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On the effects of fossil fuel prices on the transition towards a low carbon energy system

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On the effects of fossil fuel prices on the transition towards a low carbon energy system, Part B

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Abstract

One major hurdle in the road toward a low carbon economy is the present entanglement of developed economies with oil. This tight relationship is mirrored in the correlation between most of economic indicators with oil price. This paper addresses the role of oil compared to the other three main energy commodities -coal, gas and electricity, in shaping the international trading network (ITW or WTW, world trade web) in the light of network theory. It initially surveys briefly the literature on the correlation between oil prices with economic growth and compares the concepts of time correlation with the concept of spatial correlation brought about by network theory. It outlines the conceptual framework underpinning the network measures adopted in the analysis and results are presented. Three measures are taken into account: the ratio of mutual exchanges in the network (reciprocity); the role of distances in determining trades (spatial filling); and the spatial correlation of energy commodities with the whole trade network and with four trading categories: food, capital goods, intermediate goods and consumption goods. The analysis deliver five main results:1) the energy commodities network was structurally stable amid dramatic growth during the decade considered; 2) oil is the most correlated energy commodity to the world trade web; 3) oil is the most pervasive network, though coal is the less affected by distances; 4) oil has a remarkably high level of internal reciprocity and external overlapping 5) the reciprocity of the trade network is negative correlated in time with the price of oil.

Keywords: Oil Price, Energy Price, World Trade Network, Network Theory, Pearson Correlation Index

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1. Temporal and spatial correlation between oil price and economic indicators

The way toward a low carbon economy finds one major hurdle in the dependence of developed economies to fossil fuels. Among fossil fuels, oil is generally considered a special form of energy, entangled to the economic process more than any other energy commodities. Indeed, many economic indicators, like the Gross Domestic Product, the Industrial Production or inflation rate, are historically strictly -negative or positive, correlated to oil price. Why oil is so important compared to other fossil fuels? Is there a *physical* basis to correlation of oil price to economy or is it due to monetary and financial reasons? Indeed, oil enters the production function in several sectors of the economy not only as an energy source. Oil is gasoline, plastic, chemicals and finance (Ruzzenenti, 2015a). This paper addresses these questions in the light of network theory by developing a comparative analysis, with a spectrum of network indicators, of the four main energy commodities in relation to the structure of global trade. International trade after globalization became a prominent sector in world economy, whose affluence is now strictly connected to economic growth and development. Furthermore, international trade heavily relies on the transport system, a sector that is almost entirely dependent on fossil fuels and oil particularly. Hence, the World Trade Web (WTW) provides us with an interesting and informative case-study to investigated the role of oil and fossil fuel prices in shaping the world economy.

1.1 Temporal correlation, state of art

The first question that must be addressed in order to comply to the task of assessing the role of fossil fuel prices in fostering a transition toward a low-carbon economy is: what should be meant for fossil fuel prices?

Indeed, for transitioning toward a low-carbon economy, economic processes need to use either less or an alternate –thus, renewable, energy input for economic output. In both cases –we aim at substituting or reducing the fossil source, for the sake of the goal function, what actually matters it is not the price of the fuel, rather the cost of the energy service. However, the price of the fuel is embedded in the price of the energy and we need to make this relationship explicit in order to understand and assess the impact of the former to the energy path of economies. The cost of the energy service (for example: the time and the distance travelled for person) is determined by the price of energy (the price of the fuel times the fuel economy of the vehicle) and this interlinking tie

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must be extended to the analysis of any energy service and to any step of the energy transformation process (Fouquet, 2011).

Therefore, it will be clear that broadly determining the concept of energy price it is not a simple question, because energy markets display a very complex structure and because of these interdependent economic, technical and physical constrains.

Detailing the concept of energy price ultimately leads to the following hierarchical taxonomy:

1. Financial prices -> price of the energy commodities
2. Economic prices -> price of the energy service
3. Thermodynamic prices -> price in physical units

The price of oil is customarily taken as benchmark for the price of energy. Indeed many price indices in the energy market are locked to the oil price (electricity, natural gas). Moreover, this linking (or coupling) is widely considered a major factor contributing to inflation. Nonetheless, it is less widely understood why oil plays such a pivotal role in the world economy. It is commonly believed that this supremacy is due to the fact that oil is the main energy source for world economy, yet coal has recently (2012) overtaken oil (Figure 1).

Coal was the fundamental energy source centuries ago that used to shape the economy and to determine the rise and fall of nations (Jevons, 1866). Nowadays oil is indisputably dominating the world economy. Data from the second world war onward show that economic growth is intimately linked to the price of oil (Hamilton, 1983). The issue of correlation, and thereby causality, between the price of oil on one hand and several economic indicators (GDP growth, employment rate, industrial production, inflation) on the other hand, has always been debated in scientific literature (Hooker, 1996; Hamilton, 1996; Papapetrou, 2001; He et al., 2010). Although historic trends show that economy and oil prices are entangled, the extent, the time lag, and the scope of this relationship is still an open issue. However, it appears that the scientific community has converged towards some key points on the topic (Alvarez-Ramirez et al, 2010):

1. The correlation seems to be asymmetric, especially in the short run: when oil prices rise the economy slows down ,whereas the opposite relationship is more relaxed (Huang et al. 2005; Rahman and Serletis, 2010)

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2. The correlation between oil prices and world economy has diminished, reaching a peak during the oil crisis and weakening in the aftermath (Thang et al., 2010; Naccache, 2010; Alvarez-Ramirez et al, 2010).
3. The correlation increases during oil shocks, indicating that spikes of oil prices are most the most influential in affecting the economy (Hamilton, 2003; Hsu et al, 2008; Cologni and Manera, 2009; Jamazzi, 2012)
4. The causality relationship between oil prices and economic growth, measured by statistical means, is ambiguous and sometimes reversed, depending on the country selected or the time period (Narayan and Smyth, 2007; Cologni and Manera, 2009; Benhmand, 2012, Ratti et al. 2013)

It is noteworthy that the current approach to the issue aims at investigating the interlinking between economy and oil prices by assessing the temporal correlation among variables, on a country-level scope of the analysis.

We want here to seek a different perspective over the interdependence of energy and economy that goes beyond the customary temporal approach. The network structure of the productive space will be analysed in order to establish a structural correlation between commodities, class of commodities and energy sources.

2.1 From temporal correlation to spatial correlation

In statistics, the Pearson product-moment correlation coefficient is a measure of the linear correlation (dependence) between two variables C and C′, where p^c_t and (p^c_T) are the price (or log return) at time t and the average price in the time interval T of the good C. The Pearson index ranges between +1 and −1 inclusive, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation:

$$\varphi_t^{cc'} = \frac{\sum_{t=1}^{T}[p_t^c - \acute{p}_T^c] * [p_t^{c'} - \acute{p}_T^{c'}]}{\sqrt{\sum_{t=1}^{T}[p_t^c - \acute{p}_T^c]^2 \sum_{t=1}^{T}[p_t^{c'} - \acute{p}_T^{c'}]^2}} \quad (1)$$

In the Pearson corr. index, the space is one-dimensional and the summation runs over the time-variable. In a Network with N nodes, we have N(N-1) possible connections (links) and if the network exchanges two types of flows/commodities, they can be computed with the Pearson corr. index according to the sequence of nodes' links. In this case, the summation runs over the couple of nodes' indices i and j, fro the two flows c and c':

$$\varphi_w^{cc'}(t) = \frac{\sum_{i \neq j}[w_{ij,t}^{c} - \acute{w}_t^{c}] * [w_{ij,t}^{c'} - \acute{w}_t^{c'}]}{\sqrt{\sum_{t=1}^{T}[w_{ij,t}^{c} - \acute{w}_t^{c}]^2 \sum_{t=1}^{T}[w_{ij,t}^{c'} - \acute{w}_t^{c'}]^2}} \quad (2)$$

This diverse computation of Pearson index expresses a *spatial* correlation because it measures the topological relationship between every couple of links' weight in two networks that share the same nodes (Barighozzi et al., 2010; Ruzzenenti et al. 2015). In other words, the exogenous variable it is not time but topology. We will now investigate the spatial correlation in the productive space, namely, the international trade network of commodities.

The conceptual framework behind network analysis of the productive space is the same as that behind the "too-interconnected-to-fail" theory (in place of the "too-big-to-fail") that places greater attention to the most interconnected nodes and to their role in spreading contagion, rather than to the merely largest ones.

In the following, we will compare four major energy commodities in the framework of the world international trading network (world trade web) through the lens of complex network theory. Henceforth, a country will be considered as a node or vertex of a graph and a trading relationship as a link or edge. Links might have different weights according to trading volumes and the incoming or outgoing vertex might be of different size according to the GDP of the country's economy. In the world economy there are fossil fuel producers and fossil fuel consumers (in red and in blue in Fig. 1). Energy-reach countries exchange energy commodities for consumption or capital goods from energy-poor countries. The structure of this exchange relationship will be the object of the present investigation.

Arguably, the dependency of the world economy on an energy source depends, inter alia, on the degree of interconnection and its capillarity. Thus, the primary information we should look for when considering the world network of energy commodities is: what is the most interconnected and extended energy source?

2.1 Spatial correlation: binary analysis

The first step of the analysis required to answer this question concerns the binary structure of the network. A binary, directed graph is specified by a N×N adjacency matrix, A, where N is the number of nodes and the generic entry a_{ij} is 1 when there is a connection from node i to node j, and 0 otherwise. In order to assess the degree of *spreading* of a network in its embedding space, we need to develop a measure that includes both spatial constrains –distances, and topological constrains - and structure (Squartini et al., 2013). The simplest definition of a global measure incorporating distances and network structure is

$$F = \sum_{i=1}^{N} \sum_{j \neq i}^{N} a_{ij} d_{ij} \qquad (3)$$

where d_{ij} is the generic entry of the matrix of distances, D, among nodes (Ruzzenenti et al. 2012). Since we will consider networks without self-loops (i.e. a_{ii}=0), F is a measure of the total distance between different, topologically connected pairs of nodes. Equivalently F can be seen as a measure of the extent to which networks "fill" the available space.

The quantity F reaches its minimum when the links are placed between the closest vertices. Formally speaking, if we consider the list $V^{\uparrow} = \left(d_1^{\uparrow}, \cdots, d_n^{\uparrow}, \cdots, d_{N(N-1)}^{\uparrow}\right)$ of all non-diagonal elements of D ordered from the smallest to the largest $d_n^{\uparrow} \leq d_{n+1}^{\uparrow}$, the minimum value of F is simply given by$F_{\min} = \sum_{n=1}^{L} d_n^{\uparrow}$, where $L = \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij}$ is the number of links in the network. Similarly, the maximum value of F is reached when links are placed between the spatially farthest nodes. Considering the list $V^{\downarrow} = \left(d_1^{\downarrow}, \cdots, d_n^{\downarrow}, \cdots, d_{N(N-1)}^{\downarrow}\right)$ of distances in decreasing order $d_n^{\downarrow} \geq d_{n+1}^{\downarrow}$, the maximum value of F for a network with L vertices is $F_{\max} = \sum_{n=1}^{L} d_n^{\downarrow}$.

In order to compare, and possibly rank, different networks according to their values of F, a normalized quantity should be used. An improved global definition, which we will denote as filling coefficient, is

$$f = \frac{F - F_{\min}}{F_{\max} - F_{\min}} = \frac{\sum_{i=1}^{N} \sum_{j \neq i} a_{ij} d_{ij} - F_{\min}}{F_{\max} - F_{\min}} \qquad (4)$$

It is noteworthy that in dense networks with a broad degree (the sum of ingoing and outgoing links) distribution, topology may affect spatial interactions. For example: two highly connected nodes (hubs), that is to say, as two big economies, are more likely to interact regardless of their physical distance and, if we aim at assessing the role of distances, it is best to disentangle spatial effects from non spatial effects. A way to do that is by adopting a null model (NM), based on the statistics of exponential random graphs, to compare and weight our measures (Squartini et al, 2013a).

Null models are characterized by some kind of topological property (such as the link density, the degree sequence and the reciprocity) that is a priori independent of any spatial constraint. They therefore allow us to improve our definition of filling coefficient by filtering out the spurious spatial effects due to the non-spatial constraint enforced. In order to achieve this result, a comparison between the observed value of f and its expectation is needed. Consider the expected value of the filling coefficient under any of the three aforementioned null models (NM):

$$\langle f \rangle_{NM} = \frac{\sum_{i=1}^{N} \sum_{j \neq i} p_{ij}^{NM} d_{ij} - F_{\min}}{F_{\max} - F_{\min}} \qquad (5)$$

where p_{ij}^{NM} is given by one null model. The comparison between observation and expectation can be easily carried out by making use of the following rescaled version of the filling coefficient that we denote as filtered filling (Ruzzenenti et al. 2012):

$$\varphi_{NM} \equiv \frac{f - \langle f \rangle_{NM}}{1 - \langle f \rangle_{NM}} \quad (6)$$

Besides space filling, an important feature of networks is *reciprocity.* Indeed, for the present analysis reciprocity is of paramount interest: Are energy source producers more or less reciprocated in the world differentiated economic system by producers of goods and capital?

To answer this question, we consider the definition of reciprocity for a binary network

$$r = \frac{L^{\leftrightarrow}}{L} = \frac{\sum_{i=1}^{N} \sum_{j \neq i} a_{ij} a_{ji}}{\sum_{i=1}^{N} \sum_{j \neq i} a_{ij}} \qquad (7)$$

where $L^{\leftrightarrow}$is the number of reciprocated links (going both ways between pairs of vertices), and L is the total number of links (Newman Forrest and Balthrop 2002). Exactly as in the case of the filling coefficient, the binary reciprocity has a "filtered" counterpart, defined in the same way (Garlaschelli and Loffredo 2004), incorporating both the observed and the expected values under a chosen null model (NM):

$$\rho_{NM} = \frac{r - \langle r \rangle_{NM}}{1 - \langle r \rangle_{NM}} \qquad (8)$$

Results of the binary analysis are reported on Table 1. The data set employed for the analysis is BACI, developed by CEPII[i].and covers a decade from 1998 to 2007. In order to avoid anomalies due to the crisis, the scope of the analysis ends before 2008. The first notable information delivered by the binary analysis is that the structure of the energy network is stable. Although both the number of links and the trading volume of all the energy commodities considered (except electricity) grew dramatically between 1998-2007, significantly more than global trade, the spatial and symmetrical structure of the four energy markets is pretty stable. Oil grew 554% in value, 56% in mass and 57% in number of links. Coal grew 188%, 82% and 37% respectively and gas 295%, 172% and 46% whereas the world trade network grew 158% in value, 51% in mass and 33% in number of links (Table 2 and Table 3). However, if we look at the standard deviation for all the selected measures, the low values indicate that the network is structurally stable (Table 1). This means that the binary reciprocity, the connectance (density of links) and the spatial filling of energy commodities did not significantly changed in the decade considered. More in details, oil is by far the most connected energy commodity, with, on average, 1 out of 10 possible links present in the network, whereas electricity is the least connected, with a connectance of 0.02 on average. The spatial analysis indicate that crude oil and second coal present the highest spreading, perhaps not surprisingly, given that the transport of gas and electricity is bound to costly and complex infrastructures. Interestingly, coal is the energy commodity less affected by distances in transports, as the highest ϕ value indicate. This is probably due to the fact that solid energy sources are more suitable for transport than liquid energy sources. As previously highlighted, oil is a denser network and it is also much more reciprocated, as indicated by r. However, as the ρ value shows, it is not more reciprocated because it is denser. Therefore, we must deduce that countries that exports oil are much more likely to establish mutual links than other energy-commodities exporting countries.

2.3 Spatial correlation: weighted analysis

However, the binary reciprocity measure is not enlightening on the *extent* of the mutual relationship. A weighted reciprocity measure is needed in order to assess the amount of reciprocal flow. Furthermore, switching from the binary analysis to the weighted description of networks enable us to evaluate trades both in monetary terms and in mass flows. A weighted, directed graph is specified by a N×N adjacency matrix, W, where N is the number of nodes and the generic entry w_{ij} is the intensity of the connection (the amount of trade flow for WTW) from node *i* to node *j*. It is noteworthy that for every couple of interacting nodes, the reciprocated part of two counteractive flows is the *minimum* flow in between (Squartini et al 2013b):

$$w_{ij}^{\leftrightarrow} = min\left[w_{ij,}w_{ji}\right] = w_{ji}^{\leftrightarrow}\,(9)$$

Therefore, analogously to equation (7), a normalized measure of the weighted reciprocity of a network can be defined as follow:

$$r^{w} = \frac{W^{\leftrightarrow}}{W} = \frac{\sum_{i=1}^{N}\sum_{j\neq i} w_{ij}^{\leftrightarrow}}{\sum_{i=1}^{N}\sum_{j\neq i} w_{ij}}\,(10)$$

Likewise, it is possible to define a rescaled measure of the reciprocated flow in two layer, layers A and B, of a multiplex as follows interacting networks , for every couple of nodes:

$$w_{ij}^{\leftrightarrow}(AB)_{syn} = min\left[\frac{w_{ij}^{A}}{W^{A}}, \frac{w_{ij}^{B}}{W^{B}}\right](11a)$$

$$w_{ji}^{\leftrightarrow}(AB)_{rev} = min\left[\frac{w_{ij}^{A}}{W^{A}}, \frac{w_{ji}^{B}}{W^{B}}\right] w_{ji}^{\leftrightarrow}(AB)_{rev}(11b)$$

And a measure of the overlapping *synergic* (*reverse)* flows going in the same (opposite) directions within the two networks:

$$C^{AB}{}_{syn(rev)} = \frac{W^{\leftrightarrow}{}_{syn(rev)}}{W} = \sum_{i=1}^{N}\sum_{j\geq i} w_{ij}^{\leftrightarrow}(AB)_{syn(rev)}\,(12)$$

This latter measure is intended to indicate the percentage of the import/export that two networks share for every couple of nodes (countries). For example, a 25% reverse overlapping index between oil and world trade web, means that 25% of exports in the oil market is reciprocated by the world economy directly from the importing country (it could be interpreted as a *reinvestment* index or, for synergic flows, as a *complementary* index).

Table 2 shows results for the monetary and mass flows for the years 1998 and 2007. Despite the fact that world consumption of coal matched oil consumption, oil as a commodity, still represents the greatest energy commodity market in volume, by one order of magnitude. But not in mass: in 2007 oil and coal have been trade for almost the same amount. Nevertheless, the network analysis shows that oil stems out for its structural role compared to the other energy commodities. The first striking result is weighted reciprocity: oil scored in 1998 and 18% and 20% in 2007 of reciprocity. This means that one fifth of oil is mutually traded in the world. This is much higher, for one order of magnitude, compared to the other energy commodities. Indeed, oil exporters countries are also oil importers. The oil network scored in 2007 also the highest overlapping index in synergic flows and reverse flows. Oil exchange directly (reverse flows from the importing country) around 35% (34% in 1998) in value and drives complementary flows (toward the importing country) for 40% (37% in 1998) of exports in value. The results hold for the mass flows, albeit the physical reciprocity and the overlapping indices are much lower for all the networks considered (Table 3).

This analysis based on reciprocity is further confirmed by the (spatial) Pearson correlation index (equation 2). The Pearson corr. index for flows going in opposite direction of oil with the WTW is higher than any other energy commodities: 43% compared to 40% of electricity, 24% of coal and 32% of gas (average over the period 1998-2007).

We have demonstrated the centrality in the world trading network of oil compared to other energy sources by analyzing the spatial (topological and metric space) correlation among networks. It is of our interest now to investigate the temporal correlation between the network representation of world economy and the price of oil. As we have previously highlighted, weighted reciprocity (equation 10) is an insightful measure of networks. Figure 3 shows the historic trend of reciprocity (red line) compared to oil price (constant price, base year 2011, source BP). The Pearson correlation index of the two curves is -0.85.

However, as it is shown in Table 2, the world trade web is highly reciprocated, meaning that on average w_{ij} is equal to w_{ji}: the matrix is almost symmetrical.

Nevertheless, in networks with broadly distributed strengths (total export and total import) the attainable level of symmetry strongly depends on the in- and out-strengths of the end-point vertices: unless they are perfectly balanced, it becomes more and more difficult, as the heterogeneity of strengths across vertices increases, to match all the constraints required to ensure that $w_{ij} = w_{ji}$ for all pairs. Therefore, even networks that maximize the level of reciprocity, given the values of the strengths of all vertices, are in general not symmetric. Moreover, in networks with balance of flows at the vertex level (export ~import for all vertices) an average symmetry of weights is automatically achieved by pure chance, even without introducing a tendency to reciprocate. In many real networks, the balance of flows at the vertex level is actually realized, either exactly or approximately, as the result of conservation laws (i.e. balance of payments). In those cases, the symmetry of weights should not be interpreted as a preference for reciprocated interactions. We have thus developed a filtered measure of reciprocity, formally similar to the Rho in equation 11, that encapsulated a null model aimed at imposing the vertex balancing constrain. In what follows, the reciprocity adjusted measure discounts the effect of the tendency of nodes to preserve the balance between import and exports. Fig 3 shows that the adjusted reciprocity (green line) heightens the correlation with oil price (correlation index: -0.89) but down shifts the curve, indicating that the network, washed by the balancing effect, is less reciprocated.

However, the most striking and enlightening information that comes from comparing oil price and reciprocity, rests in the temporal sequence of curve peaks. Oil curves, more clearly during the first oil crisis peak *after* and not *before* the reciprocity curve, as is clearer in the small frame that shows a magnification of the two curves (Fig 3).

Indeed, the reciprocity starts declining three years before the oil shock. In spite of existing literature that suggests that the oil shock of the 1973 followed instead of preceding the economic recession, it is still widely believed that the oil crisis caused the economic crisis rather than the opposite (Cologni and Manera, 2009; Basosi, 2012). Although several economic indicators seem to follow the trend of oil peaks, it is clear by looking at trends in GDP (figure 5), or more evidently by observing the industrial production trend (Figure 4), that none of these seem to display such a clear *anticipation* of the oil peak in the 1970s as does network reciprocity.

2.4 Integrating spatial and temporal analysis

Nevertheless, the economic interpretation of reciprocity is still uncertain. Arguably reciprocity is linked to economic recession. One reason for this relationship could be the pressure exerted on balance of payments by recession and high energy prices. A global node unbalancing may cause a symmetry breaking in the network. However, as was previously explained, the adjusted reciprocity should discount the effect of node unbalancing but Rho emphasizes the reciprocity trend, rather than leveling it. Henceforth, the high correlation between Rho (the adjusted reciprocity) and oil price informs us that, beyond commercial balance effect, lower oil prices stimulate reciprocal trades. Further evidence of this stronger relationship is given by the weak correlation between oil price and reciprocated strength, that scores -0.63 of Pearson correlation index. Reciprocated strength is a global measure of the share of inflow (outflow) that is reciprocated and for the world trade web measures the counties' commercial balance.

However, the trend in reciprocity after the first oil crisis, though being still so correlated to oil prices, it seems not to anticipate oil spikes. Evidently, the first oil crisis should be considered a remarkable exception in the fundamental trend interlinking oil price and recession. It is likely that recession in the 1970s came first and the oil crisis followed, but the same it can't be said for the following oil shocks.

3 Concluding remarks

We have so far established, by means of our network analysis, a link between oil price and economic structure (reciprocity in the world trade web). However, the goal of our analysis is that of investigating the effect of oil prices on the energy pattern of economies. According to our analysis, it is very likely that lower oil prices influenced the energy consumption of world economy in two ways: by propelling economic growth and by expanding trade. Nevertheless, there are some evidences that oil shocks too had the paradoxical effect of fostering economic growth. In order to show this effect, we need to demonstrate that oil price spikes foster energy efficiency. In what follows, we will show as an example how energy efficiency globally changed the transport sector as a consequence of the first oil crisis.

Energy efficiency data set are very fragmented and there is no robust, consistent record of data concerning energy efficiency in the transport sector for a suitable scope. A scope that needs to be as broad as possible in time, space and variety of modes. A different way to indirectly assess the global evolution of efficiency in transports is that of evaluating the burden of distances over trading relationships: the more efficient becomes the transport sector the less biding become distances (Chiarucci et al, 2013). Figure 6 shows the trend in the Hurts exponent for the whole set of trading volumes, ordered, node by node, by distances. Hurts exponent scores 0.5 when the signal is completely random, it follows that, for the sake of our analysis, the closer the exponent is to 0.5, the less compelling are distances for the trading network. The grey curve shows the trend of the Hurst exponent for the deflated volumes, where the expected value of trades has been used as a deflator, generated by the same null model adopted in defining the adjusted reciprocity (Fig 3). Interestingly, washing out the topological effects, the Hurst exponent shows a clear decreasing trend after the mid 1970s, that becomes more significant after 1980s.

Therefore, according to our analysis, we can deduce that energy efficiency in the following decade of the first oil crisis improved worldwide.

Furthermore, it also possible to show that the world trade web, in the aftermath of the oil crisis and possibly because of the efficiency improvement, expanded (Ruzzenenti et al, 2013). Figure 7 shows historical trends in the binary *filling* and *phi* (equations 4 and 6). Again, filtering out the topological effects, it is possible to observe that the world trade web, after a long period of shrinking, expanded (red line). Therefore, we must deduce that efficiency in transport was a driving factor that led the trading network to grow, beyond or before, the growth in trading relationships among countries (*topological effects* in the jargon of network theory).

In conclusion, our analysis clearly shows that the first oil crisis had not caused the recession, which was already looming in the economy, but fostered a dramatic improvement in energy efficiency. It is very likely that the higher energy efficiency positively fed back to the economy, by relaxing the constrains to trades due to lower transport costs. This feed-back process hints at a global, economy-wide *rebound effect* that occurred in the aftermath of the oil crisis that involved the transport sector on one side and the production chain on the other. This process was indeed a major drive for globalization and outsourcing (Ruzzenenti and Basosi, 2008). However, the relationship between oil price and the structure of the economy is more profound and persistent in the world economy, as the correlation between reciprocity and oil price highlights. The connection between reciprocity and economic growth seems to indicate that oil price stimulates growth worldwide in a way that is not understandable on a country level. Probably this hidden relationship lies behind the complex, international production network that from the 1980s has forged globalization, though, more research is needed. We believe that network theory can provide the basis for a new and different understanding of the phenomenon.

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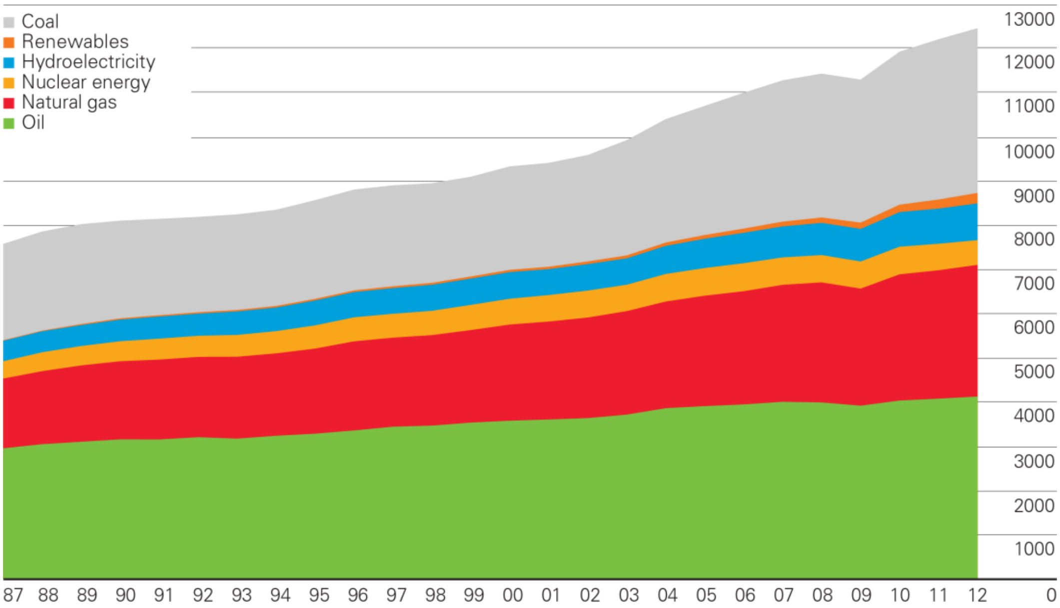

Figure 1 Primary energy world consumption -Million ton oil equivalent (Source: BP)

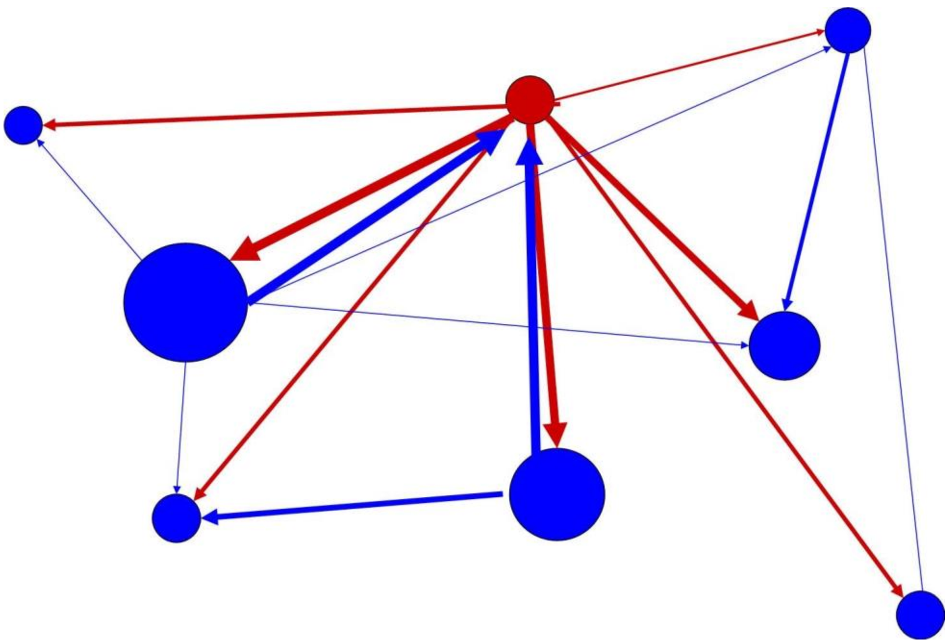

Figure 2 World trading network, graphical abstract.

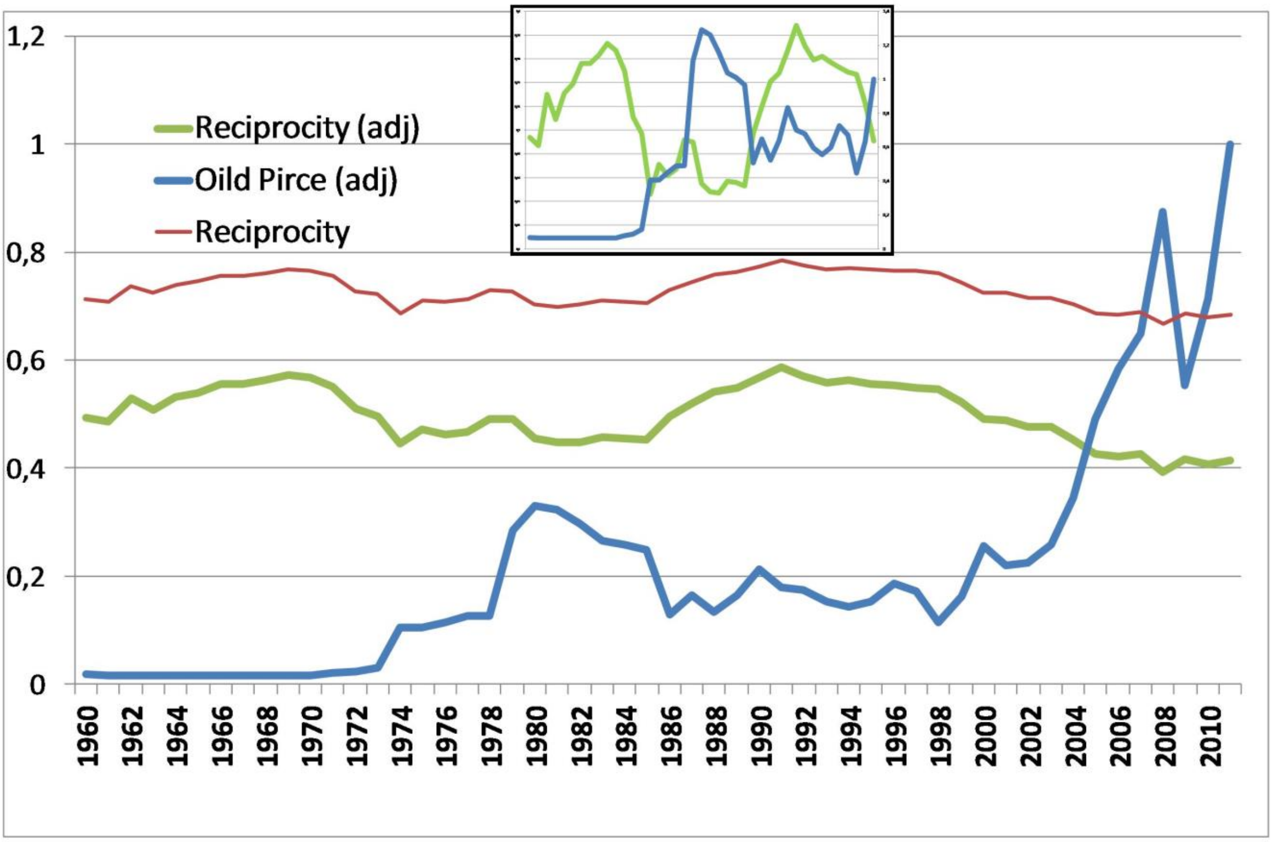

Figure 3 Oil price and network reciprocity, temporal correlation (Source: elaboration of the authors).

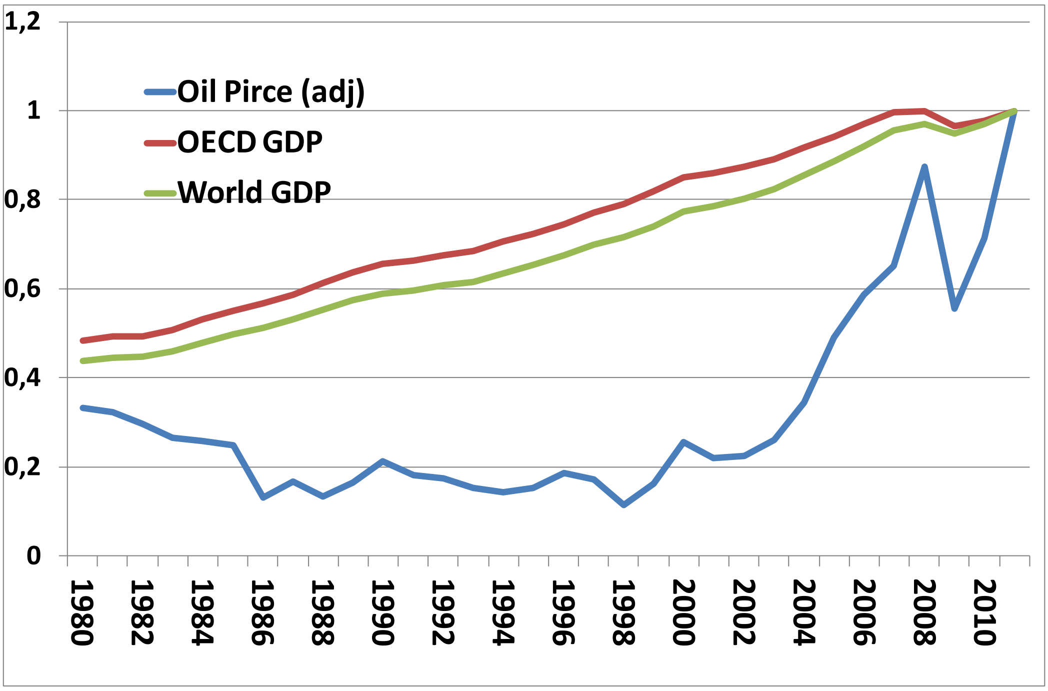

Figure 4 Oil price and GDP, temporal correlation (source: OECD).

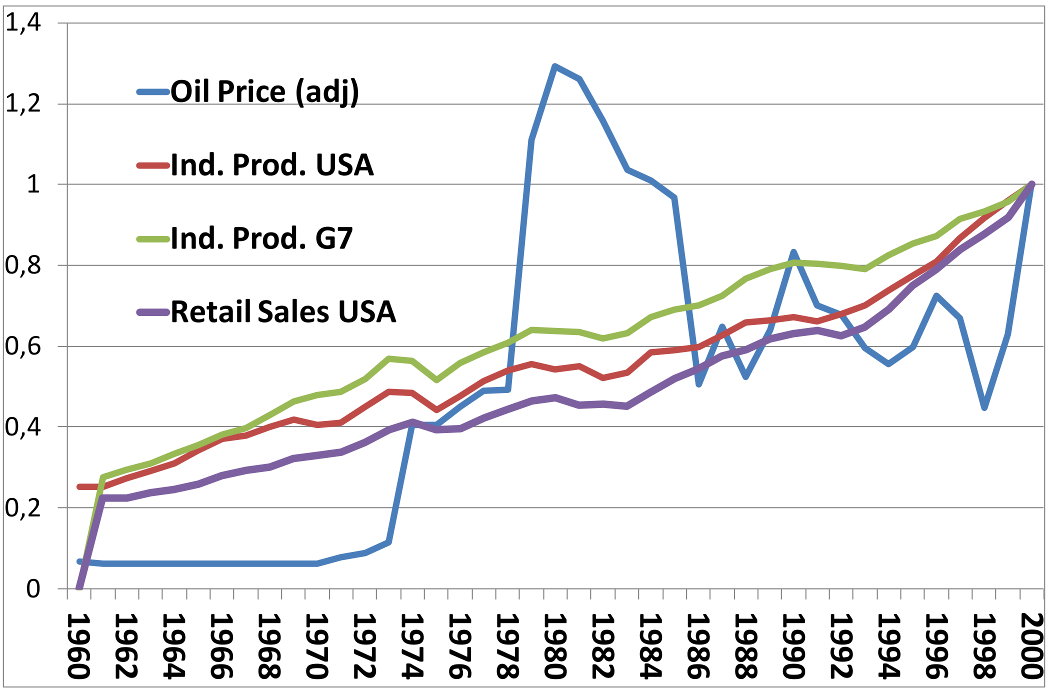

Figure 5 Oil price and Industry, temporal correlation (source: OECD).

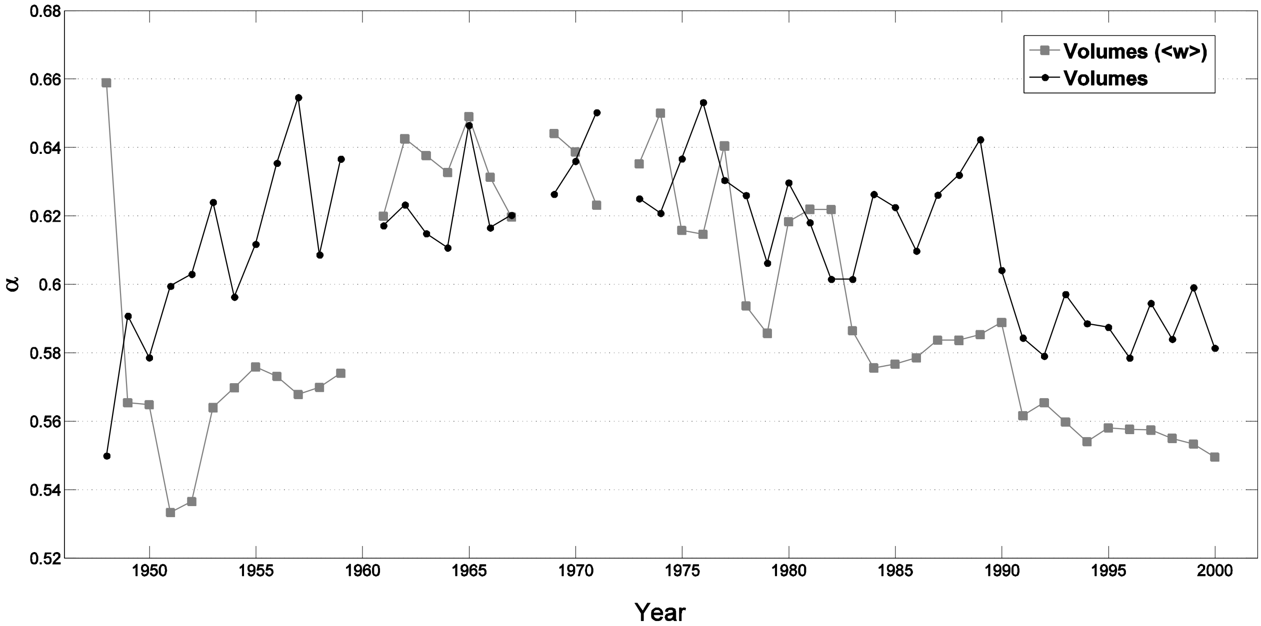

Figure 6 Hurst exponent in the world trade web, historical trend (Source: Chiarucci et al., 2014)

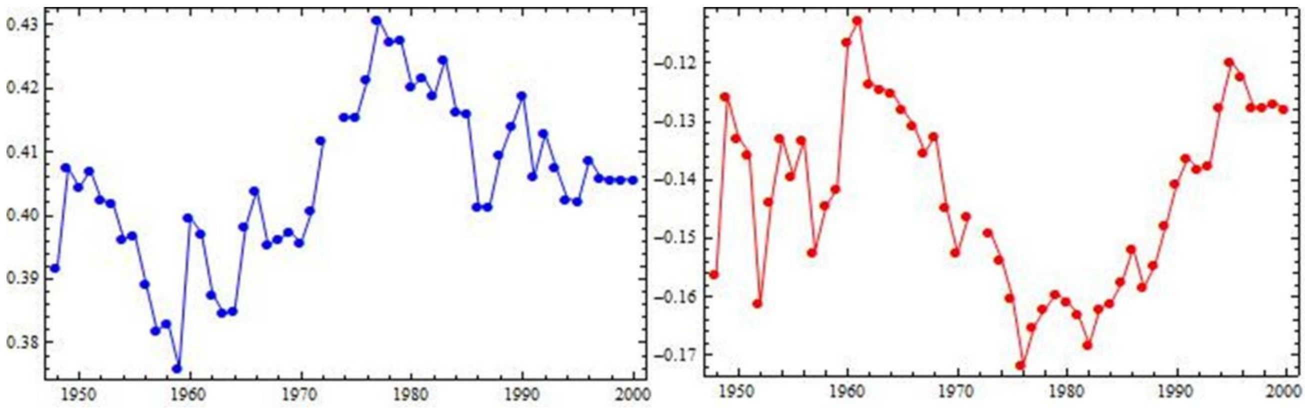

Figure 7 Spatial filling (f) and filtered filling (Phi), historic trends in the WTW(Source: elaboration of the authors).

Table 1 Binary network analysis of the energy market, mean values and standard deviation over the period 1998-2007

1998-2007					
	Reciprocity	Connectance (link density)	Spatial filling (f)	Rho	Phi
Oil	0.52±0.008	0.10-0.16	0.25±0.003	0.21±0.008	-0.17±0.007
Coal	0.36±0.01	0.04-0.05	0.23±0.004	0.12±0.01	-0.14±0.008
Gas	0.33±0.01	0.03-0.04	0.20±0.007	0.17±0.01	-0.21±0.01
Electricity	0.19±0.02	0.01-0.02	0.18±0.005	0.12±0.01	-0.29±0.01
WTW	0.84*	0.56*	0.34*	0.21*	-0.10*

Table 2 Weighted network analysis of energy market, values in thousand dollars, in 2007 and 1998.

Year: 2007 (1998)	Reciprocity	Overlapping Index: *syn* flows	Overlapping Index: *rev* flows	W tot	Growth rate	links	Growth rate
WTW	0.69 (0.76)			1.24*10^10 (4.8*10^9)	158%	2.4*10^4 (1.8*10^4)	33%
Oil	0.25 (0.21)	0.40 (0.37)	0.34 (0.35)	5.3*10^8 (8.1*10^7)	554%	6.6*10^3 (4.2*10^3)	57%
Coal	0.07 (0.11)	0.22 (0.26)	0.20 (0.24)	7.2*10^7 (2.5*10^7)	188%	2.2*10^3 1.6*10^3	37%
Gas	0.08 (0.03)	0.21 (0.16)	0.17 (0.14)	1.5*10^8 (3.8*10^7)	295%	1.9*10^3 (1.3*10^3)	46%
Electricity	0.09 (0.12)	0.20 (0.25)	0.19 (0.24)	2.5*10^5 (1.48*10^5)	79%	7.6*10^2 5.8*10^2	31%

This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no 266800

Table 3 Weighted network analysis of energy market, values in tons, in 2007 and 1998

Year: 2007 (1998)	Reciprocity	Overlapping Index: *syn* flows	Overlapping Index: *rev* flows	W tot (total volume)	Growth
WTW (ton)	0.40 (0.48)			1.1*10^10 (7.3*10^9)	51%
Oil (ton)	0.20 (0.18)	0.43 (0.39)	0.26 (0.26)	1.0*10^9 (6.4*10^8)	56%
Coal (ton)	0.04 (0.06)	0.26 (0.25)	0.13 (0.16)	1.0*10^9 (5.5*10^8)	82%
Gas (m^3)	0.07 (0.03)	0.24 (0.23)	0.11 (0.10)	7.9*10^8 (2.9*10^8)	172%
Electricity (kWh)	0.06 (0.12)	0.14 (0.16)	0.11 (0.14)	8.6*10^5 (8.4*10^5)	2%

Financialisation, Economy, Society and Sustainable Development (FESSUD) is a 10 million euro project largely funded by a near 8 million euro grant from the European Commission under Framework Programme 7 (contract number : 266800). The University of Leeds is the lead co-ordinator for the research project with a budget of over 2 million euros.

THE ABSTRACT OF THE PROJECT IS:

The research programme will integrate diverse levels, methods and disciplinary traditions with the aim of developing a comprehensive policy agenda for changing the role of the financial system to help achieve a future which is sustainable in environmental, social and economic terms. The programme involves an integrated and balanced consortium involving partners from 14 countries that has unsurpassed experience of deploying diverse perspectives both within economics and across disciplines inclusive of economics. The programme is distinctively pluralistic, and aims to forge alliances across the social sciences, so as to understand how finance can better serve economic, social and environmental needs. The central issues addressed are the ways in which the growth and performance of economies in the last 30 years have been dependent on the characteristics of the processes of financialisation; how has financialisation impacted on the achievement of specific economic, social, and environmental objectives?; the nature of the relationship between financialisation and the sustainability of the financial system, economic development and the environment?; the lessons to be drawn from the crisis about the nature and impacts of financialisation? ; what are the requisites of a financial system able to support a process of sustainable development, broadly conceived?'

THE PARTNERS IN THE CONSORTIUM ARE:

Participant Number	Participant organisation name	Country
1 (Coordinator)	University of Leeds	UK
2	University of Siena	Italy
3	School of Oriental and African Studies	UK
4	Fondation Nationale des Sciences Politiques	France
5	Pour la Solidarite, Brussels	Belgium
6	Poznan University of Economics	Poland
7	Tallin University of Technology	Estonia
8	Berlin School of Economics and Law	Germany
9	Centre for Social Studies, University of Coimbra	Portugal
10	University of Pannonia, Veszprem	Hungary
11	National and Kapodistrian University of Athens	Greece
12	Middle East Technical University, Ankara	Turkey
13	Lund University	Sweden
14	University of Witwatersrand	South Africa
15	University of the Basque Country, Bilbao	Spain

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