Network Science (2025), **13**, e23, 1–18
doi:10.1017/nws.2025.10020

RESEARCH ARTICLE

Robustness with adaptation. Ownership networks of multinationals through COVID-19

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Abstract

We study how COVID-19 affected the ownership co-location network of French multinationals over 2012–2022. Using INSEE's LiFi, we build annual country-industry co-location networks and assess robustness via topology (density, centralization, assortativity, and clustering) and edge survival (Weighted Jaccard). We then test for post-shock shifts in the determinants of dyadic co-location with multiple regression quadratic assignment procedure. Three results emerge. First, the network's core is robust: topology shows no discontinuity and centrality persists. Second, adaptation is continuous at the margin: around one-third of edges rewire, concentrated in the periphery while core ties endure. Third, after 2020 the determinants of tie weights change, with a reduced role for gravity-like factors and greater cross-sector rebalancing. Thus the system is structurally robust with active peripheral adjustment. Rather than strict resilience in the sense of a return to the pre-COVID configuration, we observe durable strategic reweighting.

Keywords: COVID-19; multinational firms; networks similarity; ownership networks

1. Introduction

The COVID-19 pandemic and the public health measures it triggered caused an unprecedented disruption to the global economy in 2020. According to the World Bank, global GDP contracted by −2.9%, marking the deepest recession since World War II—twice the magnitude of the 2009 Great Financial Crisis (−1.4%). Yet, by 2021, the global economy had rebounded with a + 6.4% growth rate, suggesting an overall rapid recovery from this massive shock.

Globalization provided the background for this shock. Since the 1990s, production became internationally fragmented, the "third unbundling" (Baldwin et al., 2012), as advances in ICT and trade liberalization supported the rise of Global Value Chains (GVCs) and changed trade patterns (Grossman and Rossi-Hansberg, 2008; Brülhart, 2009). Although the pace of globalization slowed in the 2010s, its organizational form based on GVC specialization remained broadly stable up to the COVID-19 crisis (Antràs, 2020; Gaulier et al., 2020).

Multinational enterprises (MNEs) stand at the core of this architecture. They combine cross-border task specialization with hierarchical ownership. They also intermediate a large share of world trade, above 80% by 2010 (UNCTAD, 2011), and represent a major share of employment in advanced economies such as France (Insee, 2022). Recent evidence suggests that multinationals shifted activity toward domestic plants after COVID-19 and that this shift is persistent (Marette et al., 2025). Whether this rebalancing also appears in the structure of foreign affiliate networks remains an open question.

The international trade literature offers influential theories on global sourcing and the make-or-buy decision (Antràs and Helpman, 2004; Costinot et al., 2013; Antràs and Chor, 2013), but these frameworks usually abstract from the explicit network structure of MNEs. By contrast, business studies and economic geography have long emphasized multinationals as networks of dispersed yet coordinated entities (Johanson and Mattsson, 1987; Håkansson and Snehota, 1989; Ghoshal and Bartlett, 1990). A growing body of work in international economics applies network methods to FDI and ownership data (De Masi et al., 2013; De Masi and Ricchiuti, 2018; Bolívar et al., 2019; Spinelli et al., 2020; Smith et al., 2019; Amati et al., 2021; Joyez, 2017), motivating an explicitly relational analysis of firms' global footprints. In the same spirit, research on supply chain disruption has noted the need for a network perspective: Kim et al. (2015) show that relying only on firm-level or dyadic tools obscures system-level mechanisms, since failures at nodes or arcs do not necessarily produce network failure and resilience depends on global structure. Building on this argument, Hong et al. (2023) call for network-based measures of resilience. Guided by these insights, we adopt a network perspective and examine how the structure and the drivers of co-location within multinational ownership networks respond to disruption. This scope of analysis also aligns with internationalization frameworks: in the OLI and internalization paradigm (Dunning et al., 1992), cross-border scope and internal governance are revealed in affiliate ownership. Because simultaneous location choices for a multinational firms are not independent, a network approach is therefore directly relevant for studying how internationalization strategies withstand and adapt to shocks.

When examining the vulnerability to a shock, the risk management literature makes an important distinction between resilience and robustness in supply chains, as reminds notably Baldwin and Freeman (2022) and Miroudot (2020). Robustness is the ability to withstand the shock while it occurs, with limited degradation of structure or performance. Resilience consists in a restorative capacity, and is defined as the ability of organizations to recover from disruptions in a timely manner and return to normal operations. Because multinational ownership networks are the integrated part of supply chains, both properties are relevant in examining the vulnerability of the multinationals' networks to the pandemic.

We therefore ask two related questions: (i) did the COVID-19 shock alter French multinationals' internationalization strategies as revealed by their ownership co-location networks; and (ii) what do the observed patterns imply about network robustness and resilience of these strategies?

Empirically, we use INSEE's LiFi register to observe equity links between French parent firms and their foreign affiliates from 2012 to 2022 and construct annual country-industry co-location networks.

Our contribution is threefold. First, we provide a structural diagnosis of robustness by analyzing topological similarities in density, degree centralization, assortativity, and clustering for the French MNE co-location network before, during, and after COVID-19. Second, we use the Weighted Jaccard Similarity index to track edge stability, showing a roughly constant rate of network evolution and a clear distinction between core and periphery, with high instability among peripheral linkages. Third, we show that the drivers of co-location (for example, same-industry, geographic distance, and market-size covariates) shift after the shock using multiple regression quadratic assignment procedure (MRQAP) with permutation-based inference, with a reduced explanatory power of traditional determinants.

Overall, we find a robust network structure centered on the core, while documenting ongoing adaptation, especially around peripheral nodes, whose determinants have changed since COVID-19, indicating structural adjustment by multinational firms after 2020. This adaptability should not be interpreted as resilience in the strict sense, because it does not imply a return to pre-COVID operations.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Section 3 documents the stability of network topology, with emphasis on the core. Section 4 quantifies similarity over time for the network and its subnetworks. Section 5 examines changing structural determinants using QAP. Section 6 concludes and discusses the implications of a robust yet adaptive pattern in multinational networks.

2. Data and French multinationals' network reconstruction

Multinational firms can be conceptualized as networks of production units—plants or subsidiaries—spanning multiple countries and sectors. In Coase's foundational image, firms create "islands of conscious power" within a market "ocean" of decentralized transactions (Coase, 1937). Extending this vision, Ghoshal and Bartlett (1990) explicitly characterize multinational corporations as "inter-organizational networks embedded in broader external networks" of suppliers, customers, and institutional environments. The OECD similarly describes multinationals as "networks within (Global Value Chains) networks" (Cadestin et al., 2018).

To examine these corporate networks empirically, we use the *LiFi* database compiled by *INSEE*, the French National Statistical Institute. This survey exhaustively reports equity linkages between French corporate groups and their domestic or foreign affiliates. We focus exclusively on foreign affiliates to capture the international component of firm networks. Due to a methodological change in 2012—when LiFi began integrating information from the Outward Foreign Affiliates Statistics survey—we restrict our analysis to the 2012–2022 period.

For each French group (parent company), the LiFi dataset provides the NAF 2-digit industry code, along with country and industry identifiers for each affiliate. In 2012, the dataset recorded 9,817 multinational groups with 46,146 foreign affiliates operating across 2,064 unique country-industry pairs. By 2022, coverage had expanded to 18,905 groups and 62,450 affiliates in 2,420 pairs.[1]

To harmonize industry classifications and reduce dimensionality, we map NAF 2-digit codes to the 26-sector aggregation used in the Eora Multi-Region Input–Output framework.[2] Combining this with 189 countries, we define a fixed set of 4,914 possible country-sector nodes.

Each firm's annual network is constructed as a symmetric, binary adjacency matrix $\mathbf{F}_{i,t}$ of dimension $4,914 \times 4,914$, where:

$$F_{o,d} = \begin{cases} 1 & \text{if firm } i \text{ owns affiliates in both country-sector nodes } o \text{ and } d \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

Edges are undirected and reflect co-location of affiliates across nodes within a single firm. We then aggregate these firm-level matrices to construct a weighted, undirected network of French multinationals for each year t, summarized by an adjacency matrix $\mathbf{M}_t$, where:

$$M_{o,d} = \sum_{i=1}^{N_t} F_{o,d;i}$$

Here, $F_{o,d;i}$ is the $\{o, d\}$ element of firm i's matrix and N_t is the number of multinationals observed in year t. The resulting matrix $\mathbf{M}_t$ captures how frequently French MNEs co-locate in each pair of country-industries—providing a measure of network intensity at the system level.

Despite over 12 million possible node-pair combinations,[3] these networks are sparse: less than 2% of potential edges are activated in any given year—yet this still represents nearly 180,000 distinct edges annually. Most node-pairs are linked by only a single firm, and fewer than 10% of edges are shared by more than 10 firms.

For example, in 2012 the most common edge connected the wholesale trade sectors of Germany and Spain, used by 88 firms. In 2022, the most frequent connection was similar in magnitude, linking the same country-sectors for 97 firms. These patterns reflect both strategic complementarity in affiliate placement and structural concentration in multinational production networks.

To clarify how we construct the multinational co-location network, replace with Figure 1 displays a toy example that proceeds in three steps: the initial bipartite graph linking French parent

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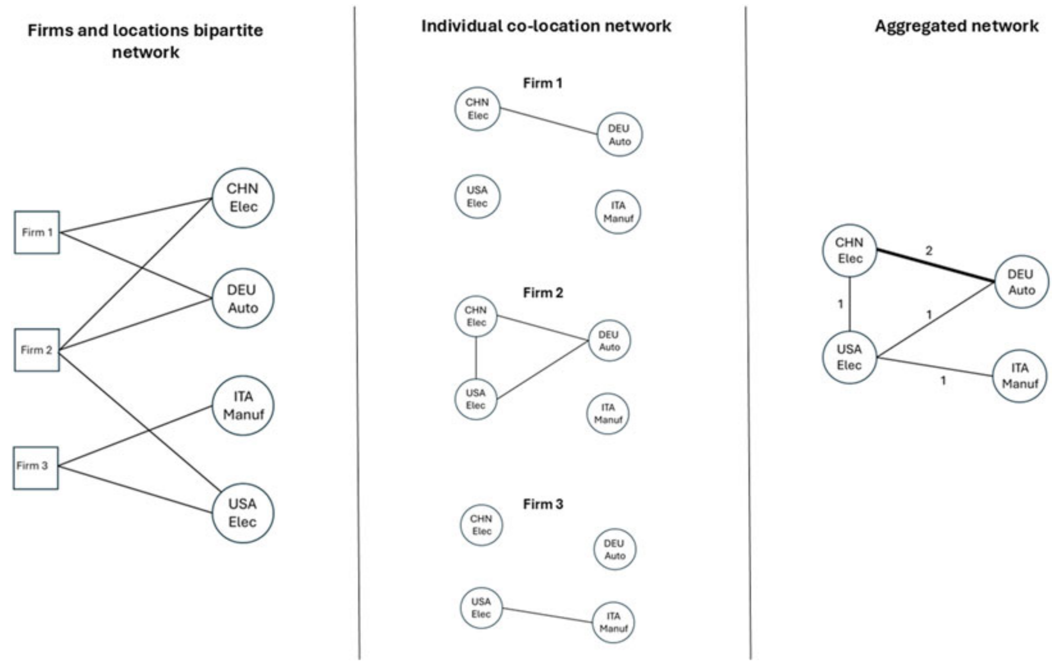

Figure 1. Illustrative example of network reconstruction.
Note: Left: bipartite network between French firms and foreign country–industry nodes. Middle: firm-level projection into the country–industry layer. Right: aggregated co-location network where edge weights count the number of firms co-locating in a pair of nodes.

firms to foreign country–industry cells (left panel); the projection of each firm's footprint into the country–industry space (middle panel); and the aggregated, weighted co-location network across all firms (right panel).

In the example, Firms 1 and 2 both operate in *China–Electronics* and *Germany–Automotive*. Their shared presence generates a weight of 2 on the *China–Electronics–Germany–Automotive* edge in the aggregated network.

We repeat this procedure for each year to obtain annual co-location networks. In the next section, we analyze them to characterize structural properties and their evolution over time.

3. A robust network during COVID-19

3.1 Network topology

We begin with aggregate topology over 2012–2022, tracking density, degree centralization, degree assortativity, and clustering. Taken together, these indicators summarize the architecture of the ownership co-location network before, during, and after the COVID-19 shock.

3.1.1 Network density

Network density measures the share of realized edges—i.e., country-industry pairs co-occupied by at least one French MNE—relative to the total number of possible node pairs. As in many large real-world networks, our network is sparse: only about 1.5% of the 12 million possible node pairs are realized in any given year. This reflects the economic irrelevance or impracticality of most potential country-industry combinations.

Nevertheless, in Figure 2 we observe a substantial increase in density between 2012 and 2017—from 1.04% to 1.78% confirming the broadening of internationalization strategies by French MNEs, that is now well documented (Joyez, 2017; de Warren, 2020, e.g.). After a slight decline,

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Figure 2. Density of the French multinational network (2012–2022).

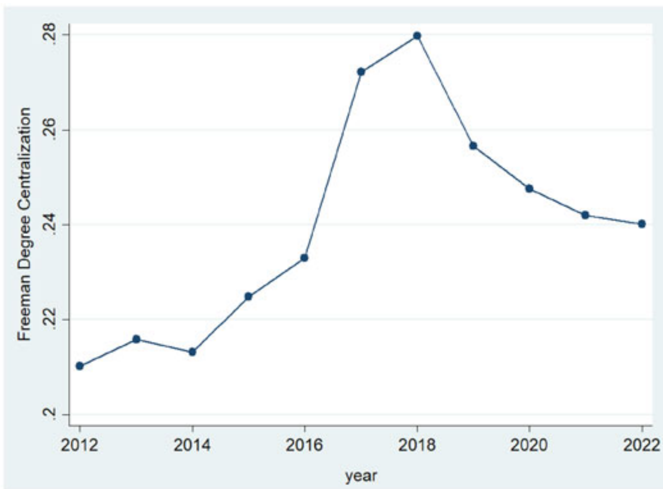

Figure 3. Degree centralization of the French multinational network (2012–2022).

the network stabilizes at a post-2017 density slightly above 1.6%. Crucially, the pandemic period (2020–2022) is not associated with any abrupt change in density, suggesting a high level of structural continuity.

3.1.2 Degree centralization

Centralization quantifies the extent to which a network is organized around a small number of highly connected nodes. Following Freeman (1979), we compute the degree centralization index, which ranges from 0 (uniform distribution of degrees) to 1 (star-like concentration). As shown in Figure 3, centralization increased modestly from 0.21 in 2012 to 0.279 in 2018—an approximate 33% rise—before stabilizing and slightly declining post-2018. Once again, we find no significant structural break associated with the COVID-19 crisis.

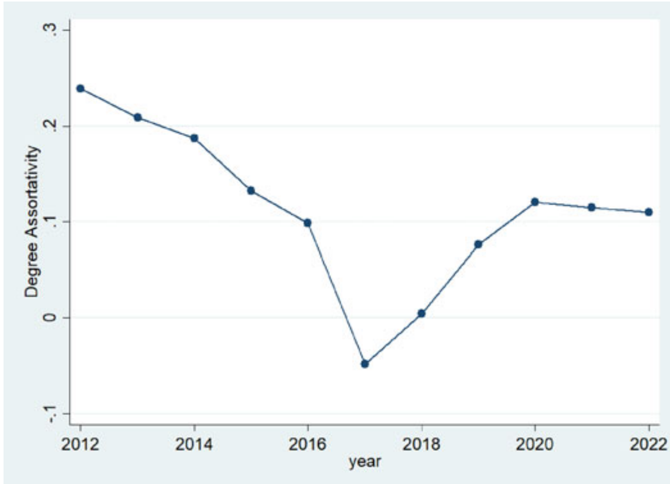

Figure 4. Degree assortativity of the French multinational network (2012–2022).

3.1.3 Degree assortativity

Assortativity measures the tendency of nodes to connect with others of similar degree. Defined as the Pearson correlation coefficient between the degrees of linked node pairs (Newman, 2002), its values range from -1 (disassortative mixing) to $+1$ (perfect assortativity). Figure 4 shows that the French MNE network is generally assortative: central nodes tend to connect with other central nodes. Between 2012 and 2017,[4] assortativity declined—consistent with firms integrating more peripheral nodes into their networks. This trend reverses slightly after 2017, suggesting a consolidation or return to more clustered network cores. Notably, no sharp discontinuity appears in 2020, 2021 or 2022.

3.1.4 Clustering

While each firm-level network is fully transitive by construction; if a firm operates in three nodes, all three node pairs are linked; this property does not carry over to the aggregate. When multiple firms overlap on different node pairs, the resulting triads can be unevenly weighted. To assess this, we compute the weighted global clustering coefficient following Fagiolo (2007), which incorporates the distribution of edge weights within triads.

Figure 5 shows a low but stable level of weighted clustering over the entire period, with no abnormal shifts in 2020–2022. This pattern is consistent with overall structural stability during the pandemic.

Overall, the evidence points to a remarkably robust structure of French multinationals' ownership networks during COVID-19. While these networks do evolve gradually, the pandemic did not trigger a significant reconfiguration of connectivity, hierarchy, or clustering. Moreover, the movements in these indices in 2020–2021 are comparable to the typical year-to-year variation observed throughout the 2010s, rather than indicating a break.

3.2 A stable core

Although the aggregate structure of multinational networks remains stable through the COVID-19 period, assessing the persistence of the most central nodes and edges is essential. Structural robustness entails not only steady global topology but also continuity in the composition of the network's key components.

Following Opsahl et al. (2010), we measure node centrality as the geometric mean of a node's degree k_i (number of connections) and strength s_i (sum of incident edge weights). This metric

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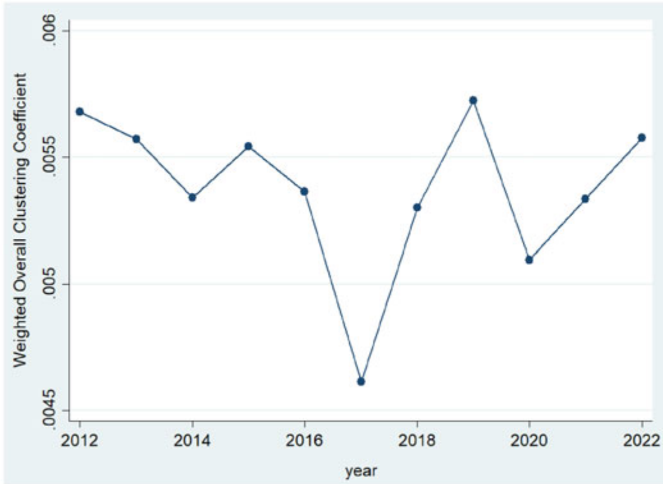

Figure 5. Weighted clustering coefficient of multinationals' network over time.

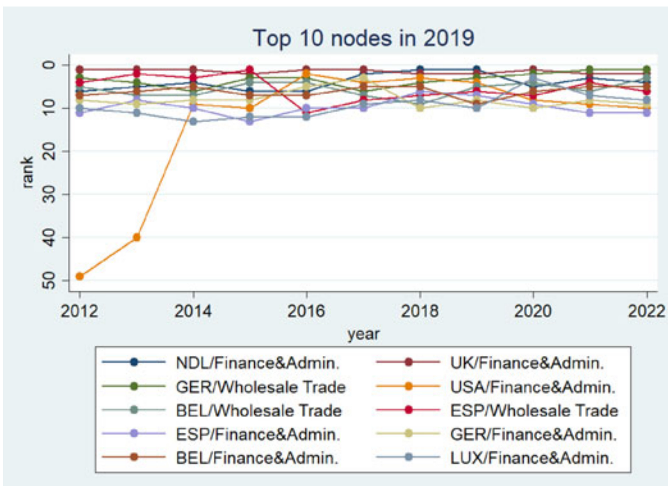

Figure 6. Central nodes stability.

captures both the breadth and intensity of a node's ties, giving higher scores to nodes that are simultaneously well connected and influential:

$$\mathrm{cent}_i = k_i^{0.5} \cdot s_i^{0.5} \tag{1}$$

We compute this centrality index annually and select the ten most central nodes in 2019, the last pre-pandemic year. Figure 6 traces their ranks over 2012–2022. Two patterns emerge. First, composition is highly persistent: eight of the 2019 top ten were already in the top ten in 2012 and remain there throughout the decade. Second, central nodes are geographically concentrated in neighboring European countries and sectorally concentrated in two industries, Wholesale Trade and Financial and Business Services.

This persistence suggests that the structural core of the French multinational network remained unaffected by the COVID-19 shock. To quantify this stability across the full distribution of nodes, we estimate an autoregressive model of centrality scores:

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Table 1. Centrality autoregression

	$cent_{2013}$	$cent_{2014}$	$cent_{2015}$	$cent_{2016}$	$cent_{2017}$	$cent_{2018}$	$cent_{2019}$	$cent_{2020}$	$cent_{2021}$	$cent_{2022}$
cent-1	1.089	1.016	1.134	0.972	1.218	0.956	0.883	0.952	0.937	0.934
	(318.25)***	(316.48)***	(397.48)***	(384.88)***	(281.38)***	(417.19)***	(303.71)***	(344.60)***	(271.89)***	(265.00)***
constant	31.123	0.945	2.926	1.457	0.268	4.038	4.860	2.252	6.390	6.120
	(5.73)***	(1.65)*	(4.15)***	(2.67)***	(0.29)	(6.62)***	(6.45)***	(3.45)***	(8.08)***	(7.85)***
R^2	0.95	0.95	0.95	0.97	0.94	0.97	0.95	0.96	0.94	0.94
Nb. Obs.	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914

t-stats in parenthesis, ***,** and * respectively indicate significance at 1,5 and 10%.

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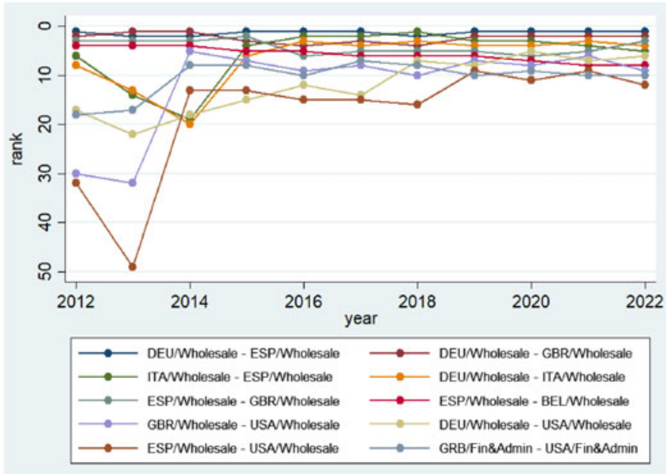

Figure 7. Main edges stability.

$$\text{cent}_{i,t} = \beta_0 + \beta_1\, \text{cent}_{i,t-1}$$

Table 1 reports OLS estimates of this model over the 2013–2022 period. The results confirm a very high degree of persistence in node centrality, with β_1 coefficients consistently close to or above 0.9 and R^2 values near 0.95. Although a mild downward trend in the autoregressive coefficient is observed after 2017, no discontinuity is visible in 2020 or 2022, reinforcing the impression of structural robustness.

Building on the node-centrality results, we ask whether the most intensively used edges—that is, the most common country-industry pairings—also remained stable during the COVID-19 period. Even if central nodes are unchanged, the network's internal organization could be reshaped through the rewiring of connections.

We identify the ten most frequent edges in 2019 and track their ranks over 2012–2022 (Figure 7). These edges are somewhat more volatile than the top nodes: about half do not remain continuously in the top ten. Nevertheless, the five most central edges are remarkably persistent. They typically connect the central nodes identified earlier, which is consistent with the positive assortativity documented in Section 4; when not linking leading European nodes among themselves, they commonly tie those nodes to major industries in the United States. The composition of top edges in 2019 is also very close to that in 2021,[5] underscoring the durability of key linkages. This pattern aligns with prior evidence on geographic homophily and the intensification of trade networks (Zhou, 2011, 2013), as well as with gravity-model findings for international investment (Kleinert and Toubal, 2010).

Despite the stability of major nodes and edges during COVID-19, robustness is not uniform across the network. We define the core as the top 5% of nodes by centrality in 2019. This set comprises 105 nodes out of 2,304 and accounts for more than 72% of total centrality, a share that remains stable over the sample period and is consistent with the Freeman centralization results. Rank dynamics also differ sharply across tiers. For the 105 core nodes, the standard deviation of rank between 2012 and 2022 is only 22.6, driven largely by the rise of China. By contrast, peripheral nodes exhibit much greater volatility, with a standard deviation exceeding 460.2. This contrast indicates a concentrated, persistent backbone alongside a highly fluid periphery.

In the next section, we further examine the similarity and changes over the complete network, and not only the core nodes.

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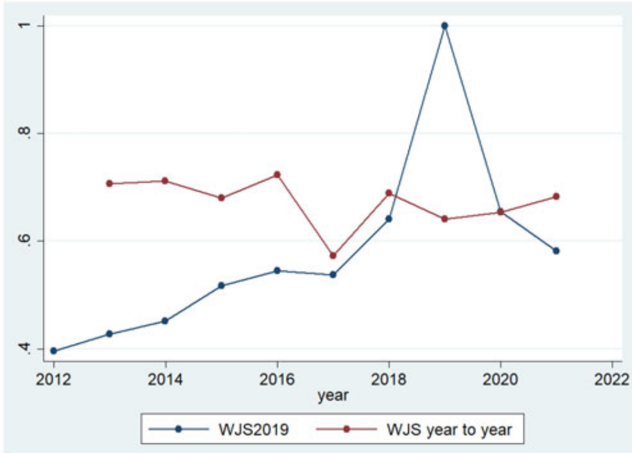

Figure 8. Weighted Jaccard similarity index: Year-to-year and with respect to 2019.

4. An adaptive network

4.1 Weighted Jaccard similarity index

To gauge the stability of network edges over time, we use the Jaccard Similarity Index (Jaccard, 1901), defined as the ratio of the intersection to the union of two sets. While the original index applies to binary data, extensions to weighted networks are essential for our setting, where edge weights reflect the frequency of co-location across firms.

Following Ružička (1958), we adopt the weighted Jaccard similarity. Let $\mathbf{M}t = (m1, t, \ldots, m_{n,t})$ and $\mathbf{M}t' = (m1, t', \ldots, m_{n,t'})$ denote the edge-weight vectors of the multinational network in years t and t', with each vector rescaled to lie in $[0, 1]$. The weighted Jaccard index is

$$WJS(t, t') = \frac{\sum_{i=1}^{n} \min(m_{i,t}, m_{i,t'})}{\sum_{i=1}^{n} \max(m_{i,t}, m_{i,t'})}$$

A value of $WJS = 1$ indicates identical edge weights across the two networks, while $WJS = 0$ implies complete dissimilarity, with non-overlapping edge activations. This generalization naturally reduces to the standard Jaccard index when all values are binary.

Figure 8 presents the evolution of similarity in French multinational network structures across time, using the weighted Jaccard index. We report both year-to-year changes and the distance of each yearly network from 2019—the last full pre-COVID year.

Overall, year-to-year similarity is high and stable over time, with no discontinuity in 2020. However, we find a roughly 30% rebalancing of edges each year, which is substantial, particularly for a network whose topological indicators remain stable. The architecture does not stand still: core metrics mask significant micro-level turnover, so the network cannot be described as identical from one year to the next.

These results are not inconsistent: substantial edge turnover can coexist with structural robustness. Following the logic of Granovetter (1973), small adjustments to critical bridges can reshape topology, whereas extensive churn among redundant links may leave the global structure largely unchanged. Given the stability of the core, most rewiring is likely concentrated at the periphery. Having established a stable backbone alongside nontrivial churn, we now test whether the determinants of edge weights have changed, which would signal shifts in firms' FDI and co-location

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Table 2. Quadratic assignment procedure

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
$\ln(\mathbf{M}_{ij,t-1})$	4.9832	4.6604	4.9687	5.0562	4.0719	5.1620	4.2903	4.6724	2.2073	2.1200
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***

MRQAP with classic node-label permutations ($R = 5{,}000$); valued, undirected symmetric network; upper triangle only (diagonal excluded). *p*-values in parentheses; ***, **, and * denote 1%, 5%, and 10% significance.

strategies. To this end, we estimate the drivers of edge weights to assess whether the post-2020 co-location pattern reflects a reweighting of the decision rules that generate ties.

5. Evolution of co-location strategies

Since conventional regression methods such as OLS are not well-suited for dyadic network data due to the violation of the independence assumption inherent in such models (Krackhardt, 1988). The interconnected nature of network structures introduces dependencies that invalidate standard inferential procedures.

To address this limitation, several statistical approaches have been developed for relational data. Among these, the quadratic assignment procedure (QAP) is particularly appropriate for our case, as it accommodates continuous-valued networks where edge weights represent the frequency of co-location. While exponential random graph models are better suited to binary or categorical outcomes, QAP provides a robust framework for linear models involving dyadic data (Dekker et al., 2007).

The QAP involves a permutation-based significance test that retains the inherent interdependence of network observations by permuting rows and columns of the adjacency matrix simultaneously (Krackardt, 1987). Extending this, the MRQAP estimates linear models for network data and tests coefficients via random (or node-label) permutations. We begin by estimating a simple autoregressive model to evaluate the persistence of edge weights across time, using unconstrained permutations:

$$\ln(\mathbf{M}_{ij,t}) = \beta_0 + \beta_1 \ln(\mathbf{M}_{ij,t-1}) + \epsilon_{ij} \tag{2}$$

All variables are log-transformed to reduce the skewness and concentration in the distribution of edge weights. As shown by Dekker et al. (2007), log transformations enhance MRQAP's performance, particularly in networks with count-based or highly concentrated edge weights.

Beyond temporal dependence, we also explore whether other structural determinants—especially gravity-related variables—affect the network's evolution. Inspired by gravity models of trade and investment (Kleinert and Toubal, 2010), we extend the model to include bilateral distance and GDP-based variables:

- $\mathbf{Dist}_{ij}$: Bilateral geographic distance between host countries i and j, sourced from the CEPII Gravity dataset (Conte et al., 2022). - $\mathbf{SumGDP}_{ij,t-1}$: Sum of the GDP of countries i and j in year $t-1$. - $\mathbf{absdiffGDP}_{ij,t-1}$: Absolute GDP difference between the two countries. - $\mathbf{SameIndus}_{ij,t}$: Dummy variable equal to 1 if the edge links two subsidiaries in the same industry.

This extended model is expressed as:

$$\begin{aligned}\ln(\mathbf{M}_{ij,t}) = \beta_0 + \beta_1 \ln(\mathbf{M}_{ij,t-1}) + \beta_2 \ln(\mathbf{Dist}_{ij}) + \beta_3 \ln(\mathbf{SumGDP}_{ij,t-1}) \\ + \beta_4 \ln(\mathbf{absdiffGDP}_{ij,t-1}) + \beta_5 \ln(\mathbf{SameIndus}_{ij,t}) + \epsilon_{ij}\end{aligned} \tag{3}$$

Specifically, to estimate this relationship, we implement MRQAP with 5,000 node-label permutations suited to valued, undirected, symmetric matrices, restricting estimation to the upper triangle (diagonal excluded). The edge weights enter as $log(w_{ij} + 1)$.[6]

The estimation results for both models are reported in Tables 2 and 3.

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Table 3. Quadratic assignment procedure

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
ln ($\mathbf{M}_{ij,t-1}$)	4.802	4.5086	4.8278	4.8740	4.0450	5.0601	4.1227	4.5210	2.8540	2.7000
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
ln ($\mathbf{Dist}_{ij}$)	−0.1396	−0.1260	−0.1631	−0.1267	−0.1806	−0.1315	−0.1424	−0.1208	−0.1190	−0.1070
	(0.15)	(0.18)	(0.03)**	(0.13)	(0.00)***	(0.01)***	(0.01)***	(0.11)	(0.36)	(0.42)
ln ($\mathbf{SameIndus}_{ij,t}$)	0.7857	0.4452	0.4021	0.6207	0.0238	1.1000	1.2893	0.8291	−1.6790	−1.5500
	(0.00)***	(0.01)**	(0.02)**	(0.00)***	(0.97)	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
ln ($\mathbf{absdiffGDP}_{ij,t-1}$)	−0.1148	−0.0878	−0.1387	−0.1505	−0.1718	−0.1107	−0.1496	−0.1245	−0.0663	−0.0610
	(0.14)	(0.20)	(0.03)**	(0.03)**	(0.00)***	(0.08)*	(0.00)***	(0.05)*	(0.47)	(0.52)
ln ($\mathbf{SumGDP}_{ij,t-1}$)	0.3426	0.2936	0.38109	0.0363	0.3828	0.2432	0.4080	0.3113	0.1418	0.1320
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.32)	(0.35)

MRQAP with classic node-label permutations ($R = 5{,}000$); valued, undirected symmetric network; upper triangle only (diagonal excluded). p-values in parentheses; ***, **, and * denote 1%, 5%, and 10% significance.

Both specifications consistently confirm the persistence of edge weights over time. The autoregressive coefficient β_1 is positive and highly significant throughout the period, indicating that the frequency with which firms co-locate in particular country-industry pairs is strongly path-dependent. However, this persistence weakens in 2021 and 2022, where the coefficient value drops by roughly half, suggesting a partial break in historical co-location patterns following the COVID-19 crisis.

The extended model offers further insight. While the influence of bilateral distance remains negative—consistent with gravity theory—its statistical significance sharply declines after 2020. The GDP-related variables, which were highly significant in earlier years (with a positive effect from total GDP and a negative effect from GDP disparity), lose significance and diminish in magnitude after 2020. This suggests a departure from previous co-location strategies, in which firms preferred pairing large and economically similar countries.

After the COVID shock, these economic fundamentals appear to have lost their explanatory power. Notably, the variable $\mathbf{SameIndus}_{ij,t}$, typically associated with a tendency to cluster activity within the same industry—also shows a marked change: while it was positive and significant in earlier years, it turns negative in 2021 and 2022. This may reflect a shift in strategic orientation, with MNEs reallocating activity across industries rather than reinforcing existing sectoral specialization.

These results point to a strategic reconfiguration of the French multinational network after COVID-19. Earlier sections documented stable core structures—density, centralization, and persistence of top nodes—yet the MRQAP evidence shows that the determinants of tie formation at the margin have shifted. Post-2020 patterns depart from the gravity-driven architecture that characterized co-location choices in the preceding decade.

In short, the pandemic did not unsettle the core topology of multinational production networks, but it changed the logic of marginal expansion: where and how firms extend or reweight their international footprint. This underscores the value of combining structural diagnostics with dyadic modeling to capture both the stability of the backbone and the evolution of decision rules that shape new or reweighted ties.

6. Conclusion

Multinational enterprises have become pivotal actors in the world economy over the past three decades, mediating a dominant share of cross-border trade, investment, and knowledge diffusion, and shaping employment and productivity at home and abroad. Because their footprints influence both global adjustment and national development paths, understanding how their strategies change in response to large shocks is of first-order importance. Ownership co-location networks are the appropriate lens here because they observe firms' simultaneous location choices across countries and industries, thereby mapping the entire internationalization strategy rather than isolated moves or short-lived flows. This paper studies how the COVID-19 shock affected the ownership co-location structures of French multinationals over 2012 to 2022. Using INSEE's LiFi, we reconstruct annual country-industry co-location networks and combine topology diagnostics, edge survival based on the Weighted Jaccard index, and permutation-based MRQAP to assess structural continuity and shifts in the determinants of dyadic co-location.

Three results organize the evidence. First, the network core is stable. Standard topology shows no discontinuity through the pandemic period, and centrality autoregressions confirm persistence of core nodes. This joint stability explains the invariance of density, degree centralization, assortativity, and clustering and indicates that the backbone of French multinationals' foreign presence remained intact. Second, the system adapts continuously at the margin. Weighted Jaccard measures reveal a sustained rewiring rate of roughly one third of edges, with churn concentrated in the periphery while core ties survive at much higher rates. This pattern reconciles unchanged global topology with observable micro-level turnover: a stable architecture can coexist with significant edge replacement outside the core. Third, the drivers of co-location shift after 2020. MRQAP estimates point to a reduced role for gravity-like covariates such as distance, market size, and income similarity, alongside greater cross-sector rebalancing. The post-2020 coefficients therefore suggest a change in the decision rules that allocate activity across country-industry cells, not merely random noise. Taken together, the network is robust, especially at its core, yet constantly adaptive at the periphery where firms reweight and replace ties. It does not meet a resilience criterion understood as a return to the pre-COVID configuration; instead we observe a new pattern of adaptation around a persistent backbone.

These findings speak to the nature of multinational strategies rather than prescribing them. The permanence of core nodes and ties indicates that equity-based international footprints are long lasting at the center of the network. At the same time, the concentration of churn in peripheral ties and the shift in estimated determinants after 2020 are consistent with firms using the periphery as an adjustment margin to rebalance portfolios across related industries and locations without dismantling the core. In this sense, the observed adaptation reflects strategic reweighting within a stable ownership architecture rather than a temporary deviation followed by a full return to the pre-pandemic configuration.

The study is descriptive on structure and explanatory on mechanism shifts; it does not identify causal effects on performance or risk. Future work could link co-location adjustments to outcomes using event studies around policy or logistics shocks, shift-share strategies based on exogenous demand or cost shifters, or difference-in-differences designs with credible comparison groups. Cross-country comparisons would help assess whether the French pattern generalizes to economies with different sectoral mixes or degrees of integration into global value chains. Continued monitoring will clarify whether the current stability of the core is a persistent feature or a precursor to slower-moving structural change in the years ahead.

Acknowledgements. We are grateful for the fruitful discussions with M. Smith. All errors remain ours.

https://doi.org/10.1017/nws.2025.10020 Published online by Cambridge University Press

Funding statement. This work is supported by a public grant overseen by the French National Research Agency (ANR) as part of the "Investissements d'avenir" program (reference : ANR-10-EQPX-17 – Centre d'accès sécurisé aux données – CASD)

Data availability statement. Firm-level data is confidential and its access is restricted upon authorization through the CASD. Description of the databases are accessibles at https://www.casd.eu/en/data-used-at-casd/.

Ethical standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

Competing interests. None.

Notes

1 See Table 4 for yearly descriptive statistics.
2 See the Eora 26 classification at https://worldmrio.com/eora26/. Sectoral breakdowns for parents and affiliates are reported in Appendix A.2.
3 With 4,914 nodes, the number of undirected pairs is $\frac{4{,}914\cdot(4{,}914-1)}{2} = 12,071,241$.
4 The year 2017 shows a significant change in this series and in others. After detailed investigation, we reject the hypothesis of methodological data discontinuity. It rather seems to be the consequence of the Brexit vote in 2016, as most impacted nodes are in the U.K. While not of our primary interest for this study, this confirms that (expected) economic shocks can transform the MNE network topology.
5 See Appendix B for an extended history of the top edges in 2021.
6 To mitigate multicollinearity in permutation inference, we also employ the double semi-partialing (DSP) variant (Dekker et al., 2007); results are qualitatively unchanged (see Appendix C).

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https://doi.org/10.1017/nws.2025.10020 Published online by Cambridge University Press

Appendix A. Sample description

A.1 Sample size

Table A1 details the sample from LIFI used to build yearly multinationals' network

Table A1. Sample size

year	Nb. MNE	Nb. Foreign Aff.	Nb. Host countries	Nb. host country-industry
2012	9817	46156	172	2064
2013	11562	51138	171	2142
2014	13265	51778	173	2169
2015	15146	58484	174	2236
2016	15784	54489	174	2236
2017	17785	59856	173	2277
2018	17512	59269	172	2293
2019	17882	59600	172	2304
2020	18754	59422	173	2309
2021	18738	61320	173	2383
2022	18905	62450	173	2420

A.2 Sectoral affiliation of parent and foreign affiliates

Eora 26 Industries	Parent firms (%)	Foreign Affiliates (%)
Agriculture	0.81	0.63
Fishing	0.10	0.02
Mining and Quarrying	0.17	0.11
Food & Beverages	2.29	2.96
Textiles and Wearing Apparel	2.07	1.34
Wood and Paper	4.71	3.66
Petroleum, Chemical and Non-Metallic Mineral Products	4.56	9.78
Metal Products	3.83	2.46
Electrical and Machinery	5.72	7.23
Transport Equipment	2.30	5.02

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Eora 26 Industries	Parent firms (%)	Foreign Affiliates (%)
Other Manufacturing	1.94	2.16
Recycling	0.32	1.15
Electricity, Gas and Water	0.37	1.44
Construction	4.26	5.21
Maintenance and Repair	1.49	0.83
Wholesale Trade	13.94	9.13
Retail Trade	4.71	4.56
Hotels and Restraurants	2.11	2.09
Transport	3.08	5.46
Post and Telecommunications	0.43	1.64
Finacial Intermediation and Business Activities	18.38	16.79
Public Administration	1.93	1.69
Education, Health and Other Services	10.16	6.65
Others	10.30	7.94
Re-export & Re-import	0.02	0.04

B. Main edges and nodes in 2021

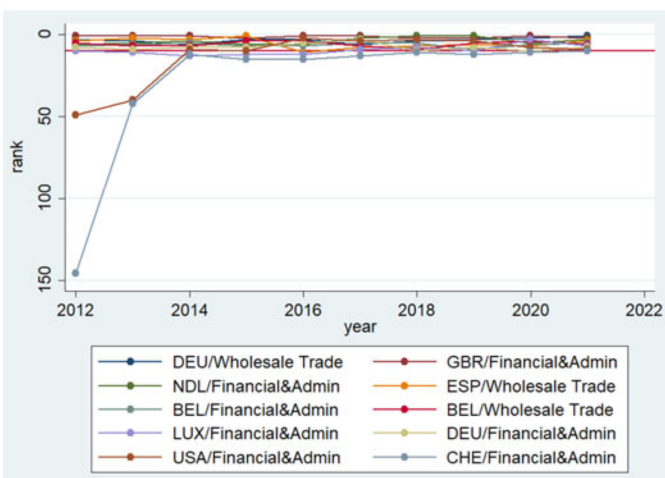

Figure B1. Top ten nodes in 2021.

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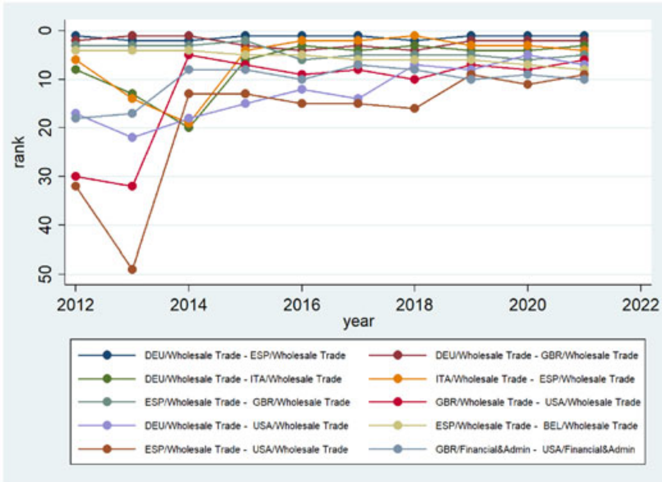

Figure B2. Top ten edges in 2021.

C. Double Semi-Partialling MRQAP

As a robustness check, we re-estimated the MRQAP using the Double Semi-Partialing (DSP) variant to strengthen permutation-based inference in the presence of correlated dyadic regressors (Dekker et al., 2007). DSP orthogonalizes predictors before the 5,000 permutations, mitigating the collinearity bias that can inflate Type I error in classic QAP. We keep the same outcome and covariates. We display the results in Table C1, which shows supporting evidence for our previous interpretation that structural gravity-like factors (distance and market size) and co-specialization (Same Industry) are stable pre-COVID, while post-shock shifts in coefficients capture adaptive reweighting rather than structural re-wiring.

Table C1. MRQAP with double semi-partialing

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
ln ($\mathrm{M}_{ij,t-1}$)	4.3000	4.1000	4.4200	4.4800	3.7200	4.6500	3.7800	4.1100	2.5500	2.4000
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
ln (**Dist**$_{ij}$)	−0.1280	−0.1190	−0.1540	−0.1180	−0.1710	−0.1240	−0.1370	−0.1120	−0.1070	−0.1020
	(0.12)	(0.19)	(0.04)**	(0.15)	(0.00)***	(0.02)**	(0.01)***	(0.13)	(0.41)	(0.44)
ln (**SameIndus**$_{ij,t}$)	0.7420	0.4120	0.3750	0.5840	0.0150	1.0260	1.1950	0.7750	−1.5420	−1.4500
	(0.00)***	(0.02)**	(0.03)**	(0.00)***	(0.98)	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
ln (**absdiffGDP**$_{ij,t-1}$)	−0.1090	−0.0810	−0.1290	−0.1410	−0.1600	−0.1030	−0.1380	−0.1170	−0.0610	−0.0580
	(0.16)	(0.24)	(0.04)**	(0.04)**	(0.00)***	(0.09)*	(0.00)***	(0.06)*	(0.50)	(0.52)
ln (**SumGDP**$_{ij,t-1}$)	0.3210	0.2790	0.3560	0.0330	0.3590	0.2260	0.3840	0.2920	0.1320	0.1250
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.35)	(0.36)

Permutation p-values in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Notes: MRQAP with Double Semi-Partialing, à la Dekker et al. (2007). Outcome is the weighted co-location matrix ($\log(1 + w_{ij,t})$). Dyadic regressors as labeled; lags as indicated. Inference via **node-label permutations** (QAP), $R = 5{,}000$.

Cite this article: Joyez C. (2025). Robustness with adaptation. Ownership networks of multinationals through COVID-19. *Network Science* **13**, 1–18. https://doi.org/10.1017/nws.2025.10020