Structural Investigation of Aluminum in the US Economy using Network Analysis

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Please cite as:

Nuss, P., W.-Q. Chen, H. Ohno, and T.E. Graedel. 2016. Structural Investigation of Aluminum in the U.S. Economy using Network Analysis. Environmental Science & Technology 50(7): 4091–4101.

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Abstract. Metals are used in numerous products and are sourced via increasingly global and complex supply chains. Monetary input-output tables (MIOT) and network analysis can be applied to inter-sectoral supply chains and used to analyze structural aspects. We first provide a concise review of the literature related to network analysis applied to MIOTs. Based on a physical input-output table (PIOT) table of aluminum in the United States economy in 2007, we identify key sectors and discuss the overall topology of the aluminum network using tools of network analysis. Sectors highly dependent on metal product inputs or sales are identified using weighted degree centrality and their hierarchical organization is explored via clustering. Betweenness centrality and random walk centrality (page rank) are explored as means to identify network bottlenecks and relative sector importance. Aluminum, even though dominated by uses in the automobile, beverage and containers, and construction industries, finds application in a wide range of sectors. Motor vehicle parts manufacturing relies on a large number of upstream and

downstream suppliers to function. We conclude by analyzing structural aspects of a subnetwork for automobile manufacturing and discuss how the use of network analysis relates to current criticality analyses of metal and mineral resources.

Keywords: complex network analysis, economic input-output analysis, physical input-output table, material flow analysis, resource criticality analysis, complexity science

1. INTRODUCTION

Metals are ubiquitous in today's society. Their use has rapidly increased over the course of the last few decades [1]. Today, there are few materials or products where metals are not present or have not been involved in their production. While a century ago the diversity of metals was limited to perhaps a dozen in common applications such as infrastructure and durable goods, today's technologies utilize virtually the entire periodic table. At the same time, increasing product complexity, outsourcing, and globalization have resulted in increasingly complex and dynamic supply chains [2] that are difficult to understand and control [3]. Future global demand for a wide range of base and specialty metals is expected to increase further as a result of rapid urbanization and new infrastructure demands in developing countries, transition to low-carbon energy technologies, and increasingly widespread use of electronics. Because modern technology is highly dependent on reliable supplies of a wide variety of metals, numerous studies in recent years have attempted to better assess elemental resources and to determine which of them are "critical", the aim being to minimize potential supply disruptions to global and national technologies and economies [4–7]. Existing criticality analysis consider the countries involved in supplying the mined concentrate or refined metal (supply side), and the downstream end-uses at the sector-level or at the level of finished products (demand side). However, supply chain actors located in between are oftentimes not further considered. In addition, today's criticality analyses do not consider structural aspects of metal supply chains that can highlight important supply chain actors, bottlenecks, and industry clusters, and provide insights into competing uses and the overall robustness of the supply chains.

At the level of whole economies, the exchange of products or transactions between different economic sectors can be obtained from economic input-output (EIO) models using monetary input-output tables (MIOT) [8,9]. EIO models have occasionally been translated into physical input-output tables (PIOT) as the physical equivalent of the MIOT in national accounts [10]. For metals, PIOTs have been used to investigate the physical flows of aluminum, lead, magnesium, zinc, chromium, and nickel in the United States [11], iron and steel associated with car production in Japan [12], lead, zinc, manganese, aluminum, and molybdenum in South Korea [13], and copper in France [14]. More recently, multi-regional input-output (MRIO) models (based on monetary units) have been used to illustrate the global supply chain of tantalum [15] and neodymium, cobalt, and platinum [16]. The study by Nansai and colleagues [16] attempts to integrate criticality information into metal supply chain data by calculating the mining risk footprint of neodymium, cobalt, and platinum using the Policy Potential Index [17] of the sourcing countries.

Based on the technical coefficients tables of MIOTs, many analytical techniques yield interesting insights into the structure of economic systems and help to identify ‘key sectors’, including the use of the Leontief output inverse, multiplier analysis, matrix triangulation, structural decomposition approaches, field of influence, extraction methods, to name a few [9]. Alternatively, an economy represented by MIOTs can also be regarded as a network consisting of nodes (sectors) and directed (and weighted) links (economic transactions) among sectors [18]. Qualitative Input-Output Analysis (QIOA) focuses on the sheer existence of edges between sectors, regardless of their weights [19–21], and allows the application of graph- and network-theoretical approaches to analyze structure [22]. Although developed for the study of sociology and complex systems, the techniques and indicators of network analysis can also be used for examining the structural features and connectivity of economies and technological systems [23].

Within the last two decades, network analysis has become one of the most versatile and visible frameworks used to analyze, understand, and optimize complex systems spanning various disciplines, including biology, ecology, engineering, sociology, infrastructure, and communications. Network analysis can be used to obtain insights into the structure (topology), functioning, and dynamics of networks present at molecular to macro scale and in natural and anthropogenic systems [24–27]. In network analysis discrete entities (e.g., individuals, genes, companies, sectors, and countries) are described as nodes (vertices) connected by directed or undirected and weighted or non-weighted links (edges) with each other. Famous examples include analyzing the world wide web [28–30], food web structure [31], metabolic networks [32], epidemics [33], communications networks [34], and the structure of financial markets [35]. Network analysis has been widely applied to look at issues of trade between countries [36–50]. Some studies have investigated trade networks for specific commodities [40,51,52]. A rich body of literature also exists on the use of ecological network analysis to materials and energy flow networks in industrial systems [53–56]. More recently, research has started to focus on the strong coupling between networks, interdependencies in networks, and spatial properties [57]. A number of researchers also apply network analysis to MIOTs (*Supporting Information: Table S1*). However, to the best of our knowledge network analysis has not yet been applied to metal PIOTs (*Supporting Information: Figure S1*).

Therefore, the goal of our study is to provide, firstly, an overview of the literature dealing with network analysis and EIO models. A discussion of material flow analysis and EIO analysis to derive PIOTS is provided in our two companion papers [58,59]. Secondly, we explore how network measures [60–62] can help to elucidate important actors in the PIOT for aluminum [58] (constructed from the United States MIOT for year 2007). Results are discussed in the context of supply risk for the metal network as a whole and more specifically from the perspective of the automobile sector. We conclude with a brief outlook on how network analysis of metal supply chains relates to the concept of metal criticality and risk analysis.

2. LITERATURE REVIEW: NETWORK ANALYSIS AND EIO-MODELS

A MIOT comprises the sectors of an economy that are interdependent of each other via the exchange of goods and services [8,9]. An input-output-based economy can be viewed as a network in which nodes represent economic sectors and the monetary transactions between sectors constitute the directed and weighted edges [63]. MIOTs are compiled at country-level at varying levels of sectoral resolution. In the United States, the Bureau of Economic Analysis publishes a MIOT consisting of 380+ economic sectors [64]. More recently, MIOTs have been harmonized and combined with trade data in multiregional input-output (MRIO) models to follow monetary transactions globally [65–68].

Within the EIO literature, a number of 'traditional' indicators and methodologies are used to assess and compare structural features of economies (e.g., backward and forward linkages, triangulation, multidimensional scaling, and coefficients sensibility analysis) [69]. Network analysis can also be used to measure structural and systemic features of MIOTs, but has been less frequently applied in that regard.

The primary goal of our literature review was to identify previous studies that examined some aspect of network analysis in the context of MIOTs. Several scholarly databases were used to carry out the literature search, including Academic Search Complete (EBSCO), Google Scholar, Lexis Nexis, ProQuest, and JSTOR. We applied backward and forward citations to all salient articles for further inclusion. A combination of search keywords, including “input-output analysis”, “network analysis”, “network theory”, “qualitative input-output analysis (QIOA)”, “key sectors”, “structural analysis”, “technological system”, “national accounting”, were used to scan the literature. *Table S1 in the Supporting Information* provides a summary of literature that has applied network statistics to MIOTs and explains their goal, data sources, and network measures used. Only articles in English language were included (although articles in other languages are included with the footnotes in Table S1). Our literature review yielded a final set of 30 articles published between 1974 to 2014 that discuss network theory in the context of EIO analysis and MIOTs [18,23,63,69–95]. Including articles in non-English language shifts the starting date to around 1969 [96–98]. The majority of studies apply network analysis to non-weighted and directed networks based on QIOA. Some studies look at innovation diffusion by combining MIOTs and research and development (R&D) embodied product flows among sectors. From this literature review, we conclude that network analysis has not yet been applied to PIOTs of metals (the goal of the present study) (see also

Figure S1). A variety of network indicators are used to analyze the structure of the economy and the position of sectors. Among the network indicators that were most commonly used to identify the position of sectors in the economy are in-degree and out-degree centrality (both weighted and non-weighted), density, clustering and community detection, betweenness centrality, and random walk models (Table S1). As a result, all of these indicators are also used, together with a few additional network metrics, in the current study. Each metric is discussed in further detail in the next section and the Supporting Information and then applied to a PIOT for aluminum.

3. METHODOLOGY

In this study, the PIOT (referred to as the *Input-Output Material Flow Network (IO-MFN)* in our companion papers [58,59]) of aluminum in the United States economy for 2007 is analyzed. Building the IO-MFN of aluminum from its corresponding MIOT is explained in our companion paper [58] and the network studied in this paper is based on this source. Building the metal network consists of several steps including, e.g. calculation of an input coefficient matrix from the MIOT, applying a physical flow filter to ensure that non-physical exchanges (e.g., services) are excluded, a yield loss filter to account for scrap/losses generated, and deriving a resulting material composition matrix [58]. The resulting 393 x 393 commodity by commodity table (see Table S4 in our companion paper [58]) is first transformed into respective nodes and edges lists and then imported into Gephi0.8.2beta network analysis software [99]. In this paper, we follow the terminology of nodes (sectors) and edges (mass flow of aluminum between sectors) commonly used in network analysis[25]. Only edges with a weight ≥ 0.001 metric tons are considered (threshold). Nodes not connected to the network after applying this edge threshold are deleted. The resulting network consists of 381 nodes (sectors of the economy) and 28,150 edges (exchanges of aluminum embedded in materials or products). In addition to the inter-sectoral network for the whole United States economy, we also analyze a subnetwork for automobile manufacturing. The subnetwork is based on the final demand of automobile manufacturing in 2007, with further details on how this network was derived provided in the companion paper [58].

Network measures are calculated using Gephi0.8.2beta [99] and Python NetworkX [100]. Modularity and clustering results are derived using Matlab™ software [101]. A variety of network measures are readily available to explore the network topology and position of nodes in a network [25,60,62,102,103]. The network measures used, and how they translate into the identification of important sectors within the United States economy, are summarized in Table 1. A more detailed description of each metric and its interpretation in the context of the metal networks is given in the *Supporting Information Section 2.*

Table 1 Network measures and their meaning in analyzing metal supply chains.

Network Measure	Short Explanation[a]	Role in Metal Network	Role Description	Risk Aspect
Weighted In-Degree Centrality[c]	Measures the number of direct incoming edges including their weights [102]	Collector	To transform or combine materials and parts into value-added products (intermediate supply chain actors) or services (end-users)	Actors highly dependent on metal inputs; Drivers of the metal supply chain. Network vulnerable to the removal of such nodes (targeted attacks, natural disasters)
Weighted Out-Degree Centrality[c]	Measures the number of direct outgoing edges including their weights [102]	Distributor	To distribute materials and products across multiple downstream actors	Actors highly dependent on metal sales; Degree of difficulty faced by firms in dealing with downstream demand Network vulnerable to the removal of such nodes (targeted attacks, natural disasters)
In-Degree Centrality (Non-Weighted)	Counts the number of incoming direct ties to a node [102]	Upstream Complexity	Number of incoming linkages	Actors dependent on a large number of incoming products. Implies a greater product complexity (e.g., multiple products used in a single assembly)
Out-Degree Centrality (Non-Weighted)	Counts the number of outgoing direct ties to a node [102]	Downstream Complexity	Number of outgoing linkages	Actors selling goods to a large number of downstream sectors. Implies demand from a large number of downstream sectors that needs to be handled [b].
Page Rank (Random Walk Model)[c]	Ranks nodes according to how often a user following edges will non-randomly reach each node [104]	Relative importance of sectors	The probability that a metal atom in the network will visit any of the sectors	Relative importance of sectors for metal use. Removal of a node with high page rank may significantly alter metal demand.
Modularity and Clustering[c]	Community detection algorithm [105]	Sector communities (modules) in the network	Sub-units of communities, which are sets of highly interconnected nodes, who trade amongst each other	Important functional modules whose removal can distort the network. Provides insights into industry clusters of importance to the metals supply chain.
Betweenness	Measures how often a node appears on shortest paths between nodes in the network [106]	Bottleneck	Number of times a node is on the shortest path between two other nodes	"Gatekeeper" nodes; any delay or operational "hiccups" caused by such an actor can hamper the functioning of the whole supply chain and cause supply disruptions
Eccentricity	The distance from a given starting node to the farthest node from it in the network [102]	Maximum number of transformation steps	Maximum number of physical transformation steps necessary to reach a certain sector	A larger number of transformation steps equal an increased likelihood of supply disruptions (from the perspective of a certain sector).
Closeness centrality	The average distance from a given starting node to all other nodes in the network [107]	Average number of transformation steps	Average number of physical transformation steps necessary to reach a certain sector	A larger number of transformation steps equal an increased likelihood of supply disruptions (from the perspective of a certain sector).

[a]Additional details for each network measure are provided in the *Supporting Information Section 2*.
[b]A higher out-degree centrality can also be translated into a higher downstream diversity (e.g., a metal product used in multiple part or platforms), which could imply lower risk.
[c]Network measure taking into account the weightings of edges (i.e., the quantity of physical flow of metal between economic sectors).

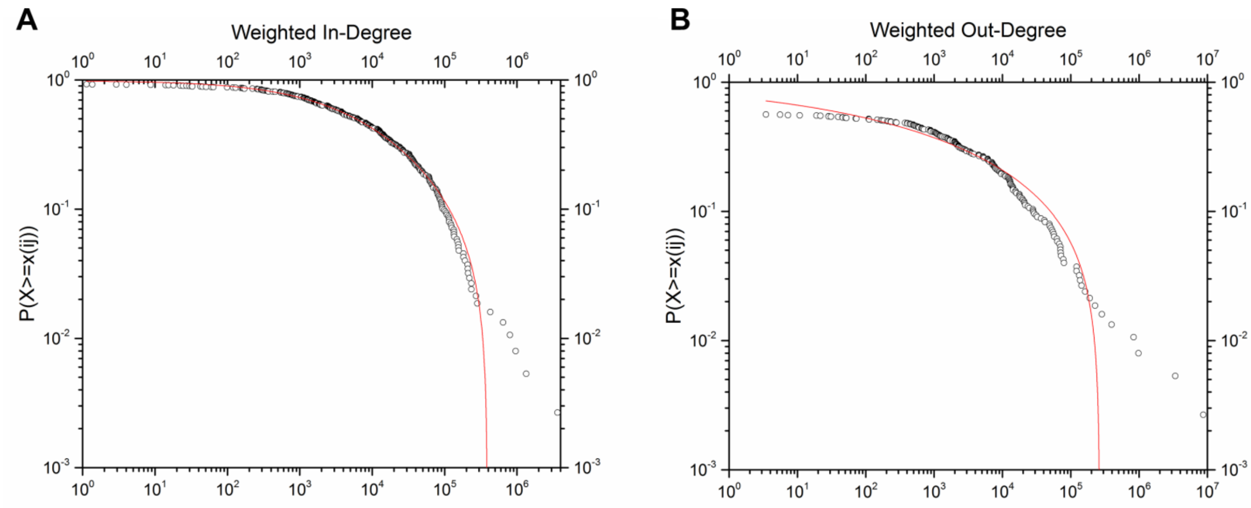
4. RESULTS

4.1 The Aluminum network as a Whole

Network topology. The network topology relates to the relationship between the number of edges and number of nodes in a network. The degree distribution of networks (random vs. real world (often also termed "scale free" [108]) is important in the context of supply chain risk, because the topology determines how vulnerable a network is to an attack [28]. Scale-free networks have been found to be relatively robust against accidental failures or random attacks, because the likelihood that a small (less interconnected) node is removed is large, as such nodes are more plentiful than the well interconnected hubs [28,109]. Furthermore, removing a less interconnected node will not alter the overall network topology significantly. On the other hand, scale-free networks are more vulnerable to coordinated attacks that target specific hubs [28,109].

Despite the fact that the aluminum network is dominated by metal flow among a limited numbers of sectors, it is clear from a visual inspection of the weighted degree distributions on a log-log scale that the network deviates from a power law (which would be indicated by a linear line on a log-log plot) (Figure 1), i.e., it is not scale-free. Figure 1 also shows that even though several high metal throughput sectors (high weighted degree centrality) are present, the majority of sectors are found at intermediate metal turnover, implying diverse uses in the US economy. This reduces the overall vulnerability of the network to a potential targeted attack on any one of the sectors when compared to a scale-free network. A detailed table of the nodes of the aluminum network and derived network metrics is provided in the Supporting Information (*Supporting Information: Table S2*).

Figure 1. Complementary cumulative distribution functions for (A) weighted in-degree and (B) weighted out-degree of the aluminum network. Both distributions deviate from a power law, i.e., they do not form straight lines on the graphs. The nonlinear curve fits are based on a logistic function.

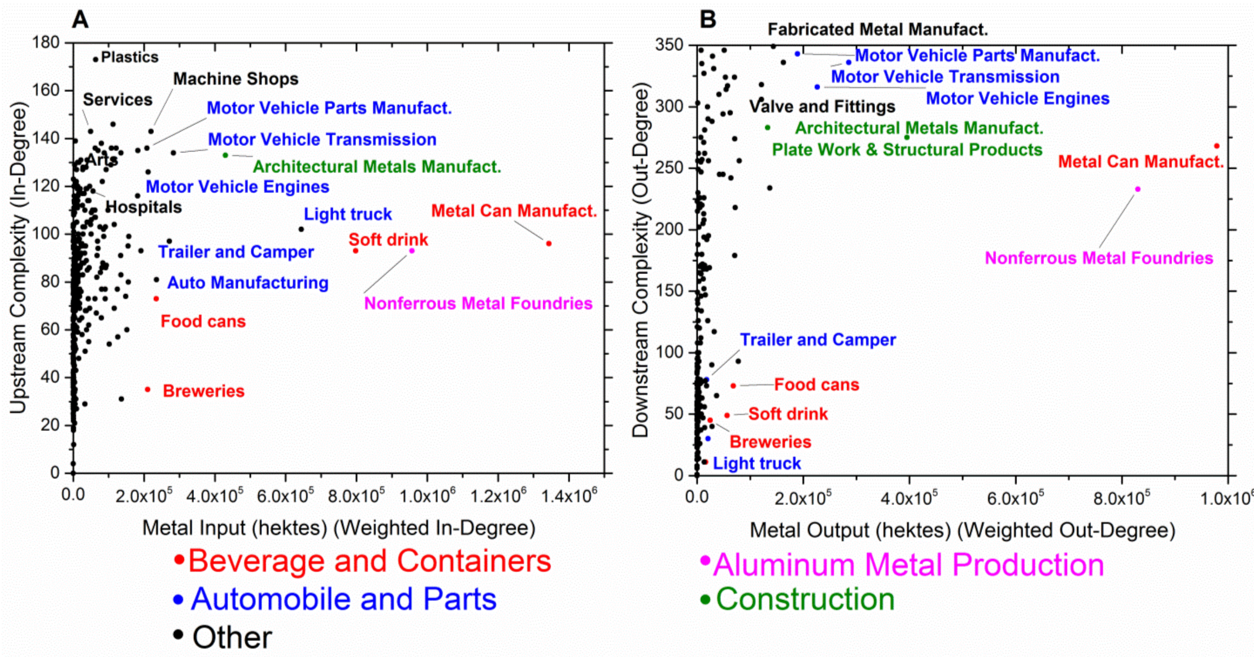


The goodness of fit of a straight line in Figure 1 can be used as an indicator of the overall risk of the aluminum network to targeted node removal (e.g., a targeted attack removing the main companies that are part of a key sector facilitating a large share of the aluminum flow).

Collector nodes. "Collector" nodes refer to supply chain actors that transform or combine metal flow into value-added products or services. They are represented by a large weighted in-degree centrality (Figure 2a). Aluminum enters the United States economy in the form of primary and secondary aluminum (from new and old scrap) [58]. Sectors highly dependent on aluminum inputs include the Beverage and Container sectors sourcing wrought aluminum for the production of Aluminum Cans, Motor Vehicle Parts subsequently incorporated into Motor Vehicles, and the Construction sector using aluminum from the Architectural Metals sector for building purposes (Figure 2a, x-axis). Furthermore, non-weighted in-degree centrality (Figure 2a, y-axis) can be seen as an indicator of *upstream complexity* as it indicates the number of inputs required per unit of sector output. The Motor Vehicle Parts and Transmission Sectors, and the Architectural Metals sectors, seem to be more vulnerable to potential supply restrictions than any of the other sectors, because they rely on a larger number of metal-containing materials, components, and parts to function (Figure 2a, y-axis).

Distributor nodes. Distributor nodes refer to supply chain actors that allocate materials and products across multiple downstream actors. They represent actors highly dependent on sales of metal-containing products as indicated by weighted out-degree centrality. Figure 2b (x-axis) shows the main distributor nodes. Aluminum spreads into the United States economy mostly through the sales of Metal Cans, Non-Ferrous Metal Foundries (melting and casting metal into desired shapes), construction-related materials uses, and Automobile Parts Manufacturing. Downstream supplier complexity (non-weighted out-degree centrality) is highest for companies producing Motor Vehicle Parts and Transmissions followed by Metal Containers and construction-related sectors (Figure 2b, y-axis).

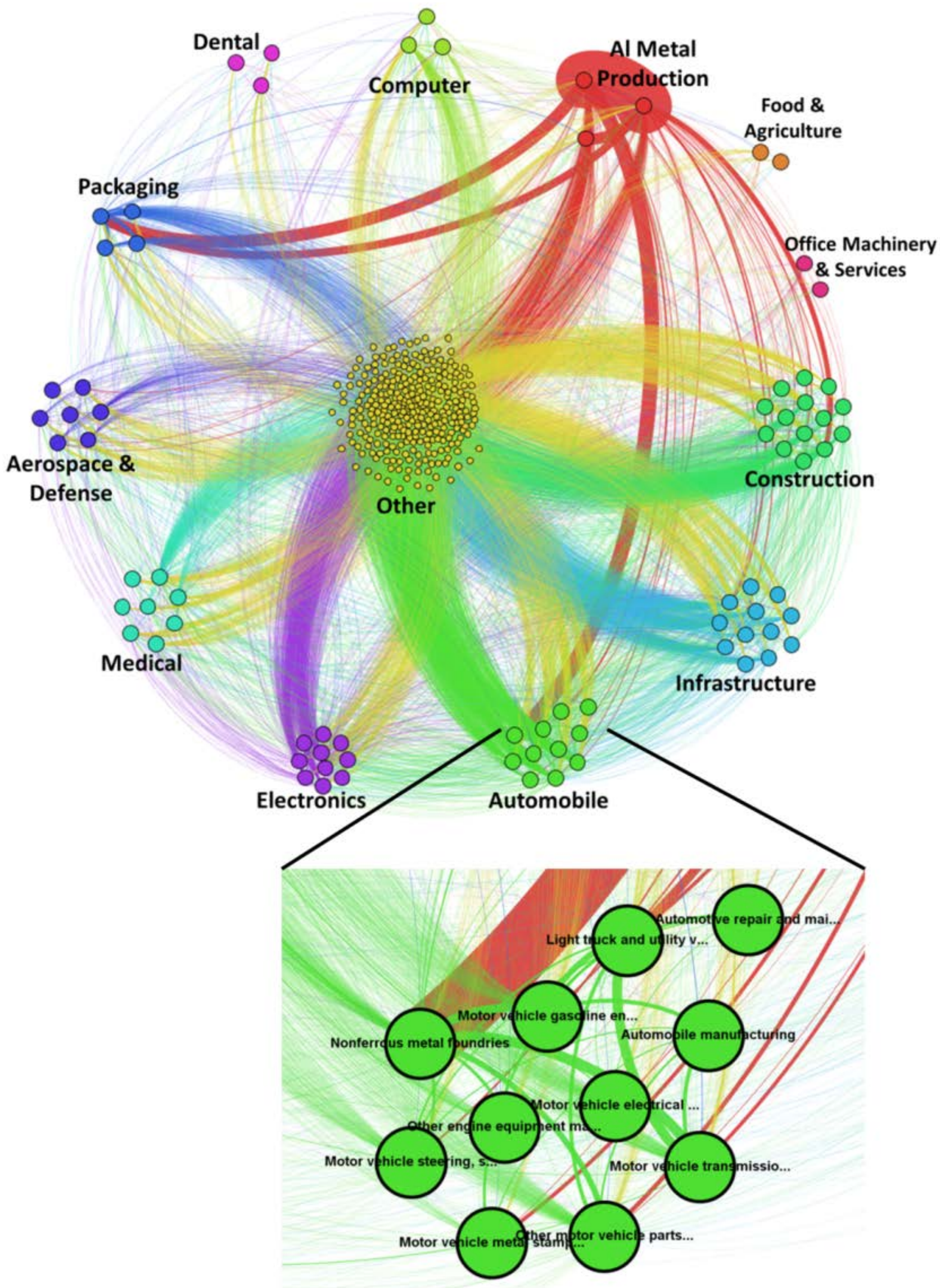
Figure 2. Sectors dependent on aluminum throughput in the United States economy in 2007. (a) Collector nodes receive aluminum inputs as indicated by their weighted in-degree properties. (b) Distributor nodes spread aluminum into the economy as indicated by their weighted out-degree properties. Alumina Refining and Aluminum Product Manufacturing were excluded from the figure. The aggregated quantities of a metal PIOT are termed “transformed metal units” (TMUs), and denominated in hektes (see also our companion paper [58]). One hekte equals approximately one metric ton of metal and is used to remind the reader that building the PIOT is based on a price homogeneity assumption as described in references [12,110]. These are terms that parallel the economist’s monetary units of dollars or yen. The hekte, pronounced “hecktuh”, is thought to have been the first metal coinage, used in Lydia [now Western Turkey] in the 7th century BPE [111].



Total Metal Turnover. The total aluminum turnover is represented by weighted degree centrality (the sum of weighted in- and out-degree centrality) and indicates sectors representing the "backbone" of the aluminum supply chain (*Supporting Information: Figure S2*). Node size is shown proportional to weighted degree centrality. Motor Vehicle Parts and subsequent Motor Vehicle production represent the key sectors facilitating aluminum flow in the US economy. These sectors are followed by metal products (Boiler & Tank & Container and Architectural Metal) and the Beverage and Food industry utilizing aluminum cans and containers. The visualization helps to visualize economy-wide supply chains from the perspective of a single sector. For example, the Motor Vehicle Parts sector (purple node on top right of the circular diagram in Figure S2) sources aluminum products predominantly from Nonferrous Foundries and the Forging & Stamping sectors. Its main customer is the Motor Vehicle sector, but it also distributes aluminum-based automobile parts in smaller quantities for the production of Agricultural Machinery, Ships, Construction Machinery, Aerospace, and Other Transportation. In addition, a small fraction of aluminum embedded in automobile parts are used internally (self-loop) and subsequently-produced motor vehicles are also required in order to produce motor vehicle parts. Furthermore, the circular layout (shown by decreasing degree centrality) indicates that the Motor Vehicle Parts industries trade with a large number of up- and downstream sectors (see also Figure 2). This puts the Motor Vehicle Parts sector in a unique position as it has to handle larger product complexity than other sectors of the US economy.

Sector communities. Identifying industry clusters in metal supply chains can help to prioritize communities that are important for maintaining the aluminum supply chain. These may be targeted, e.g., when aiming to improve supply chain efficiencies or when imposing new environmental or product policies. Figure 3 illustrates the groups of industries that cooperate by increased exchange of aluminum-containing goods. These are named based on the majority of sector nodes that are present in each of the clusters (*Supporting Information Figure S3 and Table S3*).

Figure 3. Industry clusters of the aluminum network determined using the clustering method of Kagawa and colleagues [105]. A zoom-in for the automobile sector is illustrated at the bottom. Edges are colored by source node.



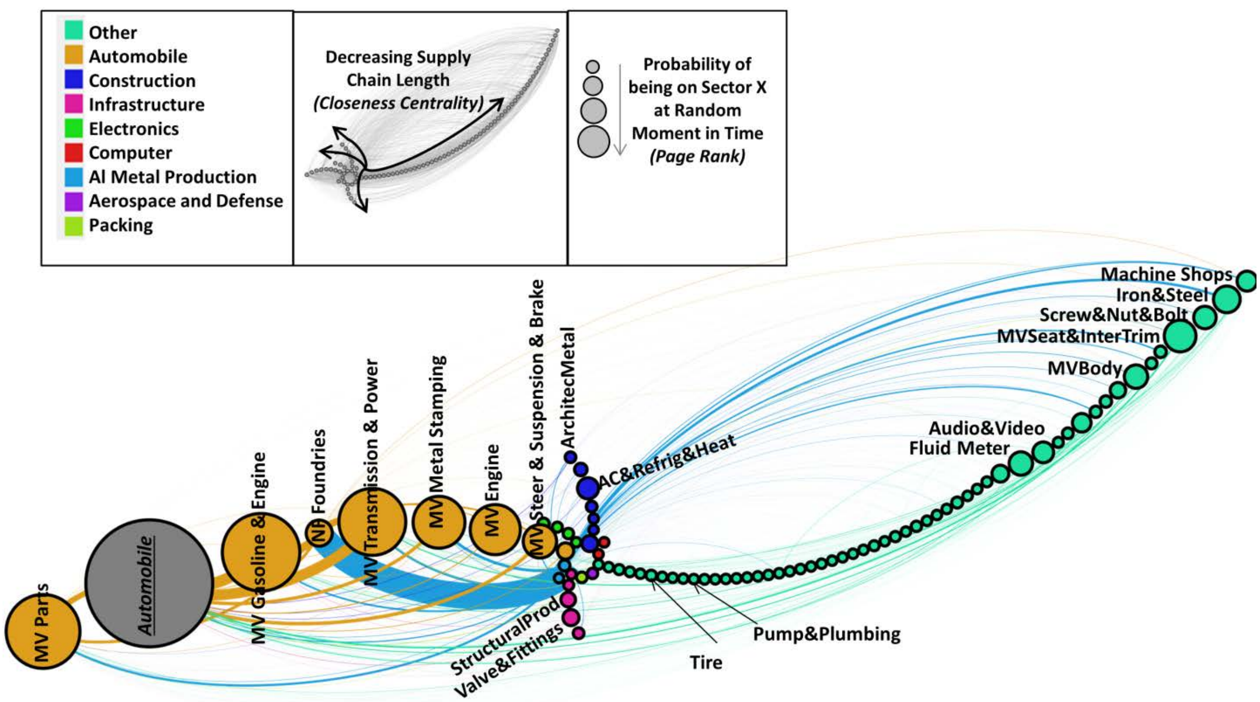
The aluminum network in Figure 3 consists of 13 industry clusters. Aluminum enters the US economy starting from the aluminum metal production cluster (red nodes on top right of Figure 3) and spreads predominantly to the Automobile, Packaging, and Construction clusters. The receiving clusters exchange aluminum-containing products within themselves in the chain of adding value before exchanging products with other industry cluster of the US economy (see for instance the automobile cluster enlarged at the bottom of Figure 3, where intra-industry flows (green edges between automobile nodes) and inter-sectoral flows (green edges leaving the cluster) as well as receiving flows from aluminum production (red edges entering the cluster) are clearly visible). Industry clusters belonging to Computer, Dental, Aerospace & Defense, and medical are only weakly connected to the aluminum supply chain and thus are less important from the perspective of someone selling aluminum into the U.S. economy. All industry clusters exchange aluminum-containing goods with a variety of "other" sectors shown in the center of Figure 3 (sectors that could not be assigned to any of the industry clusters). Figure 3 also indicates that significant exchange across industry clusters takes place. According to Hearnshaw and Wilson [112], efficient supply chains have communities with overlapping boundaries for their flows of goods (and information). Because of the diverse uses of aluminum in the US economy (both in terms of number of high-throughput nodes as well as the number of exchanges between industry clusters), the supply chain can be regarded as more efficient and relatively robust to supply chain shocks (e.g., sudden node removal) than might be the case for metals used in more specialized applications (e.g., minor metals such as tantalum or rhenium used in a small range of specialized applications [7]).

Relative sector importance. Page rank provides an indication of the relative importance of sectors for miners and metal producers that sell aluminum or wrought aluminum into the US economy (*Supporting Information: Figure S4*). The page rank of a sector is determined recursively and depends on the number and page rank of all sectors that link to it. Sectors highlighted by page rank include seminal sectors (e.g., Government, Restaurants, Residential Structures, Hospitals, Food and Drinking facilities) that initiate final demand for aluminum-containing products (e.g., in the form of beverage cans and containers or structural metal parts) (*Supporting Information: Figure S4*). In addition, intermediary sectors, including Light Trucks, Automobile Manufacturing, Aircraft Manufacturing, and Motor Vehicle Transmission and Power Train Parts Manufacturing, are important for sourcing and transforming aluminum embedded in products. The page rank can be interpreted as the relative time that a metal atom spends at each sector and highlights the importance of sectors for someone selling aluminum in its metallic form or embedded in products into the U.S. economy. Sectors identified by page rank (y-axis in Figure S4) are not necessarily associated with high aluminum turnover (x-axis in Figure S4) indicating that the algorithm provides additional supply chain insights that might not be apparent from looking at the other network metrics.

4.2 The Automobile Supply Chain in the Automobile Network

The production network for automobile manufacturing is based on the final demand of automobile manufacturing in 2007, setting all other final demand entries to zero [58]. Of the 393 sectors in the 2007 US economy, a total of 85 sectors (22%) are involved in the aluminum supply chain of automobile manufacturing (*Supporting Information: Figure S5 and Tables S4 and S5*). The supply chain length can be quantified via closeness centrality as an indication of the average number of physical transformation steps involved. With a directed closeness centrality of 1.41, the automobile manufacturing sector is found to be in a central position not far from any of the other sectors in the US economy (*Supporting Information: Table S4*). The maximum number of steps to reach the farthest other supply chain actor (i.e., maximum tier) in the supply chain is 3 (eccentricity) (*Supporting Information: Tables S4 and S5*). This is due to the high interconnectedness of exchanges in an EIO-derived network. The product complexity (in-degree) equals 51, meaning that the automobile manufacturing sector sources aluminum from a relatively large number of upstream sectors. The network does not provide information on the importance of each input to overall functioning, nor their potential substitutability. Such information can be derived from detailed criticality analysis [7] (see Discussion section). The specific position of the automobile manufacturing node in the overall supply chain network is further illustrated in Figure 4.

Figure 4. Radial axis layout of aluminum flows in the automobile supply chain taken from our companion paper [58]. Industry clusters involved in the automobile supply chain are derived using a clustering analysis [105] and shown as separate radial axes and by different colors. Nodes are ordered by decreasing closeness centrality (non-directed and non-weighted) on each axis, so that nodes closer to any other node in the network are shown on top and those farther away are shown on the bottom of each radial axis. Node size refers to increasing relative importance as determined by weighted and directed page rank. The final sector (automobile manufacturing) is shown in grey and represents the largest node (the seminal Automobile Manufacturing sector has highest page rank because all metal flow eventually reaches this sector and because it is connected to a number of nodes with high page rank upstream). Edges are colored by source node.



Of the 13 industry clusters derived previously (Figure 3), the automobile supply chain overlaps with 9 clusters to varying degrees (Figure 4), but does not touch sectors belonging to the industry clusters called

Office Machinery and Services, Medical, Food and Agriculture, and Dental (*Supporting Information Table S6*). The percentage overlap quantifies the involvement of each industry sector in facilitating aluminum trade for automobile manufacturing. The largest overlap is found for the Automobile cluster (82%) and the lowest for Aerospace & Defense (15%, consisting of only one node). Sectors on each of the radial axis (industry cluster) are ordered by decreasing supply chain length (undirected closeness centrality), which ranges from 1.17 for Alumina refining (top purple node within the “Al Metal Production” cluster) and 2.75 for Heating Equipment (bottom green node within the “Other” industry cluster) (Figure 4). The Automobile sector (grey node) is centrally located within the automobile cluster and only MV Parts Manufacturing has a lower closeness centrality score (i.e., is located closer to all other nodes in the network) (Figure 4). Nodes with low closeness centrality (shorter geodesic distance) are those located closer to the center of the graph; they display several incoming and outgoing interlinks with nodes from varying industry clusters, e.g., sectors producing intermediate vehicle parts and products.

Node size is shown proportional to page rank and indicates the probability of an aluminum atom to be found at any of the sectors of the US economy at a random moment in time (Figure 4). Because automobile manufacturing represents the ultimate “sink” for aluminum flowing through the network, its page rank is 29% (29% of aluminum is found at this sector after multiple iterations of page rank). Other sectors with high page rank include several automobile-related sectors. The page rank algorithm also helps to identify sectors that would not be obvious from a simple count of (weighted) in- or out-degrees or by looking at closeness centrality, namely the importance of a number of “Other” sectors (Machine shops; Iron & steel mills; Turned product and screw, nut, and bolt manufacturing; Motor vehicle seating and interior trim manufacturing; Audio and video equipment manufacturing; and Totalizing Fluid Meter and Counting Device Manufacturing). Aluminum is incorporated to a notable degree into products belonging to these sectors, and many of these products subsequently reach the automobile manufacturing sector. Sectors highlighted by page rank are either directly involved in the transformation of aluminum-containing intermediate products or those that are located next to important sectors (with high page rank).

The latter is true for “Air Conditioning, Refrigeration, and Warm Air Heating Equipment Manufacturing” located in the direct vicinity of some of the “most important” automobile-related sectors of the supply chain.

A number of sectors are frequently located between other sectors and act as potential bottlenecks of the supply chain (*Supporting Information: Figure S6*) (Figure S6 differs from Figure 4 in that it plots betweenness centrality instead of page rank). These include machine shops used in intermediate and final products manufacturing, motor vehicle parts required in the majority of automobile sectors, aluminum product manufacturing which sources primary aluminum from smelting and refining before distributing it into the metal network, and a number of other sectors (e.g., nonferrous metal foundries, iron & steel mills, and motor & generator manufacturing). Because of their gatekeeper position, removing any of those sectors has the potential to significantly disrupt aluminum flow in the US economy.

5. DISCUSSION

In this study, we examined the use of network indicators to highlight structural aspects of the aluminum supply chain in the US economy. The use of MIOTs allows the creation of material flow networks (IO-MFNs). Because data on real supply chains are not easily available, only a few case studies have been published to date in which network analysis is applied to physical and contractual (accounting for legal agreements between firms) supply chains [113–115]. Our study adds to this body of literature, but focuses specifically on the flow of metals (i.e., aluminum) though the economy. By doing so, our study helps to better understand and visualize the physical metabolism of economies, and can provide insights on the position of each sector within the metals supply chain – information relevant to metal producers, manufacturers, final consumers, and decision makers. Furthermore, network measures are extremely powerful in identifying ‘important’ supply chain actors (e.g., via degree centrality and page rank), the overall network topology (e.g., by looking at system-wide measures such as clustering and density) and the robustness of the network to random and targeted attacks (see discussion on scale-free networks). By doing so, network-based metrics can complement the existing literature on resource criticality [4,6,7], which does not yet look at metals criticality from the perspective of supply chain structure, but focuses instead on the geopolitical and social & regulatory framework in the sourcing countries, and additional aspects, including amongst others: companionality [116], environmental implications [117], substitutability [118], and resource depletion [7]. While some of the network metrics discussed have been applied to MIOTs (*Supporting Information: Table S1*), these metrics have not traditionally been applied to PIOTs (in fact, we only found a single study that mentions the importance of analyzing the structure of economies from PIOTs [119], but that work does not use network metrics in its analysis). It is interesting to note that a recent study applying network analysis to a life cycle inventory (LCI) network found a scale-free structure [120], while for the IO-MFN investigated in this study we do not observe scale-free properties. This is likely due to the high connectivity in economic IO networks when compared to LCI networks. It should be noted that the structure of the network analyzed depends on several assumptions made during construction (e.g., determining which flows are physical or monetary (binary matrix), assumed loss and scrap rates, and price homogeneity) which are discussed in further detail in our two companion papers [58,59]. For example, price homogeneity assumes unique sectoral prices, i.e., for a given product, the same price applies to all its users [110,121]. However, with price heterogeneity (which better reflects reality) this assumption does no longer hold and calculated metals turnover per sector (weighted in- and out-degree centrality) does not exactly equal metric tons (this is why we refer to TMUs expressed in units of hektes in Figure 2). Furthermore, we note that the MIOT for 2007 was used, because it is the latest version available at 393 sector resolution. As a result, some of the results may not reflect recent trends in the aluminum household in the United States. Therefore, results shown in this paper should be seen as providing first insights into the aluminum supply chain in the US economy. However, the ideas presented on network metrics and their interpretation in the context of risk analysis, however, hold also for further refined PIOTs and other physical supply chains. We also note that there seems potential for further combining the network metrics of metal PIOTs with environmental extensions from economic input-output life cycle assessment (EIO-

LCA) [122] to consider aspects related to environmental implications (the same could be done using the framework of social LCA [123] and, for example, indicators developed by the Social Hotspot Database [124]).The accounting of environmental issues and analysis of the structure ofn life cycle/EIO-based networks is gaining increasing interest among the scientific community [56,120,125–127]. Further extensions of this work will focus on the comparison of different metal PIOTs using network metrics and the impact of targeted and random node removal on the overall metal networks.

6. SUPPORTING INFORMATION

Details of the literature review, additional network visualizations, and network analysis results, can be found in the Supporting Information. This material is available free of charge via the internet at http://pubs.acs.org.

7. NOTES

The authors declare no competing financial interests. Philip Nuss is now working with the European Commission Joint Research Centre in Ispra, Italy.

8. ACKNOWLEDGEMENTS

We would like to thank Shigemi Kagawa from Kyushu University for providing us with the MatLab code for carrying out the clustering analysis. Details of the algorithm can be found in (Kagawa et al 2013) [105]. We would like to acknowledge the Yale Criticality Project for funding this research.

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