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Constructing and Analysing Global Corporate Networks With Wikidata: The Case of Electric Vehicle Industry

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ABSTRACT

Constructing comprehensive datasets for corporate network analysis remains a significant challenge for the business research community. This study introduces a novel Python tool, NetVizCorpy, which leverages Wikidata to generate such a dataset. We demonstrate its applications by constructing and analysing a global corporate network based on 44 seed electric vehicle (EV) companies and their three-level ownership structures. This dataset includes 1354 unique companies and 1575 ownership relations spanning 58 countries. We provide network characteristics, metrics and statistical insights, along with three detailed analytical applications. First, betweenness centrality identifies key influential companies, highlighting the role of financial institutions in industry resilience. Second, community detection reveals strategic positioning by EV manufacturers within global markets. Third, we find a nonlinear inverse U-shaped relationship between Global Network Connectivity (GNC) and Gross Competitive Intensity (GCI) at the country level. These findings offer new directions for understanding the resilience and competitiveness of the global EV industry.

1 | Introduction

Network analysis has become an interdisciplinary methodology across physical and social sciences such as anthropology, biology, economics, finance, geography, physics, political science and sociology (Borgatti et al. 2009). In recent years, it has been applied to worldwide shareholding data to investigate so-called corporate networks (Martinus et al. 2021; Riccaboni et al. 2021; Vitali et al. 2011; Wall et al. 2011). In a corporate network, the nodes correspond to legally independent firms whereas the links correspond to ownership relations connecting them (Riccaboni et al. 2021). Moreover, a global corporate network can be constructed if the ownership relations crossing country borders are considered.

Constructing comprehensive datasets for corporate network analysis remains a significant challenge for the business research community. For urban network studies, the ownership-linkage model is often preferred (Neal and Rozenblat 2021; Rozenblat et al. 2017; Zhang and Tang 2024) to explore and analyse global corporate network characteristics. However, building such datasets is often time-consuming, limited functionality or not freely accessible. It usually involves collecting data from annual reports, websites and news sites. Sometimes, these datasets are shared freely with the research community through platforms like the Globalisation and World City Data site (GaWC 2025), and reused, as shown for instance in Zhang and Qian (2023). However, in most cases, researchers rely on subscription-based services, such as Orbis VL by Bureau van Dijk (Saleem et al. 2023).

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or Thomson Reuters' Refinitiv Eikon (Choudhary et al. 2024), among others, to access relevant data.

In contrast, Wikidata (Wikidata 2025), Wikipedia's sister-site, is a free knowledge base with more than 116.7 million data items. In March 2025, there are approximately 750,000 records relating to businesses and corporations (<https://w.wiki/Dpwm>), of which about 306,000 are in English ([https://w.wiki/Dpw\\$](https://w.wiki/Dpw$)). Wikidata has attracted growing academic interest for its potential, although it is still far from mature. Real-world applications utilising Wikidata are scarce, with some examples in medical, user-centric and other knowledge integration applications (Mora-Cantalops et al. 2019).

Therefore, this study has two main objectives. First, it aims to automate the data collection process using Wikidata to generate global corporate network datasets for any company or industry of interest. To achieve this, we developed NetVizCorpy (available in the OSF repository at <https://doi.org/10.17605/OSF.IO/N6ZAF>), an open-source Python package capable of retrieving firm-level information, including ownership relations, from the freely accessible Wikidata, and visualising corporate networks within minutes with customisable functionalities. Second, we demonstrate the real-world utility of this Wikidata-based tool by constructing a global corporate network seeded at the electric vehicle (EV) industry. As a pivotal sector in advancing sustainable transportation and combating climate change, the global EV industry relies on the resilience of this interconnected corporate network, whereas any disruptions to this system can potentially impede progress towards a greener future (Ballinger et al. 2019).

In this paper we contribute to the business research community by introducing a generic Python tool that simplifies the data collection and the construction of corporate ownership networks using open data. We present a global EV industry network dataset consisting of 1354 companies and 1575 ownership relations across 58 countries. Our analysis applies (1) betweenness centrality to identify influential companies, and (2) community detection to uncover patterns of strategic global positioning among EV manufacturers. In addition, we extend Zhang and Qian (2023) framework by showing how Global Network Connectivity (GNC) and Gross Competitive Intensity (GCI) manifest at the country level, revealing a nonlinear inverse U-shaped relationship that differentiates low-, mid- and high-GNC economies. These findings lay a foundation for future research into the resilience and competitiveness within the global EV industry.

The rest of the paper is structured as follows. In the next section we detail the construction of corporate networks with Wikidata. Section 3 presents the application to the EV industry and explores future opportunities. Section 4 concludes the study.

2 | Constructing Global Corporate Networks Based on Wikidata

2.1 | Wikidata Database

Wikidata has gained increasing attention in academic research as a valuable resource for structured and open data. Researchers

employ its vast knowledge base for various applications, including bibliometric analysis, linked open data integration and semantic web research (Smith-Yoshimura 2020; The University of Edinburgh 2024). For instance, the Gene Wiki Project (Waagmeester et al. 2020) utilises Wikidata to document biomedical science information, advancing accessibility for researchers. Similarly, libraries and archives explore Wikidata to improve metadata management and authority control, as seen in projects like the 'Project Passage' where the OCLC Research institute (Godby et al. 2024) partnered with 16 American libraries to demonstrate the impact of linked data. In addition, Wikidata has been used in historical research, such as mapping the Scottish reformation, where scholars structured historical data to handle large volumes of textual, temporal and geographic data for visualisation and analysis (Langley 2023). Despite its growing adoption, Wikidata remains in an early stage of development for research, with challenges related to data completeness, consistency and domain-specific adaptation (Smith-Yoshimura 2020; The University of Edinburgh 2024). As academic interest continues to grow, our study represents a concrete step towards supporting and advancing its real-world applications, thereby contributing to Wikidata's maturity as a research resource.

According to Wikidata's statistics (<https://www.wikidata.org/wiki/Special:Statistics>) the site—which is maintained in a decentralised manner—has nearly 9 million registered users, with approximately 25,000 active users, and about 300 active bots in March 2025. It currently has about 750,000 records that directly relate to businesses and corporations, of which about 306,000 are in English. These records are sourced from publicly available information, including company websites and news articles. The five most frequently referenced sources are nytimes.com, worldcat.org, routers.com, bloomberg.com and forbes.com (Lewoniewski et al. 2023). As shown in Figure 1, Wikidata records—representing company-related content in our case—are depicted as boxes with their names displayed at the top in grey boxes and are linked based on specific attributes or properties. To explore a firm's ownership network, such as a seed firm, four key fields in these records can be utilised. For upward relations, a company may have a parent company and/or shareholders holding specific percentages of shares. For downward relations, a company may have subsidiaries (within parent–subsidiary relationships) or hold shares in another company. While Figure 1 presents a simplified network structure of a hypothetical seed company to illustrate different levels of ownership, real-world scenarios can involve both significantly more complex and simpler relationships between companies.

2.2 | Corporate Network Retrieval and Visualisation Tool (NetVizCorpy)

To automate the data collection process, we developed a generic Python tool called NetVizCorpy (Baruwa et al. 2025). This tool can retrieve any requested company's information from Wikidata and visualise corporate ownership networks across various levels, as specified by the user (including both upward and downward relations). NetVizCorpy follows these steps to collect data, build corporate network datasets and visualise them:

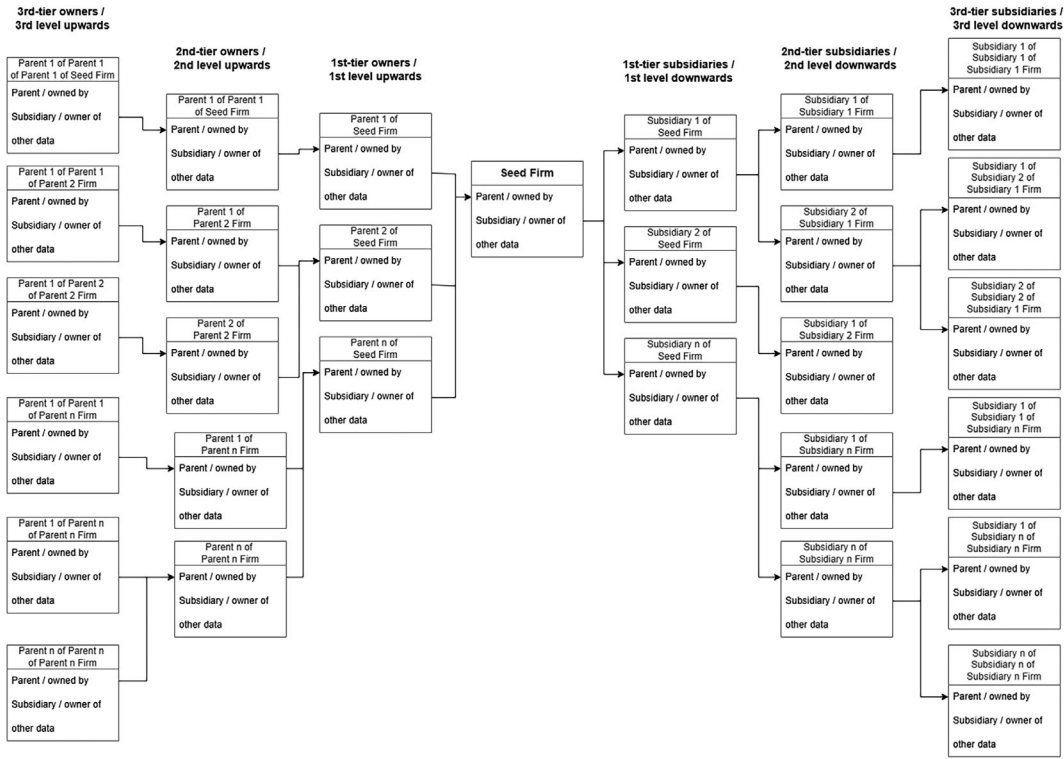


FIGURE 1 | Simplified Wikidata records showing linkages to the upward and downward relations of a seed firm.

Step 1. The user specifies the seed company or companies they want to identify from Wikidata. This will return a list of tuples with either a single result (when searched with an ‘exact’ match) or multiple results (when searched with ‘all’). Each tuple contains two values: the Q Identifier (QID), which is the unique identification number of the company in Wikidata, and the company name. The QIDs are required for the subsequent steps, and either a single QID or multiple QIDs should be included in a list, such as QIDs = [‘Q123’].

(‘Q2033642’, ‘Volvo Trucks’),
(‘Q2033664’, ‘Volvo Aero’),
(‘Q1751470’, ‘Volvo Penta’),
(‘Q2373435’, ‘Volvo Buses’)]

Step 2a. User specifies the levels of corporate relations to be retrieved, which can take four parameters according to the data available from Wikidata,

Example: Searcher(‘volvo’, ‘all’).choose_company()

Returns the following output:

[(‘Q617322’, ‘Volvo Construction Equipment’),
(‘Q7941313’, ‘Volvo Financial Services’),
(‘Q17093889’, ‘Volvo Rents’),
(‘Q383097’, ‘Volvo Cars gent’),
(‘Q215293’, ‘Volvo Cars’),
(‘Q19978726’, ‘Volvo On Demand’),
(‘Q1621085’, ‘Volvo Halifax Assembly’),

$$levels = (i, j, k, l), \quad i, j, k, l \in \mathbb{N}_0$$

Where the first two positions are for upward relations i.e., i is for parent companies, j is for owned by (shareholders) companies; and the last two positions are for downward relations i.e., k is for subsidiaries and l is for owner of (or has a share in) companies.

Step 2b. The algorithm retrieves all available relations as specified in previous steps, where each additional level will expand the network with all new companies’ relations from the previous level. Along with the relations the algorithm also collects (wherever is available), the industry or industries the company operates in, the country of origin, the proportion of

ownership (authorised capital) and the total revenue and its corresponding year.

Example:

```
QIDs = ['Q215293']
```

```
levels = (3,3,3,3)
```

```
companyNetwork = NetworkBuilder(QIDs, levels).get_companies_network()
```

Step 3. This step involves combining and cleaning the data gathered from the previous step (e.g., removing duplicates). The cleaned data are returned as a data frame (i.e., a data structure in pandas, <https://pandas.pydata.org/>), which can then be used for various analyses and for visualising the network.

Example:

```
cleanedNetwork = Cleaner(companyNetwork).clean_join()
```

Step 4. In this step, the algorithm uses the dynamic Pyvis package (Unpingco 2023) to visualise the network, incorporating additional functionalities. For example, by default, nodes are colour-coded by industry and shaped based on their corresponding continents. The output of this step is an HTML file (e.g., “Volvo_Level3_Demo.html”).

Example:

```
Visualiser(cleanedNetwork, “Volvo_Level3_Demo”).visualise_b2b_network()
```

The dataset returned in Step 3 of the algorithm contains 21 columns (variables), with their characteristics outlined in Table 1. Based on these variables, various network metrics can be calculated depending on the scope and purpose of the analysis. The literature highlights several commonly used network metrics for exploring network characteristics and their effect on various phenomena, such as resilience (Dixit et al. 2020; Choudhary et al. 2024). Key metrics include network type (Zhao et al. 2011; Gopalan and Xie 2011; Agostini 2018), network size (Dixit et al. 2020; Florez-Jimenez et al. 2024), degree and average degree connectivity (Atwood et al. 2015; Piva et al. 2021), betweenness or closeness centrality (Choudhary et al. 2024), density (Dixit et al. 2020), average clustering coefficients and community detection (Ostroumova Prokhorenkova et al. 2016; Carchiolo et al. 2019; Carmen et al. 2022; Wang et al. 2024; Artime et al. 2024; Abba et al. 2025), diameter and average path length (Takes and Kusters 2011; Kim 2020; Luna-Pla and Nicolás-Carlock 2020), spatial complexity (Reggiani 2021; Cardinale et al. 2022; Herold and Marzantowicz 2023; Garretsen et al. 2025) and cross-sector complexity (Laeven and Levine 2008; Nell and Andersson 2011; van Tulder and Keen 2018).

3 | A Case Study of the Electric Vehicle Industry

This section presents a case study of the EV industry to explore the use of Wikidata for corporate network analysis. We demonstrate how the dataset retrieved using NetVizCorpy can support investigations into global corporate structures and offer insights into network dynamics in the EV industry. We highlight practical examples that may encourage further research on both the dataset and the tool, particularly in areas such as assessing corporate network resilience and country competitiveness. Section 3.1 details the characteristics and summary statistics of the global corporate network constructed for EV and closely related battery manufacturers. Section 3.2 explores the use of betweenness centrality to identify influential nodes in the network. Section 3.3 applies community detection methods to uncover clusters, whereas Section 3.4 investigates country competitiveness through the lens of GNC and GCI.

3.1 | Dataset and Network Construction

We included all the EV manufacturers listed on Wikipedia (2024a) together with the largest battery manufacturers (Wikipedia 2024b), which were 82 companies in total. We have verified and cross-checked this information against the lists provided by other popular sources such as <https://ev-volumes.com/>. The data collection process was carried out in two phases. The first phase, on 21st February 2024, focused on validation by incorporating a company list from Wikipedia and extracting direct (one-level) ownership relationships from both Orbis and Wikidata, as detailed in Appendix A.1 in the [Supporting Information](#). The SI, along with the datasets, source code and analyses, is available in our OSF repository (Baruwa et al. 2025). The second phase, on 27th February 2024, involved retrieving the three-level ownership network of the final 44 seed companies—listed in Table 2—from Wikidata for exploratory data analysis. We have included some of the network metrics we computed for this network in Appendix A.2 in the [Supporting Information](#).

The seed companies originate from 15 countries, as depicted on the left side of the Sankey diagram in Figure 2, and, together with their three-level network, they span 58 known countries. As it can be observed from this diagram, seed companies from Japan, Germany, the USA, China and France dominate most of the direct (downward) relations. It is also visible that nearly all seed companies have most of their subsidiaries or shares in companies from their own country. The most significant proportion of this same-country ownership can be observed in the case of Japan as highlighted in peach colour. We also highlighted in the figure the relations from the seed companies originating from the USA (in turquoise) to demonstrate the wide range of countries they have interest in.

The three levels of upward and downward relations for the seed companies resulted in a network comprising 1354 unique companies (nodes) with 1575 relations (links). A descriptive summary of the dataset variables is presented in Table 3. Since only a few variables are numerical, we placed their corresponding statistics in the last column. While we would expect the unique

TABLE 1 | Variables in the returned data frame.

Variable	Description	Type	Wikidata property
pQID	QID of the parent or 'owned by' company	Text	P127 (owned by), P749 (parent organisation)
Parent	Name of the parent or 'owned by' company	Text	Label for the QID
parent_country	Country of the parent or 'owned by' company	Categorical	P17
p_industries	Industries (possibly more than one) of the parent or 'owned by' company. If no industries are listed for a company, the algorithm will use its description instead. For human owners, as industries do not apply, their description will always be used.	Categorical	P452
p_total_revenue_in_millions	Total revenue in millions for the parent or 'owned by' company.	Numeric	P2139
p_total_revenue_date	Year to which the revenue of the parent or 'owned by' company refers.	Numeric	P2139 / P585
cQID	QID of the subsidiary or 'owner of' company	Text	P355 (has subsidiary), P1830 (owner of)
Child	Name of the subsidiary or 'owner of' company	Text	Label for the QID
child_country	Country of the of the subsidiary or 'owner of' company	Categorical	P17
c_industries	Industries (possibly more than one) of the subsidiary or 'owner of' company. If no industries are listed for a company, the algorithm will use its description instead. For human owners, as industries do not apply, their description will always be used.	Categorical	P452
c_total_revenue_in_millions	Total revenue in millions for the subsidiary or 'owner of' company.	Numeric	P2139
c_total_revenue_date	Year to which the revenue of the subsidiary or 'owner of' company refers.	Numeric	P2139/P585
p_proportion	Relates to the ownership. It includes the percentage of shares, ranging from 0+% to 100% for shareholders. Additionally, it contains categorical values: parent relations (2), unknown values (3) and ended relations (4).	Numerical ($0 < x \leq 1$) and categorical (2,3,4)	P127/P1107/P1013 (Q144368)

(Continues)

TABLE 1 | (Continued)

Variable	Description	Type	Wikidata property
proportionofLabel	In Wikidata, there may be instances where multiple types of share proportions are listed, such as ordinary shares, alongside authorised capital, which might lead to conflicting values, therefore the algorithm will always prioritise authorised capital and record it in this column, even if other options are available they will be disregarded.	Text	Label for P1013 (Q144368)
Pointoftime	Point of time of the shareholding proportion.	Datetime	P127/P1107/P585
Starttime	Starting time when the shareholding proportion becomes effective.	Datetime	P127/P1107/P580
Endtime	End time of the shareholding proportion.	Datetime	P127/ P1107/ P582
top_p_industries	Since a (parent) company can have interests, divisions, or products across multiple industries (listed in column p_industries), the algorithm will determine which industry appears most frequently in the retrieved network and assign it as the top industry, as it is the most closely related to the dataset's characteristics. If no industries are listed and only the description is available, this field will categorise them as 'other'.	Categorical	N/A
top_c_industries	Same as above, but referring to a subsidiary company.	Categorical	N/A
parent_continent	Based on the parent_country variable and with the help of the 'pycountry_convert' python package, the algorithm will determine which continent the parent company is located in.	Categorical	N/A
child_continent	Same as above, but referring to a subsidiary company.	Categorical	N/A

values in variables 'pQID' and 'parent', as well as in 'cQID' and 'child', to be equal, discrepancies arise because not all labels are available in Wikidata for every QID.

To illustrate the three-level network of a single seed company, Figure 3 presents Volvo Cars' network, visualised using Gephi

(Bastian et al. 2009). The nodes are colour-coded according to the top industries that have been identified in the network. As it can be observed, two other seed companies—Geely and Mercedes-Benz Group—also appear in its ecosystem. According to the information on Wikidata, Geely has a 78.7% share in Volvo Cars. While Mercedes-Benz Group appears as a joint

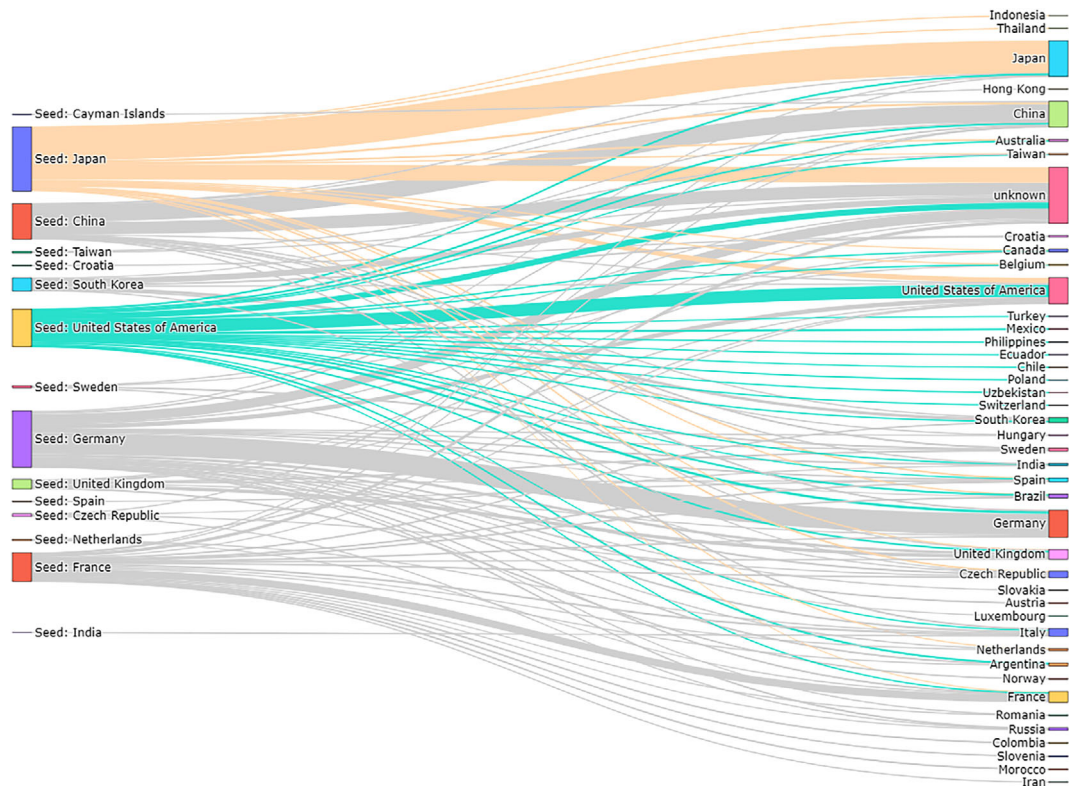


FIGURE 2 | Countries of seed companies and their direct (downward) relations.

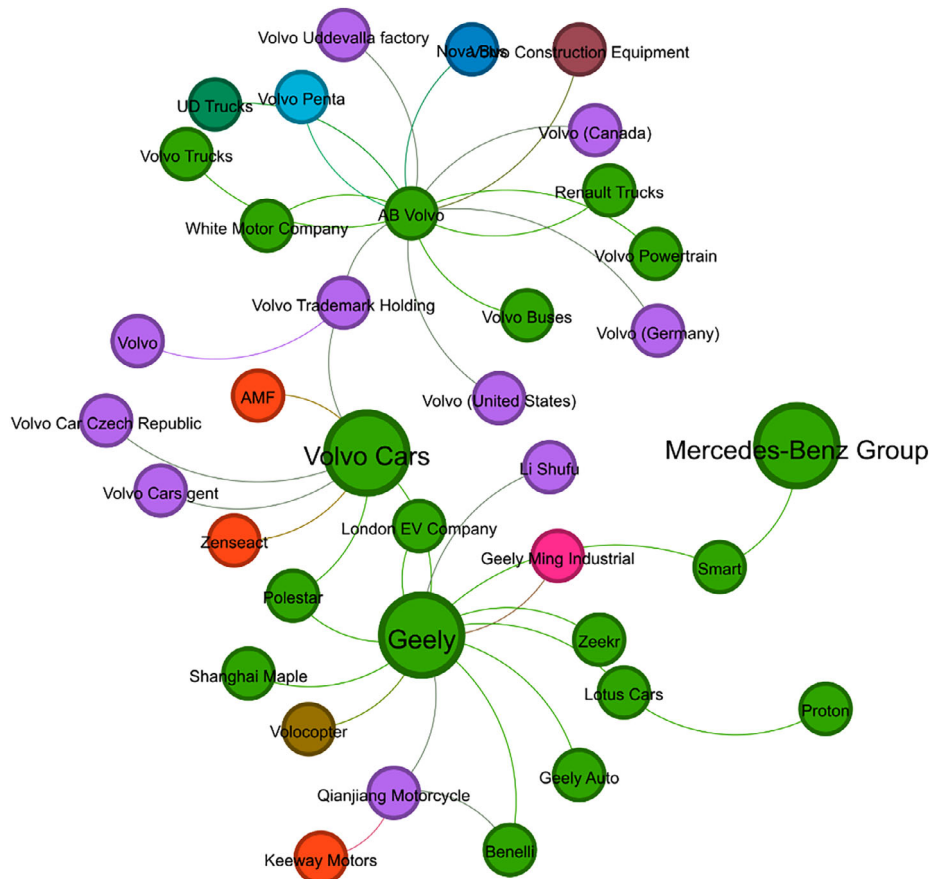


FIGURE 3 | Volvo Cars 3-level corporate relations visualised with Gephi (Bastian et al. 2009).

TABLE 2 | List of the 44 seed companies.

BYD Auto; Changan Automobile; Chery; Dongfeng Motor Corporation; FAW Group; Ford Motor Company; Geely; General Motors; Great Wall Motor; Guangzhou Automobile Group Co., Ltd.; Honda; Hyundai Motor Company; JAC Motors; Jaguar Land Rover; Kandi Technologies; Kia; Mahindra & Mahindra; Mazda; Mercedes-Benz Group; Mitsubishi Motors; Nanjing Automobile; Nissan; Panasonic Holdings Corporation; Porsche Automobil Holding SE; Renault; Rimac Group; Rolls-Royce; SAIC Motor; Samsung SDI; SEAT; SK Innovation ; Škoda Auto; Stellantis; Subaru Corporation; Tata Motors Ltd ; Tesla, Inc.; Toyota; Volkswagen Group; Volvo Cars; XPeng; Yulon Motor

TABLE 3 | Descriptive statistics of the 3-level network collected in February 2024.

Variable	Count	Unique values	Missing values	Mode	Numerical/categorical (Mean; Std. Dev; median; min; max; earliest; latest)
pQID	1598	343	0	Q724759	
Parent	1598	342	0	NBCUniversal	
parent_country	1503	32	95	Japan	
p_industries	1575	195	23	Automotive industry	
p_total_revenue_in_millions	794	72	804	150,017	Mean: 10,832,234; median: 156,735; Std. Dev.: 47,488,288; min: 0.00000156; max: 302,231,360
p_total_revenue_date	792	10	806	2022	Mean: 2019.7; median: 2021; Std. Dev.: 2.725; min: 2012; max: 2023
cQID	1598	1217	0	Q513679	
Child	1598	1209	0	Central Japan Railway Company	
child_country	1344	55	254	Japan	
c_industries	1377	519	221	Automotive industry	
c_total_revenue_in_millions	211	109	1387	1,756,980	Mean: 8,677,581; median: 48,693; Std. Dev.: 46,247,216; min: 0.00000156; max: 302,231,360
c_total_revenue_date	210	13	1388	2022	Mean: 2018.9; median: 2019; Std. Dev.: 3.5116; min: 1988; max: 2023
p_proportion	1598	289	0	3	Mean: 2.0337; median: 2; Std. Dev.: 1.1585; min: 0.00061; max: 4
proportionofLabel	1	1	1597	Authorised capital	
Pointoftime	69	26	1529	2022-09-30	Earliest: 31/12/2015; latest: 30/06/2023
Starttime	97	64	1501	2021-01-16	Earliest: 01/01/1909; latest: 12/06/2023
Endtime	0	0	1598		
top_p_industries	1575	65	23	Automotive industry	
top_c_industries	1377	130	221	Automotive industry	
parent_continent	1492	4	106	Asia	
child_continent	1340	6	258	Europe	

venture partner with Geely in the car manufacturing company Smart.

Naturally, the extensive network includes all the seed companies without duplications and encompasses every company,

natural person owner, as well as the brands or products they own. However, the search terminates upon reaching a natural person or brand/product, as no further ownership relations between companies exist beyond this point. For instance, Li Shufu appears as the majority owner of Geely, but the

TABLE 4 | Dataset and network characteristics.

Dataset and network characteristics	Value			
	Level 1* (2025)	Level 2* (2025)	Level 3 (2024)	Level 3* (2025)
Companies (nodes)	595	919	1354	1510
Relations (edges)	627	1084	1575	1805
Network type	Scale-free	Scale-free	Scale-free	Scale-free
Network Size (nodes + edges)	1222	2003	2929	3315
Average degree	2.0739	2.2807	2.3264	2.3232
Average degree centrality	0.0035	0.0025	0.0017	0.0015
Average degree connectivity	4.8447	5.3521	5.0923	5.0410
Average betweenness centrality	0.0061	0.0058	0.0046	0.0037
Average closeness centrality	0.0842	0.1173	0.129	0.1210
Density	0.0035	0.0025	0.0017	0.0015
Average clustering coefficient	0.0366	0.0703	0.0755	0.0775
Clusters/communities	27	32	38	44
Diameter (within communities: min; mean; max)	1; 2.5926; 5	1; 3.8438; 6	1; 4.4737; 10	1; 4.1136; 10
Average path length (within communities: min; mean; max)	1; 1.9423; 2.9767	1; 2.3067; 3.5359	1; 2.5195; 4.7983	1; 2.4435; 4.7437
Spatial complexity (no. of known countries)	49	57	58	64
Cross-sector complexity (unique industries; unique industries that appear more than once)	57; 26	98; 49	141; 81	160; 91
Number of parent-subsidiary relations	12	236	326	365
Number of shareholding relations with more than 50% shares	113	210	250	273
Number of shareholding relations with less than 50% shares	126	198	260	303
Number of relations with unknown share values	350	383	708	785
Number of historical relations (ended at some point in time)	26	57	54	79

Note: For comparison purposes these networks were retrieved in April 2025.

algorithm stops searching further as Li Shufu is a natural person.

In addition to the dataset retrieved in February 2024, we collected data on the network of the 44 seed companies again in April 2025 to compare their network metrics across Levels 1, 2 and 3, and to assess differences between the two three-level networks—the ones collected data on in April 2025 and the earlier dataset from February 2024. These metrics are shown in Table 4.

3.2 | Betweenness Centrality

Betweenness centrality (Freeman 1977) quantifies how often a node acts as a bridge along the shortest path between two other nodes. By applying this metric to the three-level network (retrieved in 2024), we identify the most influential companies within the global corporate network seeded at EV/battery manufacturers. In Table 5, we observed that 4 out of the 10 most

influential companies are financial institutions. Not only the most influential company—Mitsubishi UFJ Financial Group—a financial institution, but BlackRock, The Vanguard Group and Nippon Life Insurance Company also appear among them. Three EV manufacturers are also present on this list: Mercedes-Benz Group, Volkswagen Group and Toyota. Meanwhile, Mitsubishi Motors' parent organisation, a Japanese rail company, and a battery manufacturer—Panasonic Holdings Corporation—are also among the most central companies in the network, suggesting their unique position in their supply chains. It is also noteworthy that these most influential companies originate solely from three countries: Japan, Germany and the USA.

There are several directions in which these results can be utilised to explore the EV industry's corporate network resilience. One promising approach is to assess the extent to which financial institutions influence the EV industry. Financial resources represent the backbone of corporate resilience, enabling firms to navigate crises and adapt to changing environments. Empirical studies underscore the significance of financial access during

TABLE 5 | Most influential EV/Battery companies in the three-level network.

The 10 most influential companies by betweenness centrality				
Rank	Company name	Country	Industry	Betweenness centrality
1	Mitsubishi UFJ Financial Group	Japan	Financial services	0.2209
2	Mercedes-Benz Group	Germany	Automotive industry	0.2090
3	Volkswagen Group	Germany	Automotive industry	0.1972
4	BlackRock	United States of America	Asset management	0.1789
5	Nippon Life Insurance Company	Japan	Insurance company	0.1485
6	Panasonic Holdings Corporation	Japan	Electronics; semiconductor industry; video game industry; home appliance	0.1472
7	Toyota	Japan	Automotive industry	0.1467
8	Central Japan Railway Company	Japan	Rail transport	0.1467
9	The Vanguard Group	United States of America	Financial services	0.1409
10	Mitsubishi	Japan	Trade	0.1294

crises. Levine et al. (2018) and Niu et al. (2024) provided evidence that robust financial resources enhance firms' crisis recovery capabilities. However, the heterogeneity in financial access also plays a pivotal role. Angori et al. (2020) found that smaller firms and those with weaker banking relationships face heightened challenges in securing credit. This aligns with McKinsey's report (Natale et al. 2022), which links financial health to strategic adaptability and innovation during the COVID-19 crisis. The emphasis on external debt for new firms, as noted by Robb and Robinson (2014), further highlights the critical role of credit markets in enabling growth and resilience.

Another approach could be to utilise betweenness centrality metrics alongside other indicators to assess their predictive power in measuring corporate network resilience (Choudhary et al. 2024).

3.3 | Community Detection

We utilised the Clauset–Newman–Moore (CNM) algorithm of greedy modularity maximisation (Clauset et al. 2004) with the NetworkX Python package (Hagberg et al. 2008) to detect communities within the EV industry network. We used the default resolution value of 1 and the number of communities detected with other resolution values are available in Figure A3 in the Supporting Information. We identified 38 communities and we present the seed companies' community memberships along with relevant characteristics in Table 6. As shown, the 44 seed companies are distributed across 24 communities. Community 1 is the largest, comprising six seed companies out of the total 93, spanning 26 countries across four continents. A list of the largest companies in communities where seed companies are not present can be found in Table A7 in the Supporting Information.

Figure 4 visualises the 38 detected communities, where the communities are colour-coded, and the nodes representing the

seed companies are enlarged for better visibility. For instance, Community 10 is shown in pink, with Ford Motor Company and Changan Automobile as enlarged nodes. We also slightly enlarged (with oval shape) the most influential companies that emerged from our previous analysis of betweenness centrality. For instance, Mitsubishi UFJ Financial Group (highlighted in orange) belongs to Community 5. It is clearly noticeable, that communities are mostly inter-connected, however some of them are isolated, such as Mahindra & Mahindra or SK Innovation.

The battery manufacturers (highlighted in yellow circles) appear in their own 'little kingdoms'. As shown in Figure A3 in the Supporting Information, they only began to group with other EV manufacturers when the resolution value fell below 0.4. In other words, there is no direct connection or integration of these battery manufacturers with other EV manufacturers. However, through some smaller entities within their network, they do maintain connections with larger EV manufacturers. For instance, in the case of Samsung SDI, Wikidata indicates that Samsung Card holds a 1.91% share in Renault Korea Motors, which is owned by Renault and the Renault–Nissan–Mitsubishi Alliance but Geely also holds a 3.4% share in it. BYD Auto is a special case, as it is both a car and battery manufacturer, thus occupying a more central position in the graph.

It is important to note that companies within these communities also have relations with other communities. Table A8 in the Supporting Information provides an overview of the inter-connectedness of those communities that include the seed companies. In summary, some communities are highly inter-connected with other communities—such as communities 1, 2, 5 and 7 – while others are moderately connected or entirely isolated. This adds another dimension to our understanding of how strategic relationships are formed within the global EV industry. For instance, Communities 1 and 5 were among the most local communities based on their continent and country level spatial complexity (as can be seen in Appendix A.3.1. in the

TABLE 6 | Seed company membership across communities with key characteristics.

Community	Seed company (origin)	Total no. of companies	No. of unique countries (known)	No. of unique continents (known)
Community 1	Audi (Germany); Porsche Automobil Holding SE (Germany); Rimac Group (Croatia); SEAT (Spain); Skoda Auto (Czech Republic); Volkswagen Group (Germany)	93	26	4
Community 2	Mitsubishi Motors (Japan); Nissan (Japan); Renault (France)	79	17	5
Community 4	Stellantis (Netherlands)	72	13	4
Community 5	Mazda (Japan)	69	4	3
Community 7	Mercedes-Benz Group (Germany)	64	12	4
Community 8	General Motors (USA); Nanjing Automobile (China); SAIC Motor (China)	63	18	5
Community 9	BMW (Germany); Chery (China); Jaguar Land Rover (UK); Tata Motors Ltd (India)	61	9	3
Community 10	Changan Automobile (China); Ford Motor Company (USA)	59	16	4
Community 12	Samsung SDI (South Korea)	55	13	3
Community 13	Subaru Corporation (Japan); Toyota (Japan)	55	10	4
Community 14	Panasonic Holdings Corporation (Japan)	46	7	3
Community 16	Guangzhou Automobile Group Co., Ltd. (China); Honda (Japan)	40	7	4
Community 17	Geely (Japan); Volvo Cars (Sweden)	38	12	3
Community 19	BAIC Group (China); Dongfeng Motor Corporation (China); FAW Group (China); Yulon Motor (Taiwan)	35	2	1
Community 20	Hyundai Motor Company (South Korea); Kia (South Korea)	32	3	3
Community 22	BYD Auto (China)	20	5	4
Community 23	Rolls-Royce (UK)	20	7	2
Community 28	Tesla, Inc. (USA)	14	5	3
Community 29	SK Innovation (South Korea)	14	1	1
Community 34	Mahindra & Mahindra	6	4	3
Community 35	Great Wall Motor (China)	5	1	1
Community 36	Kandi Technologies (China)	2	2	2
Community 37	JAC Motors (China)	2	1	1
Community 38	Xpeng (Cayman Islands)	2	1	1

Supporting Information), but their inter-connections with some of the most diverse or global communities could be observed here. This suggests two different strategies that EV manufacturers use to build or improve their resilience and competitiveness, which could be tested in future studies. On the one hand, there are heavily local corporate groups with clear connections to more globally present companies and communities. On the other hand, there are corporate groups with an overall strong global presence. However, there are some local and isolated EV manufacturers that rely solely on one, or at most two countries in which they operate. Any disruption within these countries would presumably greatly affect these companies.

3.4 | Country Competitiveness

In the previous sections we explored the most influential companies in terms of betweenness centrality as well as the communities around the seed companies in their three-level network. We now extend our analysis to the country level, examining the competitiveness of different nations in the EV industry. This involves identifying strategies employed by EV firms to maintain resilience amidst global competition. Given a global corporate network, country level competitiveness can be assessed by how unique (i.e., more difficult to be replaced) or similar (i.e., less difficult to be replaced) the pattern of connections a country has

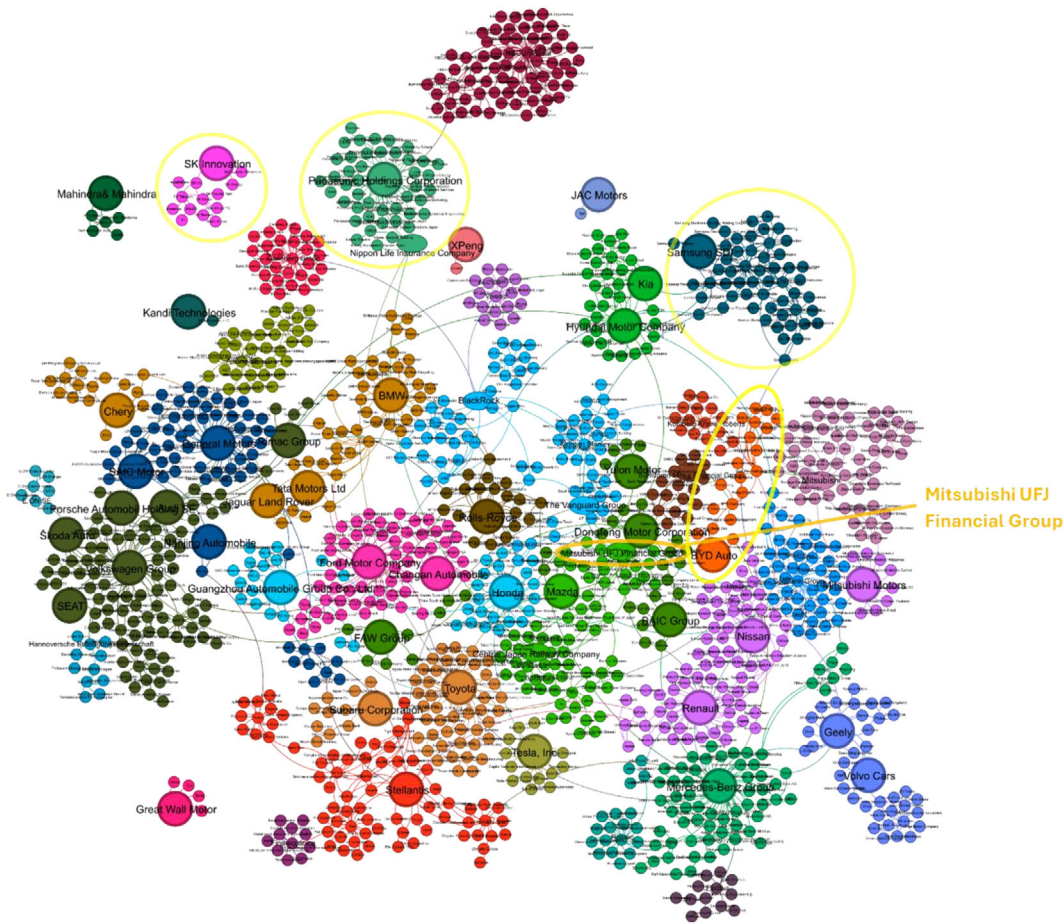


FIGURE 4 | Community detection (graph visualised with Gephi).

in this network relative to others (Zhu et al. 2018). Drawing on Zhang and Qian (2023) approach to analyse companies' global network connections (GNC) and their GCI we applied their formula at the country level rather than the city level, using the following steps:

Step 1. We created a matrix of 44×58 representing the seed companies and the total known countries. We assigned for each seed company all the countries that appear in their 3-level (upwards and downwards) relations within their own ecosystem. Value zero indicates where no company in the seed companies' network is present in a given country. Values can take up any large integer numbers based on the number of unique companies present in a country within its own network.

Step 2. We calculated country-dyad connectivity (CDC_{ij}) for each country pair in the matrix for the shared presence of companies in each seed companies' network.

$$CDC_{ij} = \sum_a v_{ia} \times v_{ja}, (i \neq j)$$

where v_{ia} and v_{ja} are the number of companies (both parents and subsidiaries) present in country i and country j for seed company a .

Step 3. We calculated the GNC for each country i by aggregating their CDC.

$$GNC_i = \sum_j CDC_{ij}, (i \neq j)$$

Countries with higher GNC scores indicate that they have more relations (connections) in the global cooperative network, which ultimately supports the diversification and therefore resilience of the seed companies based on these countries.

Step 4. We calculated the competition based on the dissimilarity between each country-dyad i and j compared with all other countries k with the following formula.

$$\text{Competition}_{ij} = 1 - \text{Dissimilarity}_{ij}$$

TABLE 7 | The 10 most connected countries based on the Global Network Connectivity (GNC) score.

The 10 most connected countries—Global Network Connectivity		
Country name	GNC score	GNC (%)
Japan	49715	100.00
Germany	49448	99.46
United States of America	43071	86.64
China	26997	54.30
France	21914	44.08
United Kingdom	14462	29.09
Russia	13731	27.62
Italy	10192	20.50
Czech Republic	9572	19.25
Spain	7630	15.35

$$= 1 - \frac{\sqrt{\sum_k (CDC_{ik} - CDC_{jk})^2}}{\sqrt{\sum_k (CDC_{ik})^2} + \sqrt{\sum_k (CDC_{jk})^2}}, (i \neq j \neq k)$$

Step 5. Finally, we computed the GCI for each country by summing country i competition scores with all other countries in the network.

$$GCI_i = \sum_j \text{Competition}_{ij}, (i \neq j)$$

Comparing the shared presence of country-dyads in the seed companies' three-level networks, we see that Japan, the USA, Germany, China, France and the Czech Republic are among the most connected country pairs (CDC) (Table A10 in the SI). The GNC scores represent the aggregated CDC scores for each country. Table 7 lists the ten most connected countries based on their GNC scores. We applied maximum value standardisation to ease the comparison. As expected, there are no surprises among the five most connected countries; however, the United Kingdom, Russia, Italy, the Czech Republic and Spain also demonstrate significant shared connections within the seed companies' networks. Looking at the percentage values, we observed notable gaps between the USA (86.64%) and China (54.4%), between France (44.08%) and the United Kingdom (29.09%) and between Russia (27.62%) and Italy (20.5%). This suggests that the first three countries are highly connected globally, while the others exhibit more moderate connectivity. Next, we explore the intensity of competition between the country pairs.

To get the countries' GCI scores, we first calculated the inter-country competition for each country-dyad based on their dissimilarities compared to all other countries, and listed the 20 most competitive pairs in Table A11 in the SI. Essentially, this shows that intense competitions existing between both intra-regional countries such as Chile and Ecuador, and cross-regional countries such as Qatar and Slovakia. By aggregating the competitive scores

for each country, we arrive at its GCI score. We listed all countries from the EV Industry network by their GCI scores and included their GNC scores as well in Table A12 in the SI.

Similar to previous—city level—findings (Zhang and Qian 2023), we observed an inverted U-shaped curve between countries' global connectiveness and their gross intensity of competition in Figure 5. It is visible that half of the most unique positions in terms of GCI are those with the largest GNC, and the other half with the lowest GNC scores. Another notable observation, that one of the most competitive country pair, the United Kingdom and Russia (Table A11 in Supporting Information), has very similar global reach and GCI. Evidently, there are some major differences in their role in the EV industry. While the United Kingdom is leading in EV adoption and manufacturing, Russia is rich in natural resources such as lithium. Similarly, Italy and the Czech Republic placed very close to each other on these two dimensions. As Zhang and Qian (2023) stressed, the GCI score indicates potential competitive relations in the ecosystem of a given industry since it is grounded on structural equivalence. These potential competitive factors could be favourable conditions for business operations such as tax-friendly and other supportive policies, which is particularly relevant for the EV industry, where many countries are dedicated to establishing a welcoming environment to accommodate more EVs on their streets.

According to the International Energy Agency's Global EV Outlook 2023 report (IEA 2023a), the number of countries is increasing where policies aim to boost manufacturing not just the EV deployment. For instance, both Indonesia and Morocco support battery manufacturing through their policies to attract investors and manufacturers. Although some type of policy support is started to phase out in some developed countries, there are various other ways that these countries are still aiding the growth of their EV market and thus closing the gap between their sustainability goals. For example, China shifted from supporting customers with subsidies to directly support EV manufacturers and related companies along the supply chain with initiatives (IEA 2023a). In other countries such as Slovenia or Romania legislative policies are still supporting EV purchases with grants (IEA 2023b). But the potential competitiveness naturally could also mean a desirable market reach, access to crucial resources, talents and/or economical labour force and so on.

In Figure 5, we grouped together several countries around the peak curve, starting with the most globally connected and progressing to the least. Group A consists of three seed companies based in Spain, Sweden and South Korea. Group B includes two seed companies, located in the Netherlands and India, while Groups C and D each contains one seed company, in Taiwan and Croatia, respectively. Countries within Group C are considered more easily replaceable by others if a more attractive environment emerges for the progression of EV industry manufacturers or their supply chains.

The correlation analysis between GNC and GCI scores across multiple methods reveals a complex relationship that extends beyond simple linear trends (Appendix A.4.1 in the Supporting Information). To examine these correlations, we categorised the countries into three groups based on their GNC scores. The first

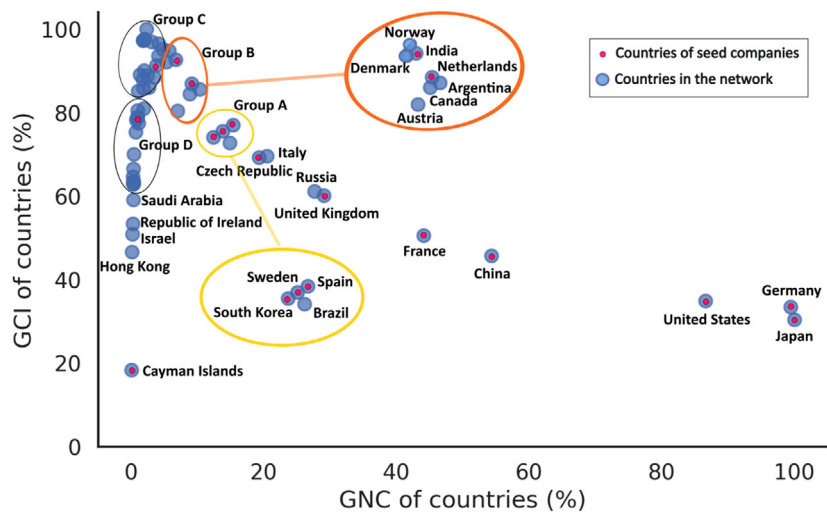


FIGURE 5 | Global Network Connectivity (GNC) and Gross Competitive Intensity (GCI) of the countries in the network of the EV industry.

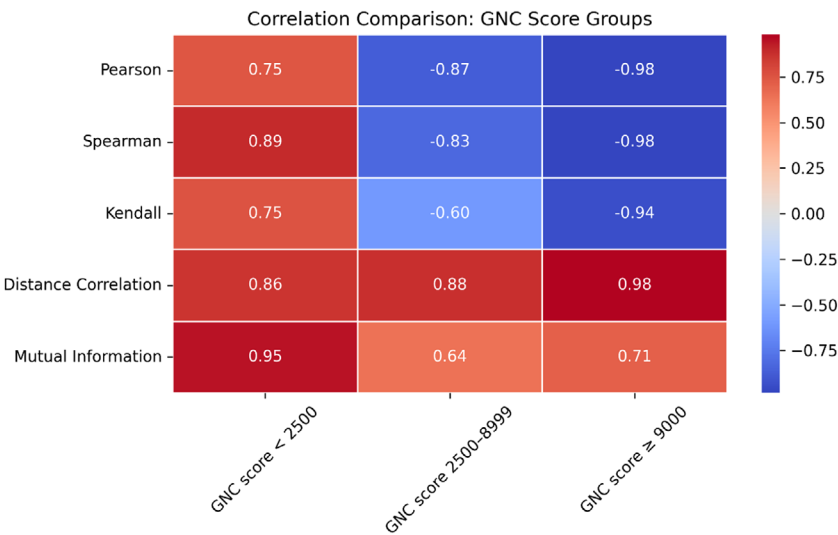


FIGURE 6 | Comparison of correlation metrics: GNC and GCI scores grouped by GNC scores.

group, representing low-GNC countries, includes those with a GNC score of less than 2500 (or 5% of the scaled score), spanning from zero to Group C in Figure 5. The mid-GNC group consists of countries with GNC scores between 2500 and 9000 (Groups A and B in Figure 5). Finally, the high-GNC group comprises countries with GNC scores above 9000 (or approximately 19% of the scaled score).

As Figure 6 shows, the correlation trends across GNC subgroups reveal a distinct threshold effect in the relationship between GNC and GCI. In low-GNC countries (< 2500), competition intensity increases as connectivity grows (Pearson 0.75, Spearman 0.89, Kendall 0.75), suggesting that firms in these nations face fiercer market dynamics as they expand their ownership networks. At this stage, growing connectivity pushes nations to compete aggressively, likely due to integration into global supply chains, positioning struggles or industrial expansion efforts. This pattern indicates that until countries reach mid-GNC levels, rising connectivity equates to heightened competitive intensity rather than market consolidation.

In mid-GNC countries (2500–8999), competition intensity begins to decline as connectivity increases (Pearson −0.87, Spearman −0.83, Kendall −0.60), indicating a transition phase where network integration stabilises market competition. Firms in this range likely benefit from strategic ownership ties, alliances, market consolidation or industry stabilisation, reducing the need for direct rivalry. The distance correlation (0.88) suggests that while the overall trend is negative, the relationship is shaped by structural complexities rather than a simple linear decline. The mutual information score (0.64) reinforces that GNC remains predictive of GCI, but other economic and geopolitical factors also influence competitive intensity at this stage.

Finally, in high-GNC countries (≥ 9000), we observed highly negative correlations (Pearson −0.98, Spearman −0.98, Kendall −0.94), confirming that as ownership ties increase, competitive intensity significantly decreases. The distance correlation (0.98) suggests a strong dependency, meaning the connection between GNC and GCI is systematic, though likely driven by structural factors beyond simple linearity. The mutual information (0.71)

suggests GNC is predictive of GCI, but at this level of connectivity, nations are less replaceable—often acting as market leaders—reinforcing that intensive interactions among well-connected economies experience diminished competitive pressures (Zhu et al. 2018), focusing more on strategic dominance than direct market rivalry.

This analysis could be extended in several directions. For example, deeper segmentation could examine whether ownership structures vary between legacy automakers and emerging EV manufacturers, revealing different competitive dynamics within high-GNC and low-GNC countries. In addition, incorporating supply chain dependencies, such as battery material sourcing and global manufacturing networks, could clarify whether certain ownership ties create resilience or exclusivity, influencing competitive intensity differently. For instance, research highlights the role of vertical integration (Ballinger et al. 2019; Wellener et al. 2022), capitalising on unique capabilities to secure supply chain advantages (Ulrich and Lake 1991; Deszczyński 2021; Abbasi Kamardi et al. 2022; Förster et al. 2022), and how ownership structures influence innovation within the EV sector (Bohnsack et al. 2014). Another direction could involve policy and regulatory influences, assessing how government incentives, trade agreements or industrial policies impact ownership connectivity and competitive positioning. Expanding in these ways would refine the structural thresholds observed, offering more actionable insights into the competitive dynamics shaping the global EV industry.

4 | Conclusion

This study contributes to the business research community by developing a generic Python tool, NetVizCorpy, which facilitates data collection and the construction of corporate ownership networks using the freely accessible Wikidata. As a case study, we compiled a dataset with three levels of upward and downward ownership relations of the EV industry, seeded with 44 EV and battery manufacturers, comprising 1354 companies (nodes) and 1575 ownership relations (links) across 58 countries. We provide detailed characteristics, network metrics and statistical insights into this dataset, demonstrating its applicability for various analytical approaches.

By calculating betweenness centrality, we identified the most influential companies within this network, highlighting the strong presence of financial institutions, such as Mitsubishi UFJ Financial Group, BlackRock, The Vanguard Group and Nippon Life Insurance Company, alongside established automakers—a factor that could strengthen the EV industry's resilience. We further applied community detection techniques, revealing strategies employed by EV manufacturers to reinforce their global presence through various ownership structures. Our analysis also revealed a potential vulnerability in the EV industry's supply chain integration. Specifically, we observed distinct communities formed by battery manufacturers, separate from those of EV manufacturers. One notable exception is BYD Auto, which uniquely operates as both an EV and battery manufacturer, thus enjoying a substantial advantage in terms of resilience within this competitive landscape. Finally, we extended the work of Zhang and Qian (2023) by applying GNC and GCI at the country

level, uncovering a nonlinear inverse U-shaped relationship that differentiates low-, mid-, and high-GNC countries. The most competitive countries turned out to be Japan, Germany and the USA, with China emerging as a significant contender in the global corporate network. These findings pave the way for future studies on competitive dynamics shaping the global EV industry, offering valuable insights into policy implications, industrial networks, corporate strategies and global competitiveness.

As outlined above in the case study, the analysis can be extended in several directions. In addition, integrating firm-level data such as financial reports could enrich the analysis of corporate resilience, offering deeper insights into the financial health and performance of individual companies within the network. Moreover, incorporating a time dimension into the analysis could provide a more comprehensive understanding of how the global corporate network seeded at the EV industry has evolved and continues to evolve over time. It may also offer valuable insights into firm performance during specific crisis episodes such as the COVID-19 pandemic.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in OSF at <https://doi.org/10.17605/OSF.IO/N6ZAF>, reference number N6ZAF.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting File 1: glob70029-sup-0001-SuppMat.docx