Comparative Analysis of Metals Use in the United States Economy

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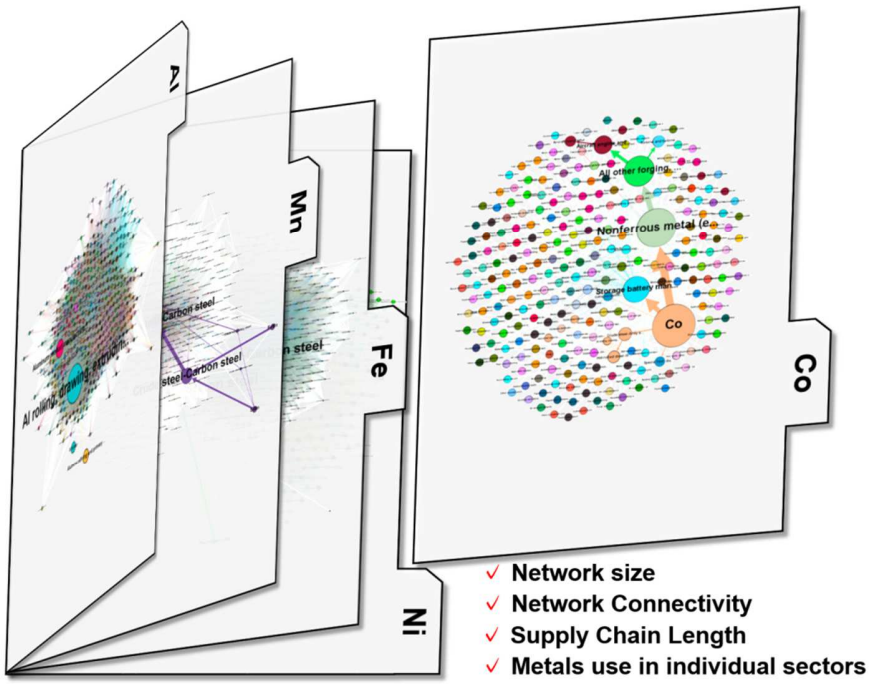
Abstract. Building a circular economy requires knowledge of physical material flows and stocks. One approach for obtaining data on the intersectoral exchanges of materials in an economy is with physical input-output tables (PIOTs). Using PIOTs of eleven alloying metals (aluminum, vanadium, chromium, manganese, iron, cobalt, nickel, copper, niobium, molybdenum, tungsten) for the entire United States economy in 2007, we apply network-based metrics and visualizations to identify key sectors and compare different PIOTs with each other. Some 40–45 % of all

intersectoral trade contains the major metals aluminum, copper, and iron, while this number ranges between only 11–15% for minor metals (e.g., cobalt, vanadium, niobium, molybdenum, tungsten). The majority of sectors rely on products containing the major metals, reflecting widespread use of those products in our modern economy. Network size provides an indication of supply chain steps required to move from metal production to finished product manufacturing. Supply chains for the minor metals require an average of 5-8 steps, while those of major metals involve 3 steps on average. Cobalt is used extensively to illustrate these results because its status as a "technology-critical material" demonstrates how these analytical approaches can reveal sector usage and dependency for a metal of potential supply concern. We conclude by presenting automobile supply chain networks and discuss the position of the automobile production sector in the US economy. The analytical and visualization approaches presented result in an improved understanding of metal flows and can help to better communicate underlying data, e.g., in a policy context.

Key words: Mixed-unit input-output tables, network visualizations, material flow analysis, resource criticality analysis, science-policy interface, complexity science

Graphical Abstract:



1. INTRODUCTION

Since the late 18th century, humans have been altering Earth at an unprecedented and unsustainable rate and scale (Hoekstra and Wiedmann, 2014). While environmental challenges such as climate change (IPCC, 2013) and water scarcity (Ridoutt and Pfister, 2010) have been widely recognized and studied, elemental scarcity linked to the tremendous increase of metals use in modern technologies (Greenfield and Graedel, 2013) has only recently gained attention. Indeed, in a world that will have some nine billion people by 2050 (United Nations, 2011), providing sufficient and stable supplies of raw materials while at the same time lowering environmental burdens and fostering social welfare across product supply chains will be an important challenges for humanity in the coming decades (Bringezu and Bleischwitz, 2009).

Material flow analysis approaches have been used widely over the past decade to characterize the life cycles of the major metals (Chen and Graedel, 2012). Understanding the whole

system of anthropogenic material flows can help to manage their use more wisely and protect the environment (Brunner and Rechberger, 2016, 2004). In the policy context, material flow analysis and related data visualizations (Sankey diagrams and material supply chain networks) are becoming of increasing interest when evaluating and effectively communicating the progress of resource efficiency measures (BMUB, 2016; DG ENV, 2015; UNEP, 2016), monitor the level of circularity of countries or regions (EC, 2018; Mathieux et al., 2017; Mayer et al., 2018), and to better map the raw materials situation for individual countries or regions (BIO by Deloitte, 2015; Passarini et al., 2018).

Among the scientific community, past research has focused largely on generating material flow analysis studies at the level of countries, regions, or the planet. These elemental cycles treat production and manufacturing at a coarse level (e.g., by aggregating several economic activities into a single end-use application). One approach to increase the resolution of material flows in an economy is through the use of input-output (IO) tables and analysis. IO analysis (Miller and Blair, 2009) has a rich history in economic analysis at national and sub-national levels, and increasingly at the regional or global level through the use of multi-regional input-output (MRIO) analysis (Lenzen et al., 2012; Tukker et al., 2013). While inter-industry relationships within an economy are regularly collected in monetary input-output tables, little is known about the physical flow of metals among economic sectors. However, it is also possible to convert monetary transactions in IO tables into physical flows of materials (Nakamura et al., 2007; Nakamura and Nakajima, 2005; Weisz and Duchin, 2006) and the resulting material flow tables have been derived and analyzed, e.g., for plastics (Nakamura et al., 2009), steel alloying elements (Nakajima et al., 2013; Nakamura et al., 2017, 2017; Ohno et al., 2017, 2014), automobile parts (Ohno et al., 2015), and nitrogen (Wachs and Singh, 2018). Recent work (Chen et al., 2016; Ohno et al., 2016) has developed a

related approach for transforming the 2007 monetary (economic) IO table (MIOT) of the United States into physical IO tables (PIOTs) specific to metals with broad industrial uses and generated related data tables consisting of approximately 393 sectors (USBEA, 2014) (Supporting Information Table S1).

Viewing the resulting PIOTs through the lens of network analysis (Brandes and Erlebach, 2005) can help to highlight important economic sectors based on their connectivity and flow magnitude (Nuss et al., 2016a). In the context of policy making the use of network visualizations and indicators helps to utilize and communicate large data sets and complex interrelationships as they are common in material supply chains to non-scientific audiences and in the policy context (EC, 2010; Grainger et al., 2016; Nuss and Ciuta, 2018). However, so far no comparative analysis between different material PIOTs has been carried out using network-based measures.

Against this background, the *goal of this paper* is to apply network analysis and visualization techniques to a number of metal PIOTs to highlight specific metal features in the economy and compare a range of metals with each other (both from the perspective of the whole economy as well as for a single sector). Firstly, in the “Materials and Methods" section the approach of converting MIOTs of the United States economy into their corresponding PIOTs is presented in some detail and the network measures for analyzing the PIOTs are explained (a detailed discussion of the creation of the PIOTs is available in (Chen et al., 2016; Ohno et al., 2016)). Secondly, the “Results and Discussion” section compares network statistics and visualizations for the PIOTs in order to highlight unique metal features. This includes a comparison of automobile networks for each metal. Finally, the “Conclusions” discuss the applicability of the indicators and data visualizations in the context of material criticality studies and the wider policy context.

2. MATERIAL AND METHODS

This study targets eleven physical metal PIOTs (i.e., aluminum (Al), vanadium (V), chromium (Cr), manganese (Mn), iron (Fe), cobalt (Co), nickel (Ni), copper (Cu), niobium (Nb), molybdenum (Mo), and tungsten (W)) published previously by Ohno and colleagues (Ohno et al., 2016). These PIOTs show the physical flow of metals (embodied in products) between different economic sectors in the United States economy in 2007. All metal networks were derived by transforming monetary input-output tables (MIOTs) into their physical counterparts (physical input-output tables (PIOTs)) (Ohno et al., 2016). The approach is briefly described below.

Based on the mixed unit IO table $\mathbf{X}^*$, PIOTs for target metals were obtained based on the methodology of an IO-MFA (Nakajima et al., 2013; Nakamura et al., 2010, 2007; Nakamura and Nakajima, 2005). In $\mathbf{X}^*$, direct inputs of metal materials (e.g. ferroalloys, ingots and some kinds of scrap) to industries are described in the physical unit (i.e. metric tons), and others are in monetary unit (i.e. USD). Matrix for metal compositions in products of sectors in the extended IO table: $\mathbf{C}_{\mathrm{MP}}$ are obtained as follows.

$$\mathbf{C}_{\mathrm{MP}} = \widetilde{\mathbf{A}}_{\mathrm{MP}}\left(I - \widetilde{\mathbf{A}}_{\mathrm{PP}}\right)^{-1} \tag{1}$$

Where $\widetilde{\mathbf{A}}_{\mathrm{MP}}$ and $\widetilde{\mathbf{A}}_{\mathrm{PP}}$ are parts of the "filtered" input coefficient matrix (Miller and Blair, 2009) calculated based on the matrix of inter-industrial transaction: Z which is a part of $\mathbf{X}^*$ representing inputs of materials (M) to products (P) and inputs of products (P) to products (P), respectively, and I represents an identity matrix. The units of $\widetilde{\mathbf{A}}_{\mathrm{MP}}$ and $\widetilde{\mathbf{A}}_{\mathrm{PP}}$ are metric ton/million USD and no unit (i.e. million USD/million USD), respectively. "Filtered" refers to two different types of filters that are multiplied by the input coefficient matrix. The first, the physical flow filter ($\mathbf{\Phi}$), filters non-physical flows such as services, and physical flows that do not incorporate any metal in the final

product (such as process catalysts). The second, the yield loss filter ($\mathbf{\Gamma}$), removes the mass of inputs that becomes process waste. So the filtered input coefficient matrix was distinguished by indicating tilde over the character: $\widetilde{\mathbf{A}} = \mathbf{\Gamma} \otimes (\mathbf{\Phi} \otimes \mathbf{A})$ ($\otimes$ represents the element-wise product, the so-called Hadamard product).

By utilizing $\mathbf{C}_{\mathrm{MP}}$, $\mathbf{X}^*$ can be converted to PIOTs for target metals. Here, the mth row of $\mathbf{C}_{\mathrm{MP}}$: $\mathbf{C}_{\mathrm{MP}}(m,\cdot)$ represents contents of material m in one unit of products of IO sectors. Multiplying diagonalized $\mathbf{C}_{\mathrm{MP}}(m,\cdot)$ by $\mathbf{X}^*$, a PIOT for material m $\mathbf{U}^m$ is obtained as follows.

$$\mathbf{U}^m = \begin{pmatrix} \mathrm{diag}(\mathbf{C}_{\mathrm{MP}}(m,\cdot))\mathbf{X}^*_{\mathrm{PP}} \\ \mathbf{X}^*_{\mathrm{MP}}(m,\cdot) \end{pmatrix} \tag{2}$$

Where $\mathbf{X}^*_{\mathrm{PP}}$ and $\mathbf{X}^*_{\mathrm{MP}}(m,\cdot)$ are parts of $\mathbf{X}^*$ representing a part of inputs of products to products and inputs of material m to products, respectively. We note that in this study the conversion of monetary to physical units is undertaken using homogeneous sectoral prices, which does not take into account that particular metal products produced by a sector can be priced differently as they are sold to downstream sectors (Ohno et al., 2016; Weisz and Duchin, 2006). This can cause some inconsistencies between the analysis and reality and should be considered when interpreting the results. We also note that metals in fixed capital stocks, e.g., in components of buildings, infrastructure, or machines are not considered in this analysis, although they can represent substantial accumulations of capital, bulk materials, and critical metals (Pauliuk et al., 2015). Based on obtained PIOTs $\mathbf{U}^m$ for target metals, we perform network analysis. For a more detailed methodology of PIOTs derivation and data, see our previous study and its Supporting Information (Ohno et al., 2016).

For the network analysis, the PIOTS were, firstly, transformed into their corresponding node and edge tables. Nodes refer to the sectors of the PIOT (e.g., automobile manufacturing),

while edges represent the intersectoral flow of metals embodied in products traded between the different sectors in a single year. Formally, the results that follow are a "snapshot in time" for year 2007, largely because the necessary MIOTs at high sectoral resolution are compiled by the US Bureau of Economic Analysis with long time delays. However, the transformation into their corresponding PIOTs and the visualization and analysis framework proposed in this paper can equally be applied to new MIOTs once they become available. Secondly, nodes not connected to the network (e.g., nodes for service sectors in which the target metal was not involved) were removed. Finally, the networks were imported into Gephi network analysis software (Bastian et al., 2009) and Python NetworkX (Hagberg et al., 2008) for further analysis and visualization. Additionally, data visualizations were done by importing the metal PIOTs directly into Origin Lab (Origin, 2015). Subnetworks for automobile manufacturing were analyzed based on the final demand of automobile manufacturing in 2007.

A combination of data visualizations and network metrics are used to compare and discuss the eleven metal networks with each other (Table 1). An overview of the calculus behind deriving each of the metrics is provided elsewhere (Brandes and Erlebach, 2005; Jackson, 2010; Newman, 2010; Wasserman, 1994). A detailed interpretation of network metrics in the context of metal networks is discussed also in (Nuss et al., 2016a).

Table 1. Explanation of the network metrics used.

Indicator	Explanation
Number of Nodes	Counts the number of nodes (i.e., economic sectors) connected to the metal network. This provides an indication of the overall size of the network (i.e., how many sectors are involved in a domestic metals supply chain).
Number of Edges	Counts the number of edges (physical metal exchanges) between sectors (nodes) of the network. This provides an indication of how widespread metals are used in the economy.
Density (Directed)	The presence of metals in intersectoral exchanges can be captured by calculating network density (i.e., the ratio between the number of realized links and the number of maximum links possible in a directed network).

Degree	From the perspective of a single node (sector), degree centrality counts the number of incoming edges (in-degree = metal purchases), outgoing edges (out-degree = metal sales), or sum of both (degree). The average degree measure provides an average over all nodes in the network.
Weighted Degree	Captures the total quantity of metals used (weighted in-degree) or sold (weighted out-degree) by a single economic sector (node). The average weighted degree measure provides an average over all nodes in the network.
Diameter (Directed)	Maximum number of steps required to reach other sectors in the metal network. This reflects the number of transitions between metals production and downstream manufacturing sectors (maximum supply chain length of a metal network).
Average Path Length	Average number of steps required to reach other sectors in the metal networks (average supply chain length of a metal network).

For clarity in examining the flows of metals, we applied a cutoff threshold of ≥0.01 metric tons (10 kg) to all metal networks (otherwise almost all edges are shared by all metals because nearly all sectors employ tiny amounts of all metals). Nodes not connected to the network after applying this edge threshold are deleted. Figure S23 in the Supporting Information shows edge weight frequency distributions for all metal networks. Applying this threshold does not impact the overall edge weights of the metal networks, but influences the total number of edges that remain, especially for the minor metals (V, Co, Nb, Mo) which are more frequently used in small quantities (Table S2 and Figure S23).

Furthermore, we note that the PIOTs also include a number of non-physical exchanges which could not be eliminated due to the aggregated nature of IO tables and a lack of knowledge as to whether metals are present in certain inter-sectoral exchanges. As a result, the number of nodes and edges shown are to some degree overestimates. Nevertheless, the analysis provides plausible indications of which metals are more widely used than others. We anticipate that the binary matrix (used to distinguish between physical and non-physical flows in the process of deriving the PIOTs) will be capable of improvement as more information become available (see also discussions elsewhere (Chen et al., 2016; Ohno et al., 2016)). Table S3 in the Supporting Information also explores how network metrics change using a different threshold of 1 metric ton.

Finally, different sector classifications (sectoral resolution) can influence the results of the network analysis which should be considered when comparing results with similar analysis carried out on future revisions of the United States IO-tables.

3. RESULTS AND DISCUSSION

3.1. Whole Metal Network Metrics

Metal networks can be compared with each other using system-wide measures to capture network size (number of nodes and links), network connectivity (density and average degree), metal supply chain length including diameter (i.e., the longest of all the calculated path lengths) and average path length, and total metals turnover (weighted degree) (Table 2).

Table 2. Overview of network-wide measures for 11 metal networks in the United States economy.

Metal		Network Size		Network Connectivity		Supply Chain Length		Total Metals Turnover		
Atomic No.	Element	Nodes	Edges	Density (Directed)	Average Degree	Network Diameter (Directed)	Average Path Length (Directed)	Average Weighted Degree	Weighted Degree (Minimum)	Weighted Degree (Maxiumum)
13	Al	390	64,575	43%	165.6	3	1.55	75,864	89.53	17,677,526
23	V	389	18,589	12%	47.8	8	2.14	48.2	0.19	5,490
24	Cr	391	52,603	35%	134.5	4	1.65	4,359	4.12	716,409
25	Mn	391	54,624	36%	139.7	3	1.63	5,660	5.48	772,858
26	Fe	400	72,063	45%	180.2	4	1.52	1,030,419	113.17	186,639,916
27	Co	389	16,614	11%	42.7	6	2.13	58.0	0.02	8,957
28	Ni	392	48,148	31%	122.8	4	1.69	1,927	2.14	247,548
29	Cu	390	60,128	40%	154.2	3	1.58	19,974	83.56	4,099,348
41	Nb	390	22,313	15%	57.2	7	2.04	93.5	0.03	12,294
42	Mo	390	30,446	20%	78.1	5	1.90	172.2	0.04	15,302
74	W	389	21,003	14%	54.0	7	2.04	57	0.30	11,037

[a]A threshold of ≥ 0.01 metric tons was applied to all networks (i.e., edges below 0.01 metric tons were deleted).

Network size. The reliance of an economy and its downstream industries on metals is frequently mentioned (Vidal-Legaz et al., 2016), but has generally been difficult to quantify. Our analysis shows that the major metals aluminum, iron, and copper stand out in regard to the large number of

edges (links) between sectors that represent physical metal exchanges (between 60,128 and 72,063 edges exist for the three major metals) (Table 2). In contrast, vanadium, cobalt, niobium, molybdenum, and tungsten are with 16,614 to 30,446 edges present in a significantly lower number of economic transactions. This highlights the more specialized uses of minor metals, e.g., cobalt's use largely in specialty alloys or batteries. Looking at the underlying frequency distributions of edge weights (Figure S23 in the Supporting Information) shows that for aluminum, chromium, manganese, iron, nickel, and copper the majority of metal exchanges take place at medium edge weights, while for vanadium, cobalt, niobium, molybdenum, and tungsten the largest counts of edges are observed at low edge weights (edges below 10 kg were cut off because they could not be reliably traced using the IO-MFA methodology used to calculate PIOTs).

Network connectivity. The presence of metals in intersectoral exchanges can be captured by calculating network density (i.e., the ratio between the number of realized links and the number of maximum links possible in a directed network) (Table 2). For example, the density of the iron PIOT of 0.45 indicates that on average 45 % of all potential iron-containing product exchanges between sectors of the United States economy exist. For aluminum and copper, density equals 43% and 40%, respectively. In other words, our modern economy is by and large dependent either directly or indirectly on the use of these metals. In contrast, density ranges between 11% and 15% for vanadium, cobalt, niobium, molybdenum, and tungsten (Table 2). With densities of 31% to 36%, chromium, manganese, and nickel have intermediate connectivity. Similarly, the average degree centrality can be seen as an indicator for the degree of specialization, with lower degree centralities indicating fewer linkages to other sectors (i.e., greater specialization). Larger average degree centralities show that the major metals (aluminum, iron, copper) are less specialized in their

economy-wide uses (larger average degree centrality) than the alloying elements investigated in this study.

Supply chain length. The number of steps required to reach other sectors in the metal networks reflects the number of transitions between downstream manufacturing sectors and metals production (and other upstream economic activities). In networks of smaller path length and diameter, downstream sectors are connected to shorter supply chains and are thus less likely to encounter distortion in physical flows of metal-containing goods (Nuss et al., 2016a, 2016b). Furthermore, a short path length indicates that there would be a relatively low number of traverses required to connect any two nodes selected at random (Hearnshaw and Wilson, 2013) (this applies to both physical and information flows). For example, manganese is widely used as a desulfurizing and alloying agent in high and low-carbon ferromanganese and silicomanganese steels as well as in aluminum and other alloys (Nuss et al., 2014). As a result, manganese's network has a relatively short characteristic path length (1.63) and intermediate diameter (longest of all the calculated path lengths = 3). Networks for the major metals (aluminum, iron, and copper) are found to display the shortest average path length and diameter. On the other hand, vanadium, cobalt, niobium, and tungsten display networks involving many steps because of their more specialized uses in only a few of the economic sectors and the multiple steps required to reach those sectors.

Total metals turnover. The total quantity of metals exchanged within the United States economy can be captured using weighted degree centrality. For iron, the sector turnover equals about 1 million metric tons on average (i.e., the average sum of imports and exports for all sectors of the iron network). This is followed by aluminum (average weighted degree = 75,864 metric tons) and copper (19,974 metric tons) (the metals turnover is largely independent of the cutoff threshold (see also sections 4 and 5 in the Supporting Information)). For example, sectors with

larges metals turnover for tungsten include special tools manufacturing, cutting and machine tool accessories, metal alloys for applications such as wires, machinery, and aircraft, and chemicals (Figure 1). Tungsten-containing products produced by these sectors are mostly consumed as final products. However, Figure 1 shows that, e.g., for semiconductor manufacturing a share of tungsten containing products subsequently flows into downstream sectors including wired and wireless telecommunication (see Supporting Information Section 2 for network visualizations for all eleven metal networks).

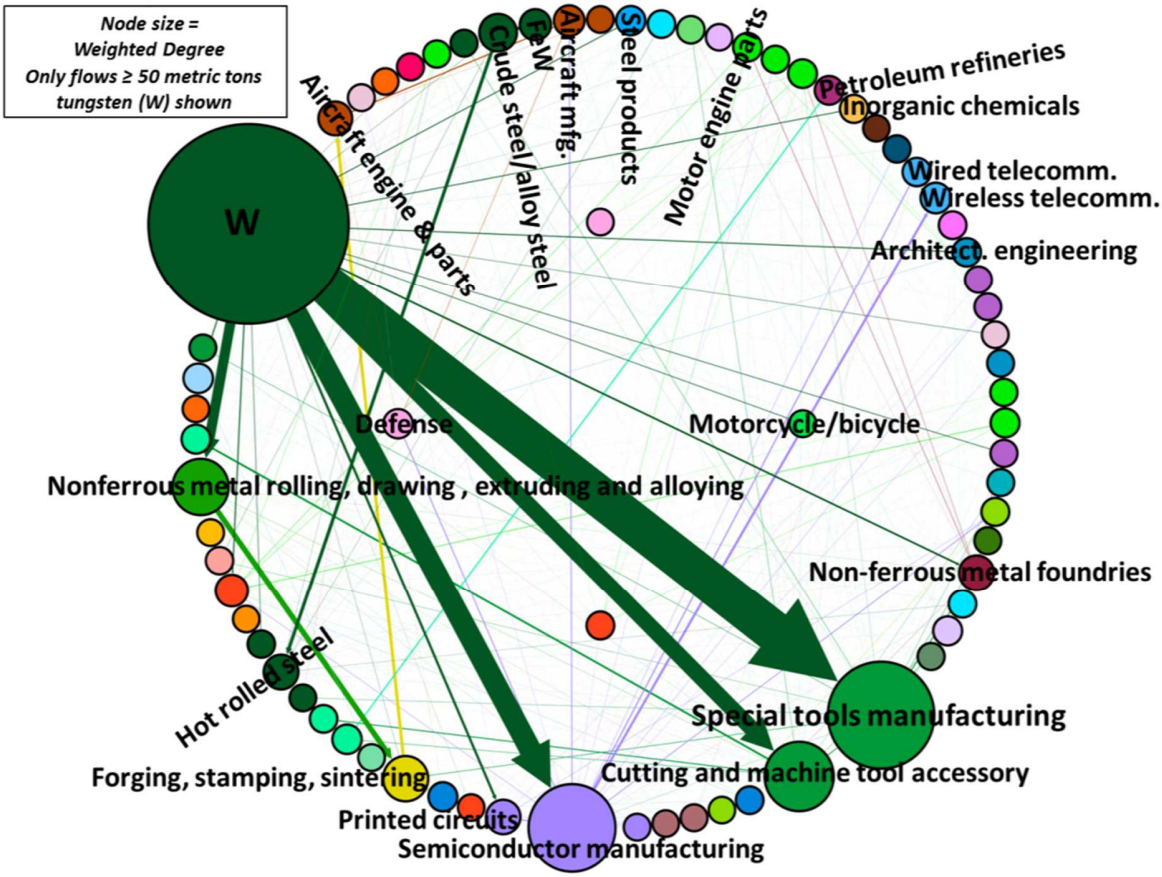


Figure 1. Tungsten (W) network of the U.S. economy in 2007 (only nodes with a weighted degree centrality ≥ 50 metric tons W are shown to allow proper visualization). Nodes are colored based on the sector type (see Table S1 in the Supporting Information).

Supply chain robustness. Figure S24 (Supporting Information) indicates that for vanadium, cobalt, niobium, and tungsten the majority of sectors are found at low weighted degree but a small number of "hubs" (sectors with high weighted degree centrality) are also present. This increases the vulnerability of the networks to potential targeted attacks (where a sector node is removed by an industrial accident, a political intervention, or some other unanticipated factor) (Albert et al., 2000), because there are only a "few" sectors at medium- to high- metal throughput (weighted in- and out-degree centrality), and removing any of these can significantly alter the metal flow. In contrast, for aluminum, chromium, manganese, iron, and copper the majority of sectors are found at intermediate metals turnover. These networks might be less prone to targeted attacks (node removal) compared to the metals networks discussed above (although due to their widespread use in large quantities a breakdown of industry could have large economy-wide effects). However, limitations with using the IO-tables for analysis of supply chain robustness exist because single sectors might be comprised of multiple stakeholders processing inputs and producing related outputs in underlying complex subnetworks. Further work is required in obtaining a picture of the stakeholders involved and their market shares within single sectors for such types of analysis. Nevertheless, discussions on network (physical supply chain) robustness, even though widespread in other disciplines (Albert et al., 2000; Barabási, 2009; Barabási and Bonabeau, 2003) have not yet found widespread use in supply chain analysis (Hearnshaw and Wilson, 2013) and resource criticality assessments (Dewulf et al., 2016), but are likely a powerful and complementary supplement to current assessment methods if data on physical material supply chains and the stakeholders are available (see Supporting Information Section 6).

3.2. Sector discrimination

With the exception of Figure 1, the network-wide measures discussed thus far (Table 2) do not show the specific sectors of the United States economy responsible for the largest metals exchanges. This property can be visualized using 3-D plots of each of the PIOTs. In Figure 2a we show such a plot for cobalt. In this figure the x- and y-axes show the two-dimensional PIOT with outputs from one sector (the x-axis, from front corner to right rear on the diagram) representing the inputs to another sector (the y-axis, from front corner to left rear on the diagram). The z-axis represents the "intensity" of the metal exchange in units of metric tons.

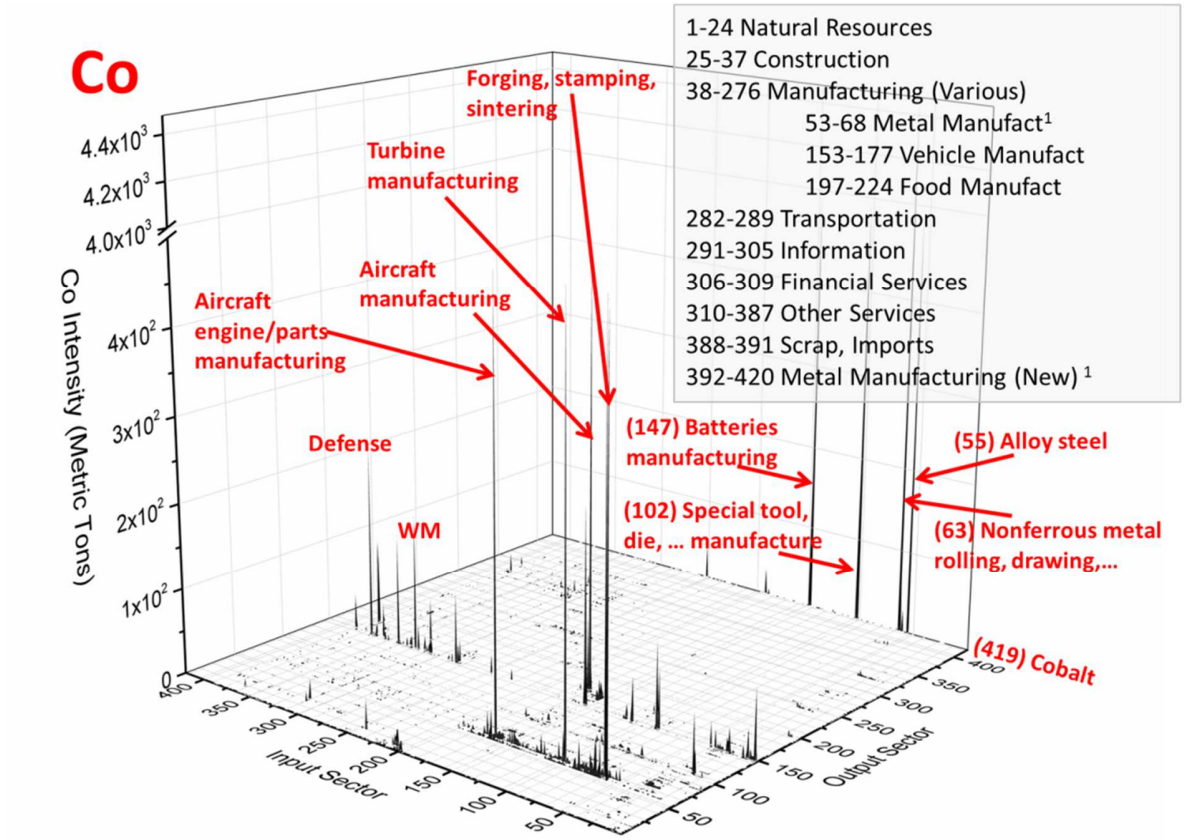


Figure 2a. Intersectoral flows for cobalt in the transformed 2007 United States IO table (similar 3d-figures for twelve other metals can be found in the supporting information). New sectors are those added in the process of generating the PIOT (Ohno et al., 2016)

Figure 2a demonstrates that cobalt is being introduced into the United States economy by sector 419 (Cobalt), which is a newly introduced sector generated in the process of disaggregating the IO table (Ohno et al., 2016). Starting from this sector, 4,480 metric tons of cobalt flow to sector 63 (Non-Ferrous Metal Rolling, Drawing, Extruding, and Alloying), 2,680 metric tons to sector 147 (Storage Battery Manufacturing), 725 metric tons to sector 55 (Alloy Steel), and 512 metric tons to sector 102 (Special Tool, Die, Jig, and Fixture Manufacturing). In turn, sector 63 sells semi-fabricated cobalt products to sector 66 (forging, stamping, sintering), sector 66 to sector 168 (aircraft engine and parts manufacturing), sector 104 (turbine and turbine generator set units manufacturing), and sector 168 to 167 (aircraft manufacturing). Other important exchanges toward higher-order input sectors include the sales of sector 167 (aircraft) to sector 382 (defense).

This general pattern of exchanges between metal-producing sectors, sectors performing intermediate processing, sectors using intermediate products for final products manufacture, and consumer sectors can be seen among all the metals in our study. Large-scale diagrams for all of them appear in the Supporting Information (Section 3). In every case the metal is introduced in natural resource sectors and then distributed widely to various manufacturing sectors and finally to a variety of using sectors.

PIOTs of all 11 metals are visually compared with each other in Figure 2b. These plots permit detailed analyses of the regions of the PIOTs with the highest physical exchanges of metal-containing products. In these diagrams the y-axes are scaled differently (iron's intersectoral exchanges are several orders of magnitudes larger than those for cobalt, for example). Figure 2b immediately shows the widespread use of the major elements aluminum, iron, and copper in the United States economy. In contrast, alloying elements such as tungsten or cobalt find use in very specialized applications. A network measure that can assist in quantifying the portion of actual

connections (metal exchanges) between sectors is network density. As discussed in Table 2, network density describes the portion of potential connections that could be present in a directed network compared to the actual connections that exist. The figure shows that 45% of all possible intersectoral exchanges are present for iron, 43% for aluminum, and 40% for copper). In other words, more than one third of all sectors in the United States economy trade products containing these three major metals. On the other hand, only 11% of all sectors exchange products containing cobalt or 12% to 14% of products containing tungsten or vanadium (not taking into account possible accumulations in in-use stocks). Density figures using an alternative higher cutoff threshold of 1 metric ton are provided in Table S3 in the Supporting Information.

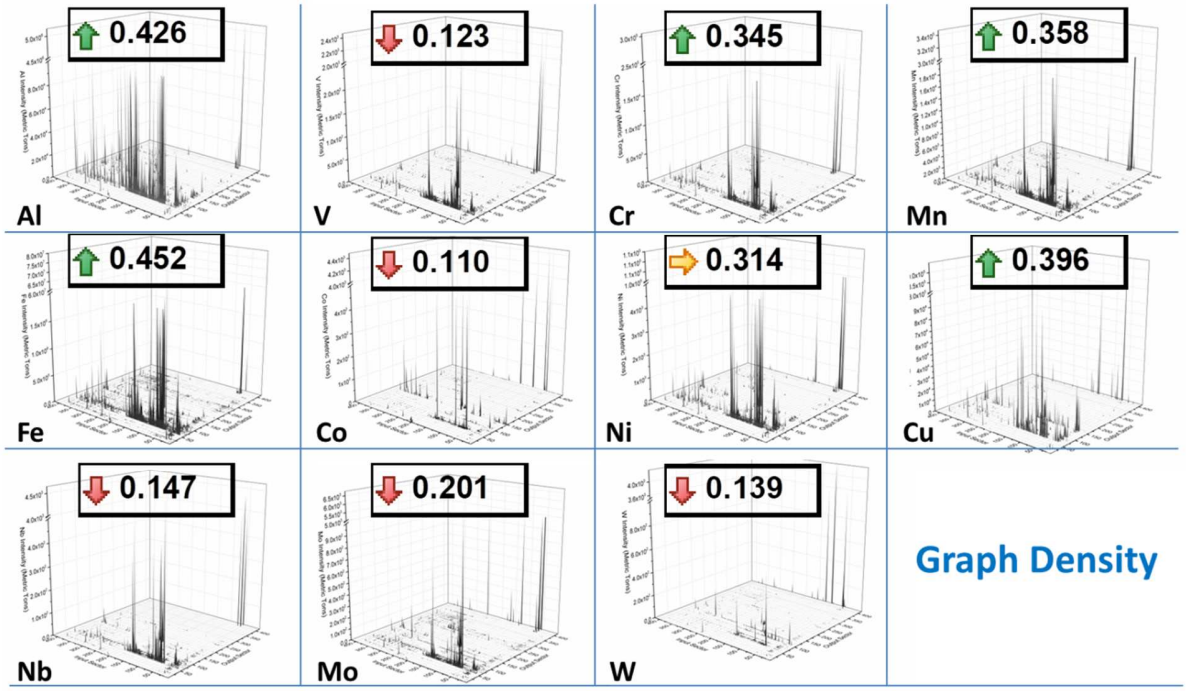


Figure 2b. Graph density of the 11 metal networks in combination with plots of the inter-sectoral metal exchanges (see section 2 in the Supporting Information for an enlarged version of each 3D plot). "Up", "Right", and "Down" arrows indicate high, moderate, and low network density. Graph density was calculated at a cutoff threshold of 0.01 metric tons (see also Table 2).

3.3. Automobile Supply Chain

The production network for automobile manufacturing (an arbitrary choice used here for illustration) can be generated from the final demand of U.S. Automobile Manufacturing in 2007 (148,115 Million USD) while setting all other final demand entries to zero (Supporting Information Section 7). Network measures such as number of nodes and edges can help to compare the overall network size of the automobile network with the economy-wide networks analyzed above. Furthermore, we examine the number of in-degrees to the automobile manufacturing sector as a proxy of the number of metal-containing products required from other sectors to manufacture automobiles in 2007 ('product complexity')) or amount of metals required (weighted in-degree) (Table 3).

Table 3. Automobile networks for the eleven metals.

Metal	Network size[a]				Indicators for the automobile manufacturing sector			
	Nodes	Nodes ratio compared to the whole metal networks (%)[b]	Edges	Edges ratio compared to the whole metal networks (%)[b]	In-degree	Weighted in-degree (metric tons)	kg per vehicle[c]	kg per vehicle (Literature)
Al	357	92%	29154	45%	179	390,977	79	28 - 61[d]
V	181	47%	1563	8%	74	363	0.074	-
Cr	358	92%	26425	50%	181	37,213	7.5	2.30 - 25.0[e]
Mn	338	86%	15127	28%	162	43,685	8.8	5 - 14[d]; 0.02 - 6.0[e]
Fe	380	95%	45364	63%	198	8,115,649	1644	-
Co	187	48%	1168	7%	71	195	0.04	0.03 - 0.06[d]
Ni	313	80%	10251	21%	144	15,569	3.2	0.010 - 0.150[e]
Cu	352	90%	22993	38%	170	111,128	23	25 - 61[d]
Nb	213	55%	2006	9%	82	632	0.13	0.063[d]
Mo	244	63%	3526	12%	100	1,274	0.26	0.010 - 0.040[e]
W	194	50%	1838	9%	85	269	0.05	0.01 - 0.175[e]

[a]United States final demand for 'automobile manufacturing' in 2007 equals 148,115 Million USD. An edge cutoff threshold of 0.01 metric tons is applied. Nodes not connected to the network after applying this threshold were deleted.
[b]Percentage of nodes and edges found in comparison to the whole (economy-wide) metal networks presented in Table 2.
[c]Assuming an average price of 30,000 USD per vehicle (US FTC, 2017).
[d] Source: Klas and colleagues (Klas and Olof, 2011).
[e] Source: Du and colleagues (Du et al., 2015).

The percentage of sectors involved in the automobile supply chain ranges from 187 sectors for cobalt to 380 sectors for iron (Table 3). The ratio of nodes and edges of the automobile networks to the whole networks provides a measure of the extent to which this single sector involves the

various metal-trading sectors of the US economy. For example, for vanadium about 47% of the sectors of the U.S. economy are involved in the manufacturing of automobiles, while the use of aluminum in automobiles involves 92% of sectors of the whole aluminum network (Table 3). Looking at the number of metal exchanges (edges) when compared to the whole metal networks shows the fraction of metal exchanges for a particular metal required to manufacture automobiles. For example, automobiles manufacturing seems to be less relevant for cobalt (7% of edges are present when compared to the whole metal network involving all sectors) than for other metals.

The in-degree metric provides a measure of the number of sectors immediately required for the manufacture of automobiles. Table 4 shows that a large number of sectors involving iron, aluminum, copper, and chromium (in-degree = 170 to 198) are required in the manufacture of automobiles. On the other hand, metals with low in-degree centrality (e.g., vanadium and cobalt) are used in more specialized applications and fewer of these relate to automobiles. Table S4 in the Supporting Information provides a summary of the top five sectors (by weighted in-degree centrality) that are providing metal-containing products to automobile manufacturing.

Assuming an average price of a single vehicle of 30,000 USD per vehicle in the United States (US FTC, 2017) allows us to approximate the amount of metal used in a single vehicle. The last two columns of Table 3 show that the quantities found using the weighted in-degree measure correspond reasonably well with estimates reported in the scientific literature (Du et al., 2015; Klas and Olof, 2011), except for nickel, niobium, and molybdenum which values differ by an order of magnitude compared to the literature values (Figure S26). Reasons for these differences include, e.g., the price homogeneity assumption (see the materials and methods section) where it is assumed that the physical metal flows are fully proportionate to corresponding monetary flows. Nevertheless, for the majority of metals examined the material flow networks presented in this

study allow a first approximation of the quantities of different metals used by various sectors of the U.S economy – information that is sometimes difficult to quantify with alternative methods (Du et al., 2015; Klas and Olof, 2011).

Finally, Figure 3 provides a network visualization of the cobalt metal subnetwork for the automobile manufacturing showing, e.g., cobalt's use in storage batteries of which a fraction (1.1% of primary input of cobalt in the U.S economy) is subsequently used in automobiles. The importance of cobalt in automobile manufacturing (edges ratio compared to the whole metal networks in Table 3) might increase in the future as cobalt-containing batteries used in electric vehicles increasingly enter the market. Additional automobile network visualizations for iron and niobium can be found in section 7 of the Supporting Information and similar visualization can be generated for all metal networks analyzed in this study.

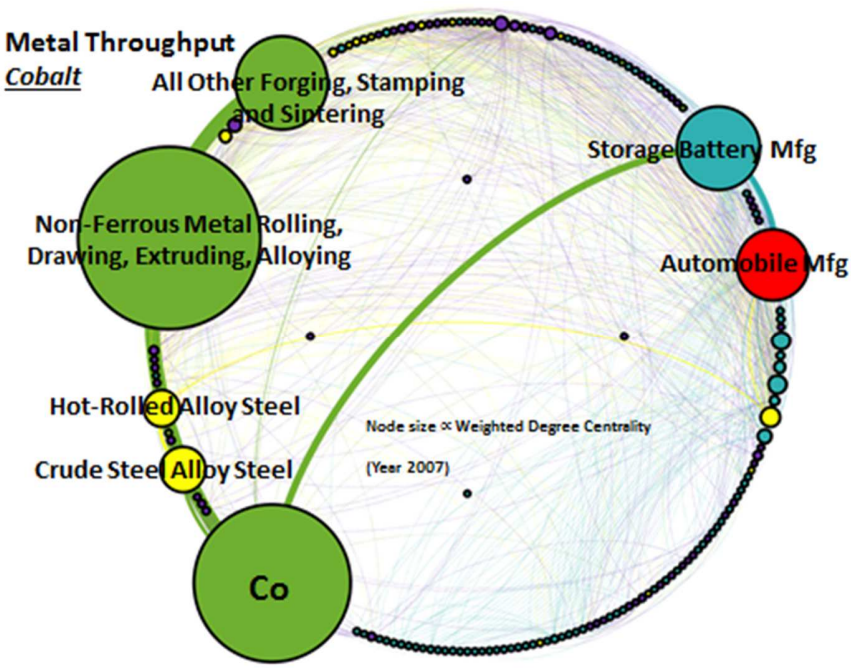


Figure 3. Visualization of the cobalt supply chain associated with the automobile manufacturing. Edges are colored by source node.

4. CONCLUSION

In the case of networks specific to individual metals, network analysis permits much to be said about a metal's involvement in a national economy. In the case of copper, for example, Figure 2b (and Figure S19 in more detail) shows a relatively well-connected network, especially in the construction and manufacturing sectors. This impression is supported by the Table 2 statistics: a high graph density and network connectivity, low supply length, and high metal turnover. As a consequence, copper can be regarded as extensively linked to the U.S. economy, and any supply constraints, should they occur, would be widely felt.

The situation with cobalt provides a notable contrast to that of copper. The cobalt network has the lowest graph density of any of the eleven metals in this study (see Figure 2b). Supply chain length is intermediate, and metal turnover is low. Figure 2a shows that the few final product sectors that involve cobalt include aircraft engines and parts, turbines, and battery manufacturers. A supply constraint on cobalt, a material often found to be "critical" for modern technologies (Hayes and McCullough, 2018), while obviously important for those sectors, would have a less widespread impact on the U.S. economy as a whole. This general situation is, of course, quite well understood by those in sectors involved in cobalt, but would not be generally known, and certainly not in this level of detail, to private and government analysts and policy makers. The details that can be obtained from the analysis presented in this study depend, obviously, on the sectoral resolution of the IO tables available. For the United States the number of sectors in the IO table is sufficient for an analysis of metal flows, while in other world regions this might not be the case (Lenzen et al., 2013).

Generating, visualizing, and analyzing IO material flows networks such as the above provides a complementary source of information on metals use is modern economies to raw

material criticality assessments (EC, 2017; Graedel et al., 2015), MFA (Brunner and Rechberger, 2016; EUROSTAT, 2013; OECD, 2008a, 2008b), and raw materials knowledge compiled by governments (Carroll, 2014; Manfredi et al., 2017; Soto-Viruet et al., 2013; Vidal-Legaz et al., 2016). The visualization possibilities provide also a powerful tool in the communication of material flow data to a wide range of audiences including policy making. The combination of PIOTs with network analysis allows a detailed assessment of issues related to the sectoral use of various materials, economic importance, and supply chain robustness. These aspects are also of importance in raw material criticality assessments and wider supply chain analysis (Hearnshaw and Wilson, 2013; Kito et al., 2014; Nuss et al., 2016b).

For example, the EU criticality assessment captures the economic importance of raw materials by accounting for the fraction of each material associated with NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) sectors at EU level and their gross value added (EC, 2017, 2014, 2011). However, it is often difficult to properly allocate end uses of a material to industrial sectors because of the multitude of uses in modern economies and use at multiple supply chain stages (Blengini et al., 2017a, 2017b). Here, the use of information from the IO material flow networks could increasingly allow for more precise allocations and to quantify the fraction of the whole economy that would be affected by a supply disruption of a chosen material.

Future work might focus on applying the tools presented in this analysis to PIOTs available for other world regions and materials. Uncertainties of the resulting PIOTs and the minimum flow magnitudes that could reasonably being captured should be further quantified. The ideas and network metrics presented should also be explored in the context of other supply chain data

available in order to obtain a better picture of global material flows and related network structure and properties.

5. APPENDIX A

The following is Supplementary data to this article: Nuss et al (2018) Comparative Metal Network Analysis_SI_RCR.docx

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