycling index only measures, statistically, the amount of value that returns to a starting point (country) after a given number of steps (trading relationships), that is, it assesses the cyclical GVCs, from the markets of the raw material, to those of the final products. Three main methodological approaches have been used to capture GVCs in the scientific literature: (1) international trade statistics on parts and components; (2) customs statistics on processing trade and (3) international trade data combined with input-output (I-O) tables. Amador and Cabral provides a detailed review of the existing methodologies [24]. More recently, network theory has been applied to disaggregate trade and I-O matrices to investigate GVCs [59,26]. Markov chain theory has been previously applied to disaggregate trade to investigate the allometric scaling of networks and the structure of GVCs [60,25]. Compared to the methods aimed at directly assessing the GVCs by measuring the traded value added in I-O matrices, our approach is different for the following reasons: (1) we do not measure just the share of incorporated value in exports/imports between pairs of countries, i.e. in bilateral relationships, we measure the value that is conserved throughout all possible paths in a network. (2) this is a statistical measure, thus, it does not rely on direct measures of value added (which can only be drawn by I/O matrices of countries). It has indeed the flaw of being a statistical measure of value, but it has the strength of assessing value through longer-than-one steps of trade (on the contrary, direct measure of value added can only assess one-step path, i.e. between two countries, inasmuch as any following step of the value added this becomes input of production). (3) it is a global (statistical) measure and asses all the possible paths of a given length. In other words, even when assessing two-step cycling, it is statistically relevant all the relationships of i and j with all other countries rather than just the relationship between country *i* and country *j*. (4) we statistically asses (with cycling) the value conserved throughout a cycle, for all products, rather than one. This is a statistical measure based on aggregate trade because at every step of the production chain (generally, but not always) products change trade category, i.e. classification: iron, engines, cars, etc. To use an example from ecological networks - in a food chain, when we want to assess the amount of mass that is conveyed through one species (prey) to the other (predator) at every step of the chain, from primary producers (grass) to the last predators (and decomposers), we cannot tag every atom and check every passage they make. We can only weight body mass of organisms through the food chain. If we know that species A feed 50% on species B and 50% on species C, we know that the atoms of the species A have 0.5 probability of coming from B and 0.5 of coming from C. We can do this for all the species of the food chain and we project this into a continuous, steady food relation. i.e., if species C feeds on species E for 50%, species A, even if it does not feed on species E, has 0.25 probabilities of having atoms from species E. Upon this, we can calculate the probabilities of an atom to go from one species to the other through all the possible direct and indirect paths. This is referred to as transition matrix, and in the transition matrix, we can calculate the share of atoms that make a cycle, i.e., that start from species A and come back to species A along all the possible paths (not only with species B and C, direct feeding, but also along species E, indirect feeding). Now, suppose we are not talking about atoms, but value of a product. If, for example, Italy sells cars to USA, where the engines of the Italian cars are produced, the share of value of car relative to engine is cyclical with USA. Suppose now that the USA buys iron from China and that Italy sells cars to China. Even if Italy does not buy directly iron from China, the share of the value of iron in the engine of the car is cyclical.

5.5. Null model as a benchmark

A popular and appropriate, to our scope, null model is the directed weighted configuration model indeed it preserves the observed intrinsic heterogeneity of vertices: all vertices have the same in-strength and out-strength as in the real network [32]. In other words, this model preserves the in- and out-strength sequences separately, and, furthermore it preserves the total weight of the original network. To evaluate if our analysis if our analysis is sound and consistent. We proceed as follows: first, for each year we built the expected network of trade using the randomization approaches of the maximum-likelihood method also called exponential random graph, second, we evaluate $\Gamma^{(S)}$ on the expected networks. See supporting information for the expected trend of $\Gamma^{(S)}$. Note that in doing so we take into account the global trade growth and for each country the distribution of import and export with foreign countries from 1960 to 2011 [32].

Authors contribution

FP developed the model, performed the analysis and wrote part of the paper and the SM; AP and KH contributed to the economic analysis and to the writing of the text; FR wrote the paper, supervised the analysis and developed part of the demonstrations in the SM; all authors revised the manuscript. The authors declare that they have no competing financial interests.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.10.129.

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