Alignment of Multinational Firms along Global Value Chains: A network-based perspective

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Abstract

This paper reveals how French multinational firms locate more and more along Global Value Chains (GVCs) since the mid 1990s. Using multinationals' firm-level data and international Input-Output tables (from Eora-Unctad dataset), I compare the co-evolution of two network structures: the multiple locations of Multinational Enterprises (MNEs), and the Global Value Chains. I first show that the two networks experience a similar decentralization trend. Then a Quadratic Assignment Procedure shows that firms are more likely to settle in countries that are tightly connected in global value chains. Moreover, this influence continuously increased from 1996 to 2011. These results hold even when controlling for gravity-like determinants of location choices in a traditional panel OLS analysis. The network analysis allows to consider simultaneously the multiple locations of MNEs to explain their further international developments. A major insight from this approach is to reveal that such alignment on GVCs are be more driven by downstream (toward VA destination) rather than upstream (toward the VA source) new locations of firms.

Keywords: Global Value Chains; Multinational Firms; Location Choices; Weighted Directed Networks.

JEL codes : F02; F23; F60 ; C45

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1 Introduction

In the last decades the emergence of Global Value Chains (GVCs) have deeply reshaped the world's production, consumption, and trade patterns. This growing organization of the production at the world scale, fragmented across national borders leads to deepening structural interdependence between countries (Baldwin et al., 2012). It has also large ongoing repercussions on the organization of firms that have to deal with a global disintegration of the production. Meanwhile, the number of multinational enterprises (MNEs) increased by more than 150% [1]. These two phenomenon are obviously intrinsically linked, but the dynamics of their co-evolution remains to be explored.

This paper investigates how the multinational enterprises' global locations followed the development of GVCs since the mid 1990s, and in which direction. In that sense, this work relates to the literature focusing on the global sourcing strategies of firms in a sequential global production including Antràs and Chor (2013); Costinot et al. (2013), and especially Antràs and De Gortari (2017) which insisted on the necessary centrality of foreign locations in the global value chains, to be close to subsequent (downstream) stages.

Yet, our approach differs from the use of indexes reflecting individual countries' position into GVCs (Antràs and Chor, 2018; Alfaro et al., 2015), and develop a formal network representation of both Global Value Chains and Multinational firms, that was underlying in previous works (Baldwin and Venables, 2013). The use of networks is increasingly popular in various fields of economics to study the structure of connections and the interdependence between actors (see Jackson (2014) for a comprehensive review). Economic geography is particularly sensitive to such tools, that fits well to study geographically clustered structures, and commonly used by geographer themselves (Glückler, 2007; Ter Wal and Boschma, 2009; Grabher and Ibert, 2005). In that sense, this work is closely related to the pioneers that already examined the network topology of GVC trade flows, benefiting from the increasing availability and coverage of international input-output tables to map the network (Cerina et al., 2015; Amador and Cabral, 2017; Criscuolo and Timmis, 2018). Yet, our topic is wider than these previous works, as we also study the geographical network of multinational firms, to compare the two networks

[1] Until the 2007 edition, the UNCTAD World Investment Report reported an estimate number of MNEs, growing from 38,000 in 1993 to 80,000 in 2006 (UNCTAD, 1995, 2007). In 2018, the Financial Times reported the estimation of 100,000 multinational firms worldwide (fDI market database, 23 Feb 2018).

structural evolution. In that regard, this work follows some geographic-oriented research that already studied the multinationals' network of locations at the city level (Ducruet et al., 2011; Rozenblat, 2015; Wall and van der Knaap, 2011). At the host-country scale we focus on, only a scarce number of paper detailed the network structure of Foreign Direct Investments (FDIs) (De Masi et al., 2013; De Masi and Ricchiuti, 2018a; Joyez, 2017).

This paper compares the co-evolution of the network of global value chains with the one of foreign locations of French MNEs, and reports how multinationals' plants are increasingly located along GVCs between 1996 and 2011. We provide clear evidence of an international reorganization of French firms following the emerging GVCs. Contrary to a common intuition on the rise of international outsourcing with global supply chains, we reveal that the MNEs alignment on GVCs is - at least for French firms - equally driven by downstream (toward subsequent stages of production) and upstream (prior stages) expansion of firms.

The paper is organized as follows. Section 2 reviews the literature that introduced a network approach of global valued chains and multinational firms. Section 3 presents the methodology used to reconstruct both GVC and MNE networks and the database used. In section 4, the structural evolution of each network is detailed. Section 5 presents the estimation strategy to estimate the networks' alignment, and its results. Finally section 6 concludes.

2 Networks analysis of Global Value Chains and Multinational Firms

2.1 GVC networks

Since the early 2000s, the overall world trade flows have repeatedly been studied as a network, spreading out of its initial field of econophysics (Serrano and Boguñá, 2003; Garlaschelli and Loffredo, 2005) to more conventional empirical literature on trade flows (Fagiolo et al., 2010; De Benedictis and Tajoli, 2011; De Benedictis et al., 2014; Kali and Reyes, 2007). These papers agree on the hierarchical structure of the World Trade Web (WTW), characterized by several network metrics, such as high clustering coefficient, a disassortative pattern, and a right-skew distribution of networks' connectivity indexes revealing a core-periphery structure.

Global value chains differ from global trade flows though. Since Hummels et al. (2001) the participation in GVCs is assessed by breaking down gross trade flows along original sources and final destination of value added. A first attempt of retracing GVCs' networks is therefore by focusing only in trade in intermediates. Using flows classified as trade of parts and components from BACI dataset, Ferrarini (2013) has been the first use network visualization tools to map "vertical trade" - an explicit reference to Hummels et al. (2001) concept of vertical specialization. Yet, an alternative methodology was rapidly adopted. Instead of using international classifications, further works relied on the increasing accessibility and coverage of international Input-Output (I-O) tables to capture more precisely trade in intermediate according to their final destination. Both Cerina et al. (2015) with the World Input-Output Database (WIOD) and Criscuolo and Timmis (2018) with the OECD Inter Country Input Output (ICIO) tables, developed this methodology at the country-sector level given in the I-O tables.

Yet progressively Daudin et al. (2011), Johnson and Noguera (2012) or Koopman et al. (2014) provide methodologies to decompose these I-O tables, and identify the foreign valued added content of a country's exports, and its detailed source. Because these flows corresponds even better to the intrinsic idea of GVCs, they recently have been studied through a network approach. Using the WIOD data, Xiao et al. (2017) divide the WTW into several flows following Koopman et al. (2014) decomposition, and details notably the network of Foreign Value Added (FVA). Also with the WIOD dataset, Amador and Cabral (2017) detail their own computation of bilateral Foreign Valued Added in exports and describe the decentralization trend from a binary network perspective from 1995 to 2011. The weighted analysis of their FVA network is detailed in Amador et al. (2018).

2.2 Multinationals networks

Despite their obvious web structure made of several plants in various countries, the networks of multinationals firms are certainly harder to capture. The confidentiality of such data can no longer justify the lack of formalization of network of multinationals, notably with the increasing availability of firm-level data, and notably public ones (e.g. Orbis data from Bureau Van Dijck). The true reason is probably the haziness of the nature of the flows behind such networks. Indeed, contrary to GVC networks, and to most empirical networks studied in the literature, the network of MNEs isn't directly defined by the flows running over its links. Such flows exist, but are of varied nature, and mostly made of private information, e.g: financial flows, technologies, goods, services, and even people transit on these edges. Yet, choosing one of these flows isn't required to define a network of multinationals. The plants are related because they belong to the same international group, no matter what kind of exchanges they realize. For our concern here - linking change in international trade in VA and global organization of firms - it is therefore sufficient to identify one firms' foreign plants, and link all hosting localization of a same firm. This has already been done at the city scale by geographers (Hussain et al., 2018; Ducruet et al., 2011; Rozenblat, 2015). At the country level (taking the host countries as the network nodes), it formally corresponds to the projection into the "country space" of the initial bipartite network made of each multinational firms and their Foreign Direct Investments destinations (see De Masi and Ricchiuti (2018b) for a detailed explanation of projection from bipartite graphs).

The examination of this network of the firms' FDI destination is somehow related to the vast literature on multinationals' location choices (see Alfaro and Chen (2017) for a recent survey), but allows to consider simultaneously all locations of a firm instead of focusing on isolated choices. This is far from being trivial because location choices of firms are largely interdepedent decisions: the set of existing foreign location of the firm necessarily influences the new ones. In traditional empirical estimations, firm-level fixed effects can be used to control for previous locations of the firm. Although they allows to reached unbiased estimates for FDI drivers, they act as black boxes, preventing precisely to study the pattern of interconnections among host countries. It is this pattern of pairs of countries jointly invested by Multinationals that this network reveals. De Masi et al. (2013) examined this network structure from Italian MNEs, Joyez (2017) used French firms and reveals the role of firms' heterogeneity into the network topology. De Masi and Ricchiuti (2018a) offer an extension to all UE28 countries, focusing on the propagation of risks created by the geographic diversification and intensification of such networks. All these works described the MNE network as a small-world network, that is highly clustered and hierarchical. Although this is a common point with the world trade web and GVC, the truth is that most of real-life networks exhibits such topology from the world wide web, to the airport hubs. This common point is insufficient to draw immediate conclusions. To look further at the networks structures' similarities, we reconstruct the two networks as detailed in the next section.

3 Data and network reconstruction

3.1 Global Value Chains networks

Following the recent developments in the GVC network literature reviewed in the previous section, and to fit closely to the initial idea of Hummels et al. (2001), we define the GVC network as the network of foreign valued added content of exports. These flows are particularly adapted to picture GVCs because unlike row intermediate trade flows, they capture the value added flows that cross at leas two borders. Yet, contrary to most of the existing works, we rely on the UNCTAD-Eora GVC database. Built on Eora multi regions I-O (MRIO) tables, the UNCTAD-Eora GVC provides a country-by-country matrix reporting, for each of the 190 exporting country, the value added contributed by all other expressed in thousands of current U.S. dollars, from 1990 to 2015. Its geographic coverage is far greater than the ones offered by the WIOD or the OECD-ICIO datasets, which respectively gather 40 and 63 countries[2]. This Eora-MRIO data have already been used to study centrality in GVC, notably by Antràs and De Gortari (2017). Our results are not likely to be driven by the estimates from the Eora dataset, or the foreign value added estimations, since we reach similar results when using the raw intermediate trade network from the OECD-ICIO dataset (see Appendix A for details). One particularity of all IO-derived measures, consists in the computation of both direct and indirect foreign valued added. Two countries are not direct trade partners can have some of each others' value added embedded in their exports, from their own imports. Because of this recursive computation, virtually all pairs countries are linked in these data. Yet, to clear the network picture we only focus on substantial GVC linkages. Marginal links below 100,000 current USD are removed[3]

Formally, for each year t we define the a weighted directed GVC network as $GVC_t = (C, E_t)$, formed by the set of nodes (countries) $C = \{i; i = 1, 2, ..., N\}$ and by the set of links E_t. It is fully characterized by its binary and weighted adjacency matrices of dimension NxN, defined

[2]For more information on the construction of Eora dataset and the necessary estimations in it, see Lenzen et al. (2012, 2013). The UNCTAD also provides comparison with OECD ICIO data at `http://worldmrio.com/unctadgvc/`

[3]The value of the threshold -from 0 to 10 millions of dollars actually doesn't substantially change the findings. Results from alternative thresholds are available on demand.

as follows. The binary adjacency matrix $A_t^G = [a_{ij,t}^G]$ with

$$a_{ij,t}^G = \begin{cases} 0 & \text{if } FVA_{ij} < 100 \text{ at year } t \\ 1 & \text{otherwise} \end{cases}$$

where FVA_{ij} is the foreign valued added from j into i's exports as reported in Eora. We set to zero all foreign value added contributions of less than 100,000 U.S. dollars, to remove the marginal linkages that are only driven by the the recursive computation of the FVA. The weighted adjacency matrix is $W_t^G = [w_{ij}]$ where

$$w_{ij,t}^G = \begin{cases} 0 & \text{if } a_{ij}^G = 0 \\ FVA_{ij} & \text{otherwise} \end{cases}$$

. While A_t^G is symmetric by construction, the weighted adjacency matrix W_t^G isn't so, and account fors the direction of value added flows. The bottom layer of figure 1 is an illustration of this network structure.

3.2 Multinationals' network of French foreign affiliates

Using any yearly wave of the firm-level survey *LiFi* (*INSEE*), we can easily identify a bipartite network made of two kinds of nodes: individual French firms (head of groups) and their respective host countries. Following closely the methodology detailed in Joyez (2017), we first draw the individual network of foreign location choices for each firm, and then compile them all to obtain the yearly network of foreign host countries of French multinationals, henceforth labeled the MNE network for simplicity. This is a weighted, non-directed network, in which the nodes are the host-countries (world countries hosting French foreign affiliates, except France), and the edges' weight indicate the number of French firms realizing the country pairing. Formally, each year t network is defined as $MNE_t = (C, F)$ where $C = \{i; i = 1, 2, .., N\}$ are the networks' nodes, and F_t describe the dyadic connections at time t. These connections are given by the binary and weighted adjacency matrices, the first one being $A_t^M = [a_{ij,t}^M]$ with

$$a_{ij,t}^M = \begin{cases} 0 & \text{if not any French MNE have simultaneously an affiliate in i and j at time t} \\ 1 & \text{otherwise} \end{cases}$$

The weighted adjacency matrix $W_t^M = [w_{ij,t}^M]$ reflects the number of French firms using any country pairing $\{i; j\}$ at time t. The network being undirected, $\forall\{i, j\},\ w_{ij,t} = w_{ji,t}$. The top layer of figure 1 illustrates this network.

3.3 Harmonizing networks

Each of the GVC and MNE networks are populated by the same type of nodes: countries. The former network details their tights in terms of trade in value added, and the latter details how often they are associated by French firms in their international expansion. Yet, to examine the structure and the co-evolution of the two networks they have to be made of the same set of countries. The GVC network dimension is constant over time, but with 190 countries, it is larger than the French MNE network that varies from 127 host countries (in 1996) to 169 host-countries (in 2011). To harmonize the networks' size, we had restrict them to the biggest set of common element, that is a sample of 108 countries that are always represented in the MNE and the GVC network[4]. The alternative option (enlarge smaller networks to fit the total coverage) is not satisfying, at it gives isolated nodes (countries that are not linked with any other ones), which prevents the computation of several network metrics. Yet, we have to keep in mind, that with 108 countries, the GVC network estimation is still far larger than the one used in previous studies using WIOD or ICIO datasets. Moreover, eliminated countries are necessarily peripheral countries in the MNE space (don't exist at all or temporarily), that is nodes that are unlikely to change radically the network structure, especially once weights are accounted. Once the two network sizes have been harmonized, we actually have built a "multiplex" or "multilayer" network (Kivelä et al., 2014), as depicted in the figure 1 below. The MNE and GVC networks can be seen as two layers -two different types of links- over a common set of countries C.

Our two networks being now defined as two layers over the same set of nodes, it becomes possible to study their correlation and co-evolution. Yet, a final change is required, to harmonize

[4]The list of all the 108 countries in the final networks is detailed in Appendix B.

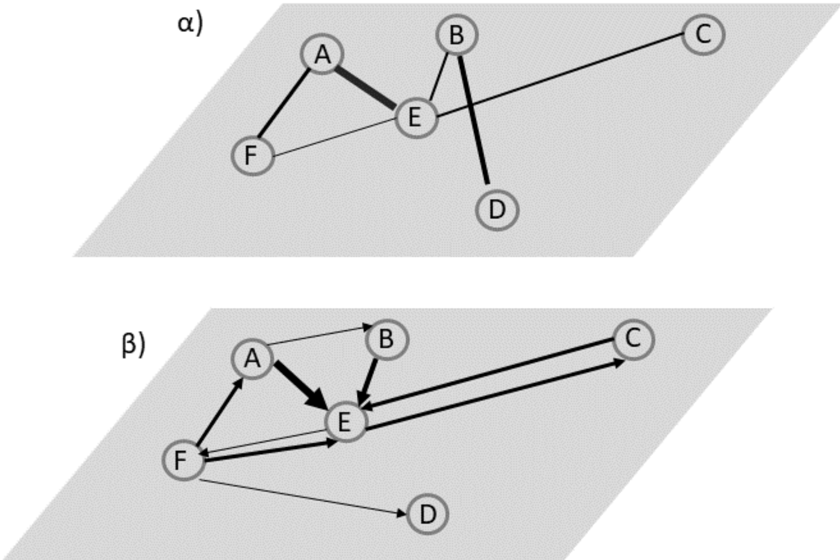


Figure 1: MNE and GVC networks as a multilayer network
Note: Nodes A to E represents the set of countries. The layer α) is undirected and illustrate the MNE network, the edges' size is proportional to the number of French firms located simultaneously in both countries. The layer β) is directed and illustrates the GVC network. The arrows represent the origin and the amount of foreign value added in exports.

the (un)directed dimension of the networks. When studying the role of GVC in determining the multiple location of foreign affiliates in two countries (from an undirected perspective), the direction of the GVC flows is irrelevant. We therefore make the GVC network undirected by summing the two bilateral arrows. This new edge indicates how much the two countries are linked into GVC, erasing the direction information. For our purposes, it is analytically similar than taking the mean of the two bilateral flows. Section 5.3 details a directed approach, and the building of a directed (sequential) MNE network to study the upstream or downstream direction of the alignment of the two networks.

4 Structural Evolution of the two networks

Before to focus on the co-evolution of the networks, it is instructive to see that the networks' structures have changed. This can be done by studying the evolution of the aggregate network metrics on connectivity and centralization. In line with previous works using WIOD data, we report a decentralization trend of the GVCs network and increasing cross-country connectivity (Cerina et al., 2015; Amador and Cabral, 2017; Amador et al., 2018). Interestingly, a similar pattern emerges from the MNE network evolution.

The most immediate metrics of connectivity is the network *density*, which reports the share of (non-null) edges over the possible number of edges. Let d_t^n be the density of the network $n = G, M$ at time t. Formally, $d_t^n = \frac{\sum_{i \neq j} \sum_{j \neq i} a_{ij,t}^n}{N(N-1)}$ where the $a_{ij,t}^n$ are the elements of the binary adjacency matrices of network n, and N its number of nodes.

The figure 2 reports the evolution of the density in the two networks. The GVC network shows a net increase in density especially since the early 2000s, implying that an increasing pairs of countries are linked through substantial value added linkages in GVC. The drop in 2009 shows how the great depression that followed the financial crisis diminished these linkages, but was rapidly recovered, although a ceiling seems reached since 2010, but this is possibly due to the high level of density that cannot increase much more. During the same period, the density of the MNE network grew even more than the GVC one, implying that a larger combination of countries have been done by French firms, denoting a diversification of internationalization pattern. The drop in 1998 is intriguing, and we have no explanation of it at this stage[5].

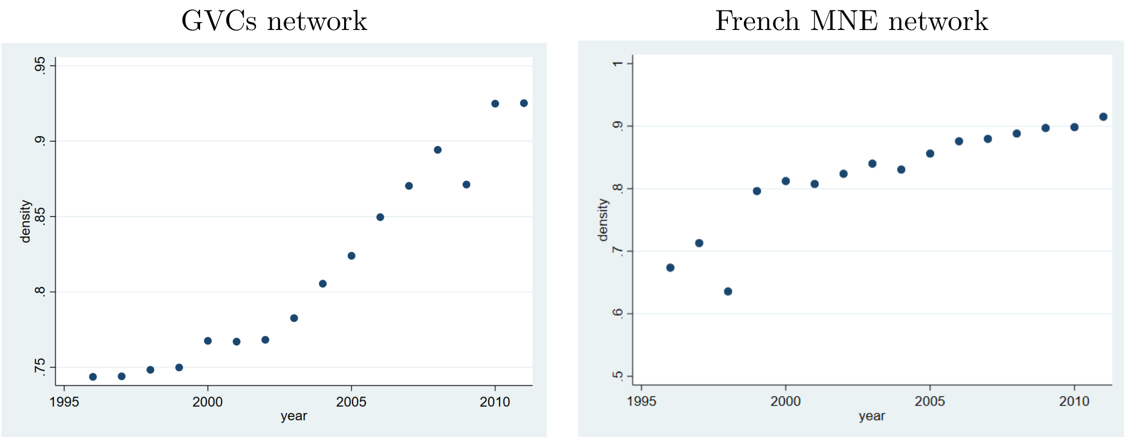


Figure 2: *Density* of networks 1996-2011

Yet, this index only partially reflects the evolution of the network connectivity because of its binary dimension. A weighted approach of the connectivity is accessible through the weighted overall clustering coefficient. The clustering coefficient reflects the tendency that two neighbors of one node are themselves directly connected, forming triangles. It is defined for each node i as $C_i = 2t_i/k_i(k_i - 1)$, where t_i is the number of triangles attached to the node, and k_i, the node

[5]More generally, the year 1998 is an outlier in several of our results concerning the MNE network. Although identifying why is a continuing question, these intriguing results are not sufficient to shift the global conclusions of this work.

degree, that is its number of neighbors $k_i = \sum_{j \neq i} a_{ij}$.

The weighted generalization of this basic index accounts for the breakdown of weights between the three edges as suggested by Onnela et al. (2005). Their index derives from the unweighted version, but replaces the number of triangles t_i with the sum of the triangles intensity.

$$\tilde{C}_i = \frac{2}{k_i(k_i-1)} \sum_{j,k} \left(\tilde{w}_{ij}\tilde{w}_{jk}\tilde{w}_{ki}\right)^{1/3}$$

Where $\tilde{w}_{ij} = w_{ij}/max(w_{ij})$ is a relative measure of the edges' weight. By construction this index reaches lower values than the unweighted version since $\tilde{C}_i \to C_i$ when the network becomes binary. The index equals one when all possible triangles are closed and equally weighted.

The figure 3 reports the evolution of this weighted clustering coefficient, which increased in the two types of networks especially since 2002. This increase in the clustering structure of the networks means that the edges of any triangle of nodes in the network are increasingly balanced, implying a better connectivity, and a lower centralization of the networks.

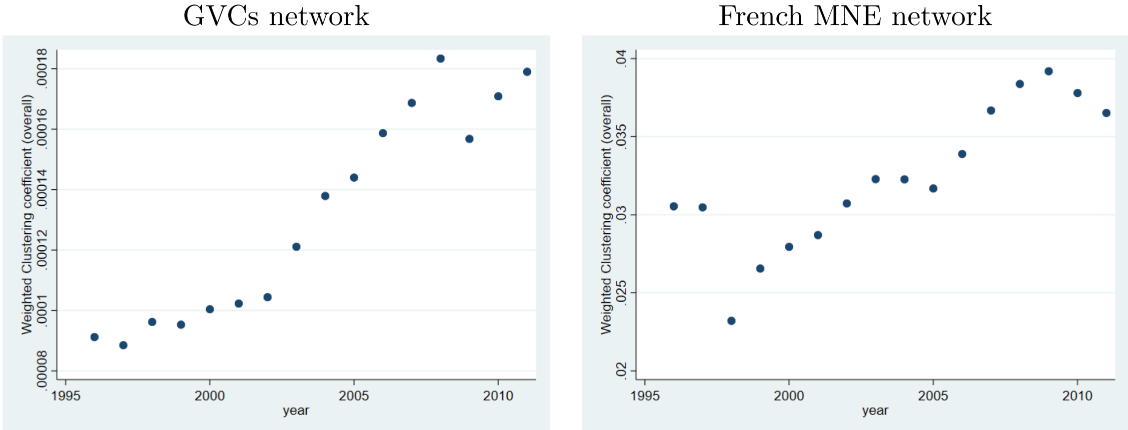


Figure 3: *Weighted clustering coefficient* of networks 1996-2011

The centralization of a network refers to the relative importance of few central nodes (cores) on the network. Traditionally, the centralization of a network is studied through the degree or the *strength* distribution. The strength is the weighted generalization of the degree index for each node, and is equal to the sum of the weights of all its edges. Formally, $s_i = \sum_j w_{ij}$. The more concentrated the degree or strength distribution, the more the network is centralized around a few number of central entities.

The figure 4 reports the inverse cumulative distribution functions (CDF) of the nodes' strength for each network in 1996 and 2011. The network of global value chains displays a largely unequal distribution of the nodes' strength, with a few numbers of nodes at the top of the distribution, i.e. largely linked with many others countries in terms of value added trade. The very long tail is made of all other countries that are far less connected to others. This is consistent with a core-periphery structure already reported in the foreign value added network (Amador et al., 2018), and more generally in the world trade web (Fagiolo et al., 2009). The pattern is less stressed in the case of the MNE network, but the convexity of the CDF also suggests a similar structure.

GVCs network | French MNE network

1996

2011

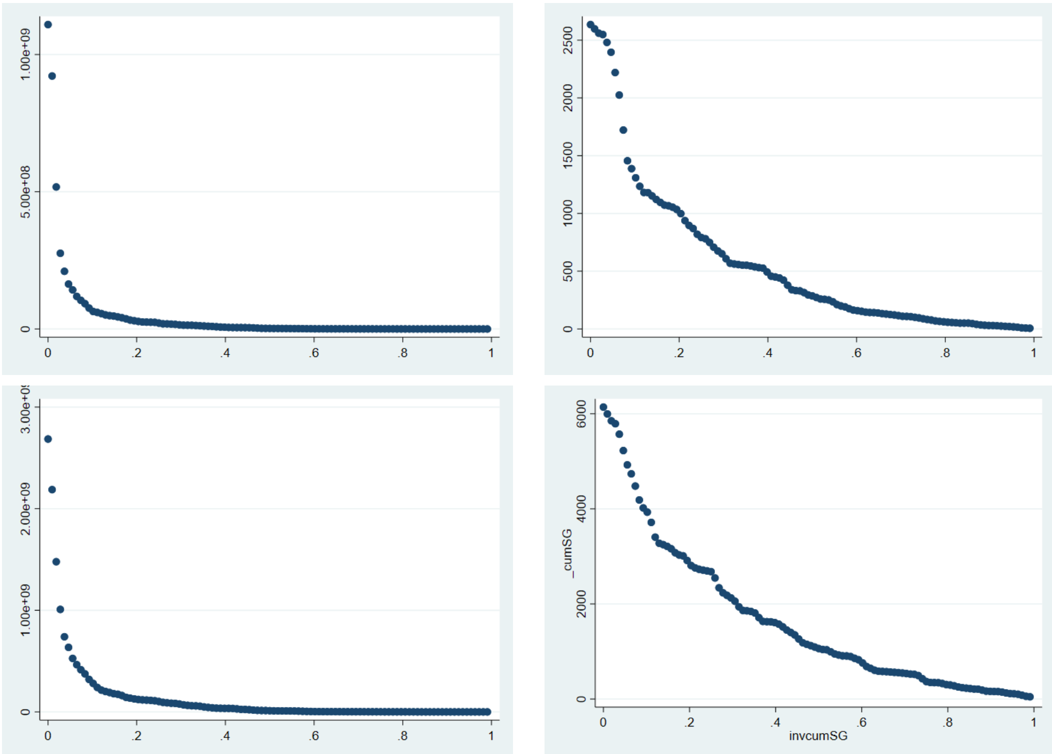


Figure 4: *Strength* Cumulative distribution function

One could notice a slightly smoother CDF for both networks' strength distribution in 2011 compared to 1996. To investigate more precisely the evolution of the strength's distribution, we report the kurtosis of the distribution from 1996 to 2011 for each network in figure 5. The Kurtosis of strength distribution is always positive in both networks, implying a right-skewed distribution, with a lot of nodes with low strength and few nodes with large strength. Yet, the two networks reflect an unambiguous trend toward a decrease in the strength kurtosis, confirming a re-balance of the nodes' strength, although the core-periphery structure is maintained, especially in the GVC network.

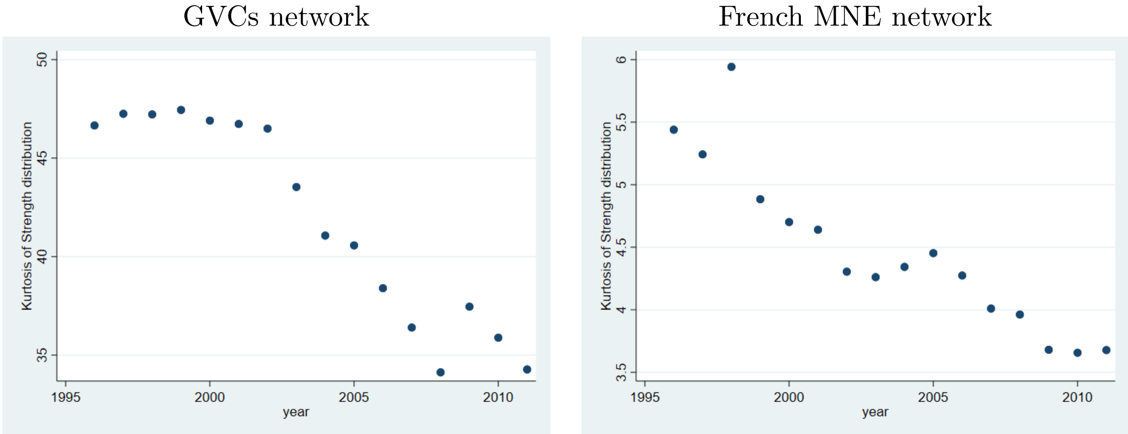


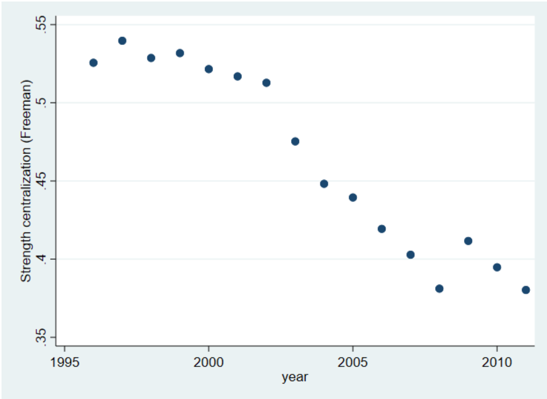
Figure 5: Kurtosis of Strength distribution of networks 1996-2011

This deconcentration of the strength distribution reveals a decentralization trend in the two networks structure, which is confirmed by a last index: the strength centralization index, a weighted generalization of Freeman (1979) centralization index, and formally defined as:

$$F_s = \frac{\sum_i^N [s_{i^*} - s_i]}{max \sum_i^N [s_{i^*} - s_i]}$$

Where $s_{i^*} = max(s_i)$, and $max \sum_i^N [s_{i^*} - s_i] = (\sum_i \sum_j w_{ij} - min(s_i))(n-1)$ is the maximum possible sum of differences in strength for a network of same dimensions (number of nodes and total weight). This centralization index have two valuable properties: it is bounded between zero and one, the higher implying the greater strength centralization. Also, this index equals the standard degree centralization index when the graph is binary. Its evolution (figure 6), is very similar to the drop in the kurtosis, and confirms a decreasing centralization of the valued network.

The several metrics describing the networks topology agree on revealing a structural change in the two networks structures, toward less centralized networks made of better and more equally connected nodes. Of course, a hierarchical structure still exists, with some nodes being more important than others. Yet, there is a clear trend in both networks toward more horizontal structure, where previously peripheral countries play a greater role in the world's production and contribution to global value chains. This actually isn't surprising but shows how the network



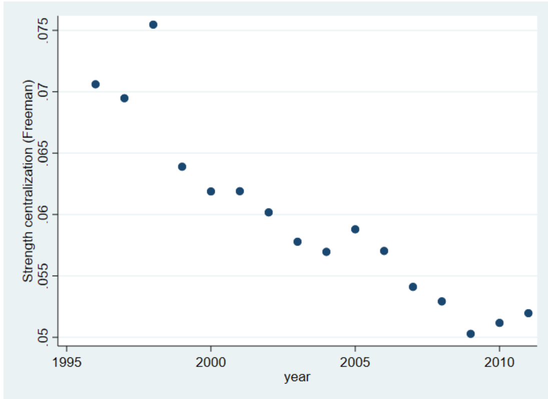


Figure 6: Strength centralization of networks 1996-2011

analysis is designed to capture the "great convergence" that accompanied recent globalization (Baldwin, 2016). Yet, these countries are also increasingly considered by French firms in organizing their global activities, and associated with others in a more diverse way. This co-movement of the two network structure is too striking not to see there some dynamics and influence from one structural change to another. The next section assesses such hypotheses.

5 Firm's alignment on GVCs

5.1 Quadratic Assignment Procedure

A popular methodology in network analysis to run regressions when both dependent and independent variables are relational matrices of same size, is the multiple regression Quadratic Assignment Procedure (MRQAP or simply QAP) as details Krackhardt (1988). The very concept of network structure is to assume that the nodes are not independent from each other, which violates the i.i.d assumption required for traditional OLS estimates. The MRQAP provides an alternative that preserves the network structure and compares the estimates of the model to the distribution of such statistics resulting from large numbers of simultaneous row/column permutation of the considered variables. This permutation method allows us to include multiple matrices in one analysis while accounting for structural autocorrelation that is inherent to social networks. The MRQAP used in this paper is therefore an OLS regression model, which incorporates relational variables and considers their inherent interdependencies when assessing their statistical relevance. Specifically, if the initial (positive) coefficient is superior to 99% of the coefficients estimated from the randomly permutated samples, it represents a significance level of 0.01. Table 1 reports two QAP estimations of the network alignment at the beginning and the end of the period. Formally, the model run is defined in equation (1) where $MNEnet_t = W_t^M$ corresponds to the overall structure of the French multinational's location over 108 countries in year t, and $GVCnet_{t-1} = W_{t-1}^G$ the network of Foreign VA in exports across the same 108 countries the year before that. This lag has a double purpose: first it aims at acknowledge the necessary time to build foreign plants. Second, it is design to control for reverse causality, i.e. the probability that it is these FDIs that create the global value chains[6]. Although there is an obvious simultaneous development between the global MNEs and GVC, we highly doubt that the development of only French affiliates we have in our sample could lead to such global value added flows. Because of the large values of GVCs' weights, it makes little sense to try to compute the marginal effect of an increase in GVC flows. Instead, We run the MRQAP using the log of GVCs edges' weights.

$$MNEnet_t = x_O + x_1 * ln(GVCnet_{t-1}) + \epsilon \tag{1}$$

Table 1: QAP estimations

	MNE net 1997	MNE net 2011
GVC net (log) 1996	2.457	
	(71.62)**	
GVC net (log) 2010		5.638
		(92.66)**
_cons	-12.512	-33.325
	(45.02)**	(0.43)**
R^2	0.31	0.43
N	11,556	11,556

* $p < 0.05$; ** $p < 0.01$

The results of the QAP estimation show a positive and highly significant influence of GVC on building MNEs' network dyads. Specifically, in 2010, doubling the foreign valued added between any two pairs of countries would have increased the number of French MNEs settled in both countries the following year by almost 6. Although this response might seem low, we

[6]Less than 3,000 french firms are identified as MNEs in our sample, averaging 3% of the world total.

have to keep in mind that opening of foreign affiliate is a long-term choice, and that only a few foreign affiliates are created each years compared to the existing stocks. The key results though is about the coefficient that has largely increased only 15 years, as it was only of 2.5 in 1996. The rise of the R-square, implies that the GVCs explain an increasing part of MNE location choices. To have a global view of its evolution, we repeated the estimation for each year, and report the coefficients and their 95% confidence interval in figure 7. The upward trend is clear and reveals two acceleration periods: the end of the 1990s and early 2000s, and since of 2009. The last point deserves particular attention, as we know the GVCs to have stabilized after the 2008 crisis. Yet, their influence, at least on location choices, haven't diminished, and are even greater despite GVCs being more stable.

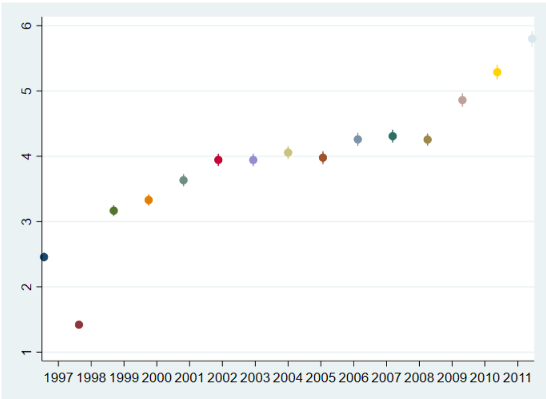


Figure 7: Evolution of the QAP coefficient 1997-2011

note: The figure reports the coefficients and its 95% confidence interval from the repetition of QAP models as reported in table 1.

5.2 Dyadic panel econometric estimations

The MRQAP though suffers limitation to account for dependent variables that aren't matrices. To include some control variables in order to confirm the preliminary results achieved by the QAP estimation we reshaped the network data into a dyadic panel, in which the unit of observation is any pairs of countries from the multilayer network of 108 countries defined above, with a time dimension being the year of observations. The inclusion of fixed effects and the use of robust standard errors should correct from the observations being non i.i.d. The dependent variable $MNE_{ij,t}$ is the number of French firms with an affiliate in both countries i and j at date t. Thus, we still are focusing on the interdependence of pluri-location choices. To estimate the role of global value chains in these, we use the value added linkages between the two countries the year before that $GVC_{ij,t-1}$, from the GVCs network. Yet, contrary to the QAP, in this traditional econometric estimation we can add control variables that don't necessarily share the network structure. In particular we use control variable derived from a gravity-like model that appear to hold in FDI location choices (Alfaro and Chen, 2017). Some explanatory variables are defined at the dyad level (bilateral distance, bilateral trade), while other are only set at the country-level (GDP, distance to France). A gravity approach of FDI location choice expects both bilateral distance and distance to France of each country to reduce the number of French firms using the dyad. To the contrary, each countries' GDP is expected to increase their attractivity for French firms. At last, we add the bilateral trade between the two destinations, to make sure the GVCs' channel doesn't only capture the fact that the two countries are trade partners. This should capture direct trade flows in final goods, and although it should also be positive, it is supposed to clear our variable of interest to truly reflect GVCs linkages. The data comes from CEPII *gravity* dataset, except bilateral trade data that comes from Correlates of War project[7]. Formally, we are estimating the model of equation (2) using an OLS, firstly without and then with dyadic and yearly fixed effects (removing the three distance variables from the estimation). All variables are log-transformed.

$$\begin{aligned} MNE_{ij,t} = a_0 + a_1 * GVC_{ij,t-1} + a_2 * Trade_{ij,t-1} + a_3 * Distance_{ij} + a_4 * GDP_{i,t-1} \\ +a_5 * GDP_{j,t-1} + a_6 * Dist_{FRA,i} + a_7 * Dist_{FRA,j} + \epsilon \end{aligned} \tag{2}$$

The result of this estimation is reported in table 2, and each variable shows high significance level and expected signs. More precisely, the bilateral distance between any two countries reduces the likelihood of being associated by French firms, as does a smaller GDP in one country, or their distance to French headquarters. Our dependent variable also shows the expected sign, with a positive and significant effect of the GVCs proximity between the pair of countries, even once controlled by bilateral global trade flows. These global trade flows appear twice as important as GVC proximity in estimations without fixed effects, but the GVCs ties appear more important once added the dyadic fixed effects in column (2). Column (3) and (4) repeated estimation of column (2) respectively for the 1997-2004 observations, and the one between 2005 and 2011, to

[7]Barbieri, Katherine and Omar M. G. Omar Keshk. 2016. Correlates of War Project Trade Data Set Codebook, Version 4.0. Online: http://correlatesofwar.org.

Table 2: Dyadic panel estimations

	(1)	(2)	(3)	(4)
	All	All	1997-2004	2005-2011
$\text{GVC}_{ij,t-1}$	0.028	0.007	0.043	0.076
	(18.05)**	(2.29)*	(21.35)**	(32.03)**
$\text{Trade}_{ij,t-1}$	0.068	0.015	0.074	0.077
	(52.15)**	(9.59)**	(41.11)**	(40.87)**
Distance_{ij}	-0.067			
	(12.70)**			
$\text{GDP}_{i,t-1}$	0.195	0.306	0.166	0.148
	(79.22)**	(27.23)**	(50.05)**	(40.19)**
$\text{GDP}_{j,t-1}$	0.175	0.317	0.146	0.145
	(72.77)**	(28.41)**	(43.51)**	(41.74)**
$\text{Dist}_{FRA,i}$	-0.121			
	(33.26)**			
$\text{Dist}_{FRA,j}$	-0.152			
	(37.00)**			
const	-5.109	-13.939	-6.746	-6.383
	(49.63)**	(64.40)**	(50.39)**	(43.79)**
R^2	0.54	0.52	0.47	0.55
N	79,928	79,928	42,436	37,492
dyad & yearly FE	No	Yes	Yes	Yes

* $p < 0.05$; ** $p < 0.01$

capture the evolution of the coefficient over time. Similarly to the QAP estimation, an increase in the GVC influence in shaping the MNE ties is noticed, with a stronger coefficient for the most recent sub-sample and a better global fit of the model with a between R-square of 0.55 in 2011.

To capture the yearly increase of the GVC influence, but still control for fixed effects we include interaction terms between yearly dummies and the GVCs coefficient in the model. The results reported in table 3 show an increasing influence of GVCs, whose yearly interacted coefficient increase over time, and quickly offsets the negative initial coefficient. These two results support the hypothesis of a progressive alignment of French MNEs over global value chains, even once controlled for other determinant of multi-location choices. An interesting feature of the interacted model result is the large increase of the GVCs influence in the last years observed, after 2009. Indeed, the global fragmentation of production has largely decreased its pace after 2009, leading to a smoother changes in GVCs structure as shows the evolution of the topology reported in section 4. Yet our result suggests that far from reducing the GVCs-implied changes of the economic environment, this stabilization of GVCs would have strengthen its enhancement power.

5.3 Upstream and Downstream alignment

After having documented this increasing alignment of MNEs along global value chains, an immediate question arises. Do the firms create new plants upstream of existing plants (closer to source of the VA) to control initial production steps, or downstream of them (closer to the final use of the good) to control subsequent production steps? To answer this question a slightly different network analysis is required, using a directed network of multinationals, in which the direction of the edge from node i to node j indicate the sequence of the firms internationalization. If two countries are targeted the same year by a firm, then the edge is reciprocate. As underlined in section 2, the GVCs network is initially undirected because the foreign content of exports isn't symmetric. Remind that each edge w^G_{ij} is equal to the value added from j embedded in country i exports, therefore an alignment of the sequential MNE network on the GVC one would characterize an upstream reorganization of firms, as going from i to j, they would go backward toward the source of the value added. To capture the downstream alignment of firms, we repeat the analysis using the transposed adjacency matrix of GVC, that reflects the reverse flow. Formally, each edge on the transposed GVC matrix can be expressed as $w^{G}_{ij}{}' = w^G_{ji}$, and reflects the VA from i into j's exports. Henceforth, an alignment between the MNE network and the transposed matrix of GVCs ($W^{G}_t{}'$), would imply that firms go follow the same path as value added, from source down to final destination. The new model to estimate becomes equation 3

$$
\begin{aligned}
MNE_{ij,t} = a_0 + a_1 * UpGVC_{ij,t-1} + a_2 * DownGVC_{ji,t-1} + a_3 * Trade_{ij,t-1} + a_4 * Distance_{ij} \\
+ a_5 * GDP_{i,t-1} + a_6 * GDP_{j,t-1} + a_7 * Dist_{FRA,i} + a_8 * Dist_{FRA,j} + \epsilon
\end{aligned} \tag{3}
$$

Where $UpGVC_{ij,t-1}$ corresponds to the value added from j embedded in i's exports, and captures the upstream alignment on GVCs of firms settling in j after i. Symmetrically, $DownGVC_{ji,t-1}$ captures the downstream alignment on GVCs.

The estimations on the whole panel without and with fixed effects confirm the co-existence

Table 3: Dyadic panel estimations

	$\text{MNE}_{ij,t}$
$\text{GVC}_{ij,t-1}$	-0.013
	(5.39)**
$\text{Trade}_{ij,t-1}$	0.009
	(6.19)**
$\text{GDP}_{i,t-1}$	0.123
	(10.08)**
$\text{GDP}_{j,t-1}$	0.153
	(11.57)**
d.1998*$\text{GVC}_{ij,t-1}$	-0.052
	(18.35)**
d.1999*$\text{GVC}_{ij,t-1}$	0.014
	(15.46)**
d.2000*$\text{GVC}_{ij,t-1}$	0.017
	(16.59)**
d.2001*$\text{GVC}_{ij,t-1}$	0.023
	(20.27)**
d.2002*$\text{GVC}_{ij,t-1}$	0.028
	(23.62)**
d.2003*$\text{GVC}_{ij,t-1}$	0.026
	(19.82)**
d.2004*$\text{GVC}_{ij,t-1}$	0.026
	(19.31)**
d.2005*$\text{GVC}_{ij,t-1}$	0.022
	(15.51)**
d.2006*$\text{GVC}_{ij,t-1}$	0.027
	(18.92)**
d.2007*$\text{GVC}_{ij,t-1}$	0.031
	(20.49)**
d.2008*$\text{GVC}_{ij,t-1}$	0.030
	(19.48)**
d.2009*$\text{GVC}_{ij,t-1}$	0.039
	(24.08)**
d.2010*$\text{GVC}_{ij,t-1}$	0.043
	(25.99)**
d.2011*$\text{GVC}_{ij,t-1}$	0.047
	(27.62)**
const	-5.663
	(50.33)**
R^2 (between)	0.52
N	79,928
dyad & yearly FE	Yes

* $p < 0.05$; ** $p < 0.01$

Table 4: Upstream and Downstream alignment estimations

	(1)	(2)	(3)	(4)
	All	All	1997-2004	2005-2011
$\text{UpGVC}_{ij,t-1}$	0.095	0.173	0.107	0.088
	(35.54)**	(18.24)**	(27.58)**	(25.27)**
$\text{DownGVC}_{ji,t-1}$	0.084	0.174	0.092	0.151
	(33.95)**	(57.34)**	(26.66)**	(46.17)**
L.lTrade	-0.003	0.011	-0.014	-0.012
	(1.66)	(4.97)**	(5.35)**	(5.73)**
Distance_{ij}	0.042			
	(9.49)**			
$\text{GDP}_{i,t-1}$	0.135	0.068	0.137	0.105
	(50.97)**	(5.73)**	(36.49)**	(30.38)**
$\text{GDP}_{j,t-1}$	0.089	0.141	0.084	0.038
	(33.78)**	(13.84)**	(22.33)**	(10.97)**
$\text{Dist}_{FRA,i}$	-0.166			
	(58.45)**			
$\text{Dist}_{FRA,j}$	-0.062			
	(20.41)**			
_cons	-4.354	-7.043	-5.950	-4.257
	(41.39)**	(26.06)**	(38.00)**	(29.19)**
R^2	0.47	0.34	0.41	0.48
N	94,084	94,084	44,772	49,312
dyad & yearly FE	No	Yes	Yes	Yes

* $p < 0.05$; ** $p < 0.01$

of both upstream and downstream alignment channels, with an overall similar effect of each, notably when controlling for country pairs fixed effects. Yet, the separate regressions on the two sub-samples show an opposite trend of each direction. The downward trend, that was less important in the initial period increases and becomes dominant in the most recent period. To the contrary, upward alignment of multinationals on GVCs decreases, although remaining positive and significant. This result is particularly interesting because it contradicts a common perception that links global value chains and international fragmentation of the production to outsourcing only. This result suggest that French firms increasingly go toward countries making subsequent stages of production in GVCs compared to their previous locations. To confirm this particularly interesting result, we run a similar interacted model than done with the undirected flows, to enable to see a yearly coefficient of both Upward and Downward alignment, to be interpreted

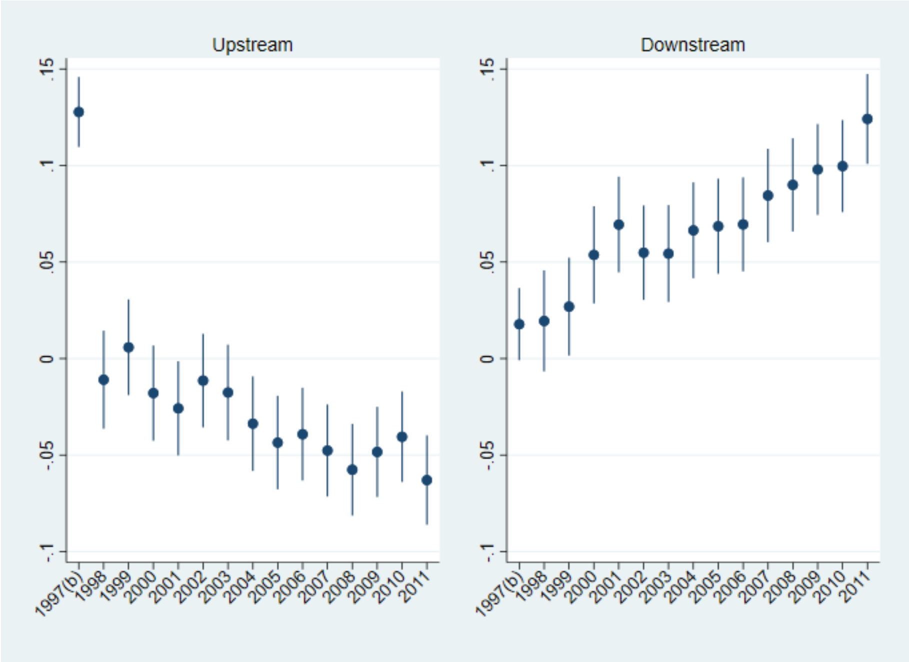


Figure 8: Upstream and Downstream interaction terms

as a yearly marginal effect compared to baseline level (of 1997). There are to many coefficients to be reported in a table, but figure 8 displays the yearly interacted coefficients of upstream and downstream alignment, and their 95% confidence interval. Each of these coefficients are significant at the 1% level

These results confirm the conclusion drawn from sub-sample analysis. with a stronger initial effect of upstream alignment in 1997 with respect to downstream trend. Yet, the upstream trend decreases each year, despite a small rebound after the 2008 crisis while the downstream channel increases at a stable pace.

6 Concluding remarks

In this paper, we develop a network based approach of Multinationals' geographical expansion using a French firm-level sample. The geographic network of French Multinational is a powerful mathematical tool to study their changing global location strategies. Specifically, the network highlights a decentralization trend toward a less hierarchical structure. We further link this deconcentration to the emergence of Global Value Chains. Following a flourishing literature, the GVC network is estimated through the foreign value added embedded from any country to any one else exports from international Input Output tables, and reflects the true international production networks. A study of the co-evolution of the two network dyadic structure through a Multiple Regression Quadratic Assignment Procedure shows that the MNEs follow more and more these cross-countries value added linkages when settling new subsidiaries abroad. French firms are more and more likely to open foreign affiliates in a country tightly connected to previous locations of firms in terms of value added flows.

Then, a directed network showing the sequence of internationalization steps of French firms allowed us to investigate whether this global reorganization of firms' affiliates all along the GVC is mainly drawn toward upstream or downstream stages of production. That is, whether the firms set up new plants in countries that control subsequent of previous production stages. Interestingly, this network analysis shows a sensitively equal downstream and upstream new location choices. The alignment on GVCs doesn't necessarily imply outsourcing strategies, but more generally longer control of production and distribution.

Despite these original results, the main limit of the paper resides in the fact that we don't show that MNEs goes in these countries to control an internationally fragmented production. Certainly such evidence would strengthen our point, but we are cautious enough not to draw this conclusion. We limit ourselves to underline the general synchronization of MNEs position with GVCs. Further extensions of this line of research should include a broader scope of MNEs. The examination of how upward or downward the firms reorganize should be investigated about the initial position of their domestic countries into GVCs.

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A ICIO data

Using the inter-country trade in intermediate from ICIO-OECD database to map the GVC leads to a drastic reduction of the size of the networks considered because of the smaller geographic coverage (54 countries). The following tables report the results from the undirected and directed QAP regression. The last figure reports the evolution of the upstream and downstream forces of reorganization.

Table 5: QAP estimations - Undirected

	MNE net (log) 1997	MNE net (log) 2011
ICIO net (log) 1996	5.212	
	(33.68)**	
ICIO net (log) 2010		10.778
		(39.84)**
_cons	-9.443	-26.062
	(24.95)**	(30.42)**
R^2	0.28	0.36
N	2,862	2,862

* $p < 0.05$; ** $p < 0.01$

These results confirm the synchronization of the two networks, as the more two countries trade in intermediate, the higher the probability that French firms goes into these two countries via FDIs. Moreover, this determinant increases over time, and offers a better prediction of multinationals' multiple location choices.

B List of countries included in the estimations.

countries marked with a O are also included in the ICIO OECD data.

Albania, Algeria, Andorra, Angola, Argentina^O, Australia^O, Austria^O, Bahamas, Bahrain, Bangladesh, Barbados, Belgium^O, Benin, Brazil^O, Bulgaria^O, Burkina Faso, Cambodia^O, Cameroon, Canada^O, Cayman Islands, Central African Republic, Chad, Chile^O, China^O, Colombia^O, Congo, Costa Rica^O, Cote d'Ivoire, Cyprus^O, Czech Republic^O, Denmark^O, Djibouti, Ecuador, Egypt, Estonia^O,Ethiopia, Fiji, Finland^O, Gabon, Gambia, Germany^O, Ghana, Greece^O, Guatemala, Guinea, Hungary^O, India^O, Indonesia, Iran, Ireland^O, Israel^O, Italy^O, Japan^O, Kenya, Korea (rep)^O, Kuwait, Lebanon, Liberia, Liechtenstein, Lithuania^O, Luxembourg^O, Madagascar,Malaysia^O, Mali, Mauritania, Mauritius, Mexico^O, Morocco^O, Mozambique, Myanmar, Netherlands^O, New Zealand^O, Niger, Nigeria, Norway^O, Pakistan, Panama, Paraguay, Peru^O, Philippines^O, Poland^O, Portugal^O, Russia^O, Saudi Arabia^O, Senegal, Serbia, Singapore^O, Slovenia^O, South Africa^O, Spain^O, Sweden^O, Switzerland^O, Taiwan^O, Tanzania, Thailand^O, Togo, Tunisia^O, Turkey^O, United Kingdom^O, United States of America^O, Uganda, Ukraine, Uruguay, Vanuatu, Venezuela, Viet Nam^O, Zambia, Zimbabwe,