A FRAMEWORK FOR DOMESTIC SUPPLY CHAIN ANALYSIS OF CRITICAL MATERIALS IN THE UNITED STATES: AN ECONOMIC INPUT-OUTPUT-BASED APPROACH

by

Miriam Stevens

A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science

Division of Environmental and Ecological Engineering

West Lafayette, Indiana

August 2021

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Shweta Singh, Chair

School of Agricultural and Biological Engineering

Division of Environmental and Ecological Engineering

Dr. Fu Zhao

School of Mechanical Engineering

Division of Environmental and Ecological Engineering

Dr. Gokce Esenduran

School of Management

Approved by:

Dr. John Sutherland

To Thomas,

whose poor timing impressively rivals mine.

ACKNOWLEDGMENTS

I am tremendously grateful to have had the opportunity to work on this project. First and foremost, I would like to thank Dr. Shweta Singh for her guidance, mentorship, and patience throughout this project; I have appreciated learning from you as an advisor and professor, and cannot thank you enough for supporting my pursuit of intellectually fulfilling research within and outside of the SINCS group. I would like to thank Dr. Fu Zhao for sharing his expertise on critical materials and for agreeing to be on my thesis committee. I would like to thank Dr. Gokce Esenduran for her expertise on sustainable supply chain management and for agreeing to be on my thesis committee. I thank the Integrated Sustainability Analysis team at The University of Sydney for allowing me to use the Industrial Ecology Virtual Laboratory (IELab) to generate the multiregional input-output models used in this work. I thank Dr. Arne Geschke for his guidance in using and troubleshooting the US IELab. I thank Dr. Gargeya Vunnava for teaching me how to more efficiently analyze MRIO data. I would like to thank the Purdue Research Computing Staff for their help in overcoming obstacles using the Brown cluster, especially Dr. Xiao Zhu. I would like to thank the faculty and staff of the Environmental and Ecological Engineering Division and the Agricultural and Biological Engineering Department for their academic and administrative support. I would like to thank Dr. Sarang Supekar for taking an earnest interest in my research on critical materials, development as a sustainability researcher, and helping me refine my master's research for application to additional materials. I would like to thank Dr. Susana Garcia Gonzalez for her recommendations for and precautionary advice on network metrics for input-output models. I would like to thank Maren Lundhaug for the open discussion of her findings on cobalt and studying critical materials as a graduate student. I thank Dr. Weslynne Ashton for her constant support of my pursuit of industrial ecology, regardless of where I am. I would like to thank my former group mates Dr. Nehika Mathur and Dr. Gargeya Vunnava for showing me through their example how to be a grad student, as well as my current SINCS colleagues Apoorva and Will for their feedback and support. I also thank Div and Thomas, and Kendrick, Utkarsh, and Dan who kept me from going feral over the last two years; thank you for your friendship.

This thesis is based upon work supported by the Purdue University Ross Fellowship and the National Science Foundation under CBET grant number 1805741. The NSF INTERN program also supported extensions of this work underway.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

DRC	Democratic Republic of Congo
EPA	Environmental Protection Agency
IELab	Industrial Ecology Virtual Laboratory
IO	Input-output
LCA	Life Cycle Assessment
MAOC	Maximum Amount of Onsite Chemical
MRIO	Multiregional Input-output
TRI	Toxic Release Inventory
US	United States
USGS	United States Geological Survey
WIO-MFA	Waste Input-output Material Flow Analysis

ABSTRACT

The increasing demand for mineral-based resources that face supply risks calls for managing the supply chains for these resources at the regional level. Cobalt is a widely used cathode material in lithium-ion batteries, which form the major portion of batteries used for renewable energy storage — a necessary technology for electrifying mobility and overcoming the challenge of intermittency, thus making renewable energy more reliable and energy generation more sustainable. This necessitates understanding cobalt's supply risks and for the United States, identifying sources of cobalt available for future use via recycling or mining. These needs are addressed in this work using single and multiregional input-output (MRIO) analysis in combination with graph theory. An MRIO-based approach is developed to obtain the trade network of cobalt and offer a more expedient way to identify potential critical material sources embodied in commodities made domestically. Commodities containing cobalt were disaggregated from two input-output (IO) models and the trade structure of cobalt at the national and state level was observed and compared. The significance of identified key sectors is measured according to several criteria and differences in sectors highlighted in the national versus subnational networks suggests that analysis at the two regional aggregation levels provides alternative insights. Results from mining the IO networks for cobalt highlight the geographical distribution of its use and industries to further investigate as potential sources for secondary feedstock.

1. INTRODUCTION

1.1 Motivation

The demand for metals and minerals to support the clean energy transition and other emerging technologies is expected to increase at an unprecedented rate in the next several decades and there is precautionary concern over the sustainability of these mineral-intensive technologies. In particular, materials that are integral to current battery energy storage systems for electrical grid and mobile applications, such as cobalt, graphite, and lithium, may see increases in demand of over four hundred fifty percent by 2050 [1]. Increasing society's dependence on these resources is necessary for developing a new energy system that substantially reduces the release of fossil fuel energy-derived greenhouse gas emissions, which have contributed most to climate change [2], and for this reason is also beneficial. However, the increased demand will also grow extractive industries [1] and has already raised international concerns over securing access to geologically or technologically concentrated resources as evidenced by recent actions of the United States and other federal governments [3]–[5]. In an effort to support the sustainable expansion of critical materials use, this research aims to develop a streamlined method for analyzing different industries' dependence on these materials throughout a national economy, focusing on cobalt use in the United States (US).

A critical material is defined by the US as a nonfuel mineral or mineral-based material whose use is essential to the economic and or national security of the country and is sourced from a supply chain that is vulnerable to disruption [6]. Other countries define the term differently and each nation generally considers a different set of materials to be critical based on its national priorities and access to natural resources [7]–[9]. In academic literature, material criticality has been defined in terms of supply risk, companionality, environmental implications, and vulnerability to supply restrictions [10]–[13]. Companionality, or byproduct status, is an important factor because it influences the responsiveness of primary production rates to demand changes, the extent of resulting environmental impact, and criticality [11]. The literature on US-defined critical materials illustrates the overwhelming dependence of the US on imports to meet its current demand, as well as the country's potential to further develop its domestic extraction and processing capacity and in ways that expand secondary material markets [6]. In the US Draft Critical Materials list, the USGS outlines how the list of thirty-five critical non-fuel minerals were identified and gives an overview of their sourcing and applications [6]. Twelve out of the thirty-five are byproducts, meaning they are not mined directly but instead recovered during the processing of a host material. While the US imports the vast majority of these materials (net import reliance is >50 percent for all but 5 materials), the country has the capacity to increase domestic mining or processes of some of these materials, such as cobalt, lithium, manganese, and rare earth elements [14]. The USGS tracks sources of annual consumption at a national level, estimates of mineral resources, and accessible reserves on an annual basis, but more subnational studies are needed to proactively evaluate potential sources and strategies for sustaining a domestic supply of critical materials through increased primary or secondary production.

Cobalt is considered a critical material by most standards because of its ubiquitous use in lithium-ion batteries and the concerns over the stability of its supply chain. Its leading use worldwide is in the cathode of batteries, but it is widely used in chemical applications as a catalyst and pigment, in machining for abrasive cutting tools, and in the US, primarily in alloys for aircraft engines [14]. Approximately 60 percent of cobalt is extracted from one country, the Democratic Republic of Congo (DRC), and China holds approximately 58 percent of global refining capacity with China, Japan, and Korea collectively controlling 85 percent of global refining capacity [15]. While several other countries mine the material, the next top global producers include Russia and Australia. The DRC is expected to remain the supplier of the majority of the world's cobalt for the next decade [14], [16]. In order to avoid shortages of the material reminiscent of the 1978 cobalt crisis, during which mining limitations caused the price of cobalt to increase from \$18/kg (\$8/lb) to \$99/kg (\$45/lb) over seven months [17], should limitations on mining capacity occur due to geopolitical conflict or export quotas from major suppliers of refined material, countries are planning to maximize recovery of end-of-life materials containing cobalt. Secondary materials are not expected to be able to fully cover demand in the short term, but could potentially offset the demand of primary materials by 30 ktonnes through 2030 [15]. Offsetting demand with secondary materials could help make shortages less sever in the face of supply chain disruptions and therefore mitigate price spikes and unregulated artisanal mining that is more responsive to short-term market fluctuations. Cobalt is a prominent critical material whose rapid increase in primary production is associated with negative social impacts and whose dominant use in the US may change over the next several decades; these are among the reasons it was chosen as the material of focus in this work.

The increase in demand for critical materials and transition to a primarily non-fuel, mineral-based energy system presents an opportunity to develop new industries that are designed to be sustainable from the start. One way to pursue this is to embed circular economy principles into life cycle design of technologies requiring critical materials. As thoroughly researched by The Ellen MacArthur Foundation, these principles include 1) design out waste and pollution, 2) keep products and materials in use, and 3) regenerate natural systems [18]. Along with designing durable products, maximizing material efficiency by not letting critical materials that have been extracted and processed become waste could help reduce global dependence on primary resources over time and simplify supply chains. Leveraging secondary materials to fulfill demand may have a greater potential to make the trade of cobalt more circular than that of other critical materials because industries are also aggressively working to reduce the amount of cobalt required in lithium-ion batteries [19], the leading global use [14]. This research aims to support building a circular economy for critical materials by contributing to the development of methods to efficiently and transparently create national accounting systems for manufactured materials with a variety of applications. Such systems could then be applied to scenario modeling to measure trade-offs of different strategies to secure critical materials and to identifying potential secondary sources for either current or emerging applications.

1.2 Methodological Background

Input-output (IO) analysis is a macroeconomic analysis method for investigating how changes in the productivity of one or more industries in the economy will affect the productivity of all others. The underlying data on the exchanges of commodities between industries in IO tables can be in either monetary, physical, or mixed units. This research employs economic IO tables as opposed to physical or mixed-unit IO tables. IO analysis involves using three main data structures: transactions tables, direct requirements tables, and total requirements tables. A transactions table is a matrix that records the observed magnitude of exchanges between industries, e.g., industry A purchases \$ x million dollars worth of commodities from industry B. In ordinary IO analysis, it is assumed that each industry makes one commodity. In reality, industries can and often do make more than one commodity, so the transactions table is split into two tables, one table that records the magnitude of commodities supplied by each industry (Supply or Make table, depending on the matrix structure) and another table that records the magnitude of commodities used by each industry and from which other industries they were supplied (Use table). The direct requirements table records the per unit inputs each industry requires directly from other industries to produce one unit of its main commodity; the exchanges in this table represent tier 1 supply chain exchanges. The total requirements table records the per unit inputs each industry requires directly and indirectly from other industries to produce one unit of its main commodity; the exchanges in this table represent the exchanges at every level of an industry's supply chain. Figure 1.1 shows the general structure and mathematical representation of the transaction, direct requirements, and total requirements tables in an ordinary IO system and in a Make and Use IO system. Most national governments maintain economic IO accounts in a Make and Use or Supply and Use system to track the structure of the economy over time, create forecasts, and evaluate the effects of economic growth or contraction.

In IO analysis, the direct requirements matrix is commonly defined $\boldsymbol{A} = [a_{\mathrm{ij}}]$ and each element is the ratio of the purchases from sector i by sector j to the total value of inputs to sector j. A is defined as $\boldsymbol{Z}\boldsymbol{x}^{-1}$, where $\boldsymbol{Z}$ is a matrix of interindustry sales where each entry represents the value of sales between pairs of sectors and $\boldsymbol{x}$ is the vector of total output per sector, which includes the sector's interindustry sales and additional final demand for its product [20]. The values of $\boldsymbol{Z}$ are estimated from government survey data. For perspective, the detailed IO tables for the US contain approximately 400 sectors [21].

The objective of an IO problem is often to solve for the total sector output, x, required to provide a certain mix of products, or to solve for the change in output due to a change demand for one or more sectors. The linear system of equations, summarized by $\boldsymbol{x} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{f}$, in terms of $\boldsymbol{A}$ and $\boldsymbol{f}$ is as follows:

$x_1 = a_{11}x_1 + ... + a_{1n}x_n + f_1$
$\mathrm{x}_n = a_{n1}x_1 + ... + a_{nn}x_n + f_n$

Solving for x can be done by taking the inverse of $(\boldsymbol{I} - \boldsymbol{A})$ and then multiplying by the vector of final demand. This IO system is often represented by the equation: $\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{f} = \boldsymbol{L}\boldsymbol{f}$. $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse, a matrix whose coefficients show the minimum inputs needed for each sector to supply an additional unit towards final demand. $\boldsymbol{L}$ is the interindustry coefficients section of an IO table. Rewriting $\boldsymbol{x}$ in terms of $\boldsymbol{L}$ and $\boldsymbol{f}$ shows that the total output of each sector is dependent on the final demand from each sector, illustrating the interdependence of different sectors in the economy:

$x_1 = l_{11}f_1 + ... + l_{1n}f_n$
$\mathrm{x}_n = l_{n1}f_1 + ... + l_{nn}f_n$

The model above assumes each industry makes only one commodity. When an industry produces multiple commodities, the $\boldsymbol{A}$ matrix is derived using the supply and use system. In the supply and use system, instead of the $\boldsymbol{A}$ matrix being derived from a single matrix $\boldsymbol{Z}$ of absolute inputs and outputs, it is derived from two separate matrices recording the production of commodities by each industry (supply table, or make table in the US IO accounting system) and the use of commodities by industry matrix (use matrix).

Disaggregating sectors from an input-output network was notably formalized by Wolsky in 1984 [22]. This work presents a solution to the problem of aggregation in national IO models by proposing a general method for extracting one sector given various degrees of data on the difference in interindustry structure. Part of this method has been widely appplied since to yield more detailed disaggregated IO models, which have been shown to be preferable to aggregated models even with limited data [23]. Input-output analysis has been applied to material flow analysis of critical materials to answer traditional questions of economy level output in response to changing demand, and has been combined with graph theory methods to investigate the economy as a complex network. Nakamura Nakajima, 2005 develop a waste IO-material flow analysis (WIO-MFA) model to determine the proportion of a material that ends up in final demand sectors of an IO model [24]. The model is an extension of the WIO model developed in an earlier paper [25]. The WIO-MFA model partitions an input coefficient matrix into two matrices: one that contains the proportion of physical inputs that enter products (A') and another that contains the proportion of physical inputs that are discarded from a sector as wastes (A"). The composition of products can be determined from the (A') matrix. This is applied in several papers [24], [26], [27] to identifying how materials are distributed among different final demand sectors. A benefit of the method is that the total weight of a material in products can be found, or the monetary value of that material in products can be found, depending on the units used for the flow in the original input coefficient matrix. The model can be crosschecked when external information is available on product price or composition by weight. For example, Nakamura Nakajima, 2005 apply the WIO-MFA model to estimate the amount of metals in final demand categories and products [24]. One such product considered was a car, and it was confirmed that the weight of metal in a car estimated using the WIO-MFA model was a good approximation for the known actual weight. The WIO-MFA model was also used for identifying the structure of metal flows in the US economy and for generating physical input-output tables (PIOTs) for metals that do not have a separate sector in the national IO tables [27], [28]. These two papers derive IO-material flow networks (IO-MFN) from the 2007 US IO table and analyze the shared edges among the sectors consuming metals to determine the degree to which certain metals coexist in the economy. Scrap and wastes can also be estimated using the method, along with the amount of a material contained in a final product. The input-output tables (IOTs) generated in these papers are referred to as Metal IOTs instead of PIOTs because the authors acknowledge that errors from the necessary assumption of price homogeneity throughout the economy likely results in IOT values that do not accurately correspond to metal flows by weight. Instead, the tables show the relative weights of materials being exchanged. Part of the reason the metals considered in these papers were chosen was because there were existing, traditional MFA studies or other sufficient information, e.g. data in US minerals year book, that could be used to crosscheck the method (in the case of aluminum), fill in data for nodes that were added, e.g. aluminum scrap transactions, and to convert monetary units to physical units. This is a challenge for building tables at the regional level or for less widely studied critical materials, because few MFA studies will be available at the required level of detail. An alternative method for disaggregating IO tables for the study of metals without an independent sector was presented in an IO analysis of cobalt mine capacity to fulfill demand under different scenarios through 2050 [29]. In this paper a 20 region MRIO model from EXIOBASE is hybridized to disaggregate cobalt from other non-ferrous metals. Since cobalt flows were less than 2.6% of the nonferrous metal sector they were bundled into, the authors just “hybridized” the table by adding data on physical cobalt requirements to appropriate sectors. The hybridized table is then scaled up to estimate future demand based on projected regional average GDP growth rates adjusted for different sectors, and future supply is estimated using a linear program combined with a dynamic stock model to determine optimal extraction patterns and resource depletion scenarios. A limitation of this work is that the supply-use table (SUT) structure the authors encountered did not perfectly match the known use of cobalt and some known cobalt-consuming industries did not “consume” any metal from the sector in which cobalt was aggregated. If one is interested in identifying unknown sectors related to the material, disaggregation rather than appending a new sector to contain the minor flow would result in a trade network containing all possible flows which would then require pruning or filtering. Additionally, applicability of the WIO-MFA to other materials is limited due to the data required to construct the filtering matrix being comparably difficult to obtain as the customary data required for a traditional, in-depth material flow analysis.

1.3 Research Objectives

Several studies have focused on the global cobalt supply chain and at the U.S. national level, but none look further into subnational material flows [27], [29], [30]. Current methods relying on empirical data that is resource intensive to produce limit the reproducibility of IO studies. Additionally, consistently maintained knowledge of regional material flows and stocks are needed for circular economy design at the national level. To address these needs, the research objectives of this study were to:

1) Develop a streamlined method for regional input-output analysis of critical materials in the US economy, and

2) Disaggregate cobalt value from a monetary, multiregional input-output (MRIO) table and determine significant sectors and regions for cobalt use with network analysis.

1.4 Outline

This thesis is organized into to following sections. Chapter 2 includes the methodology developed in this work to isolate metal flows in a national and subregional input-output model. The national and multiregional IO models are discussed in section 2.1.2. The results of the network analysis performed on the disaggregated IO networks are provided in section 2.2. The conclusions of this study and proposals for future research based on this work are presented in Chapter 3.

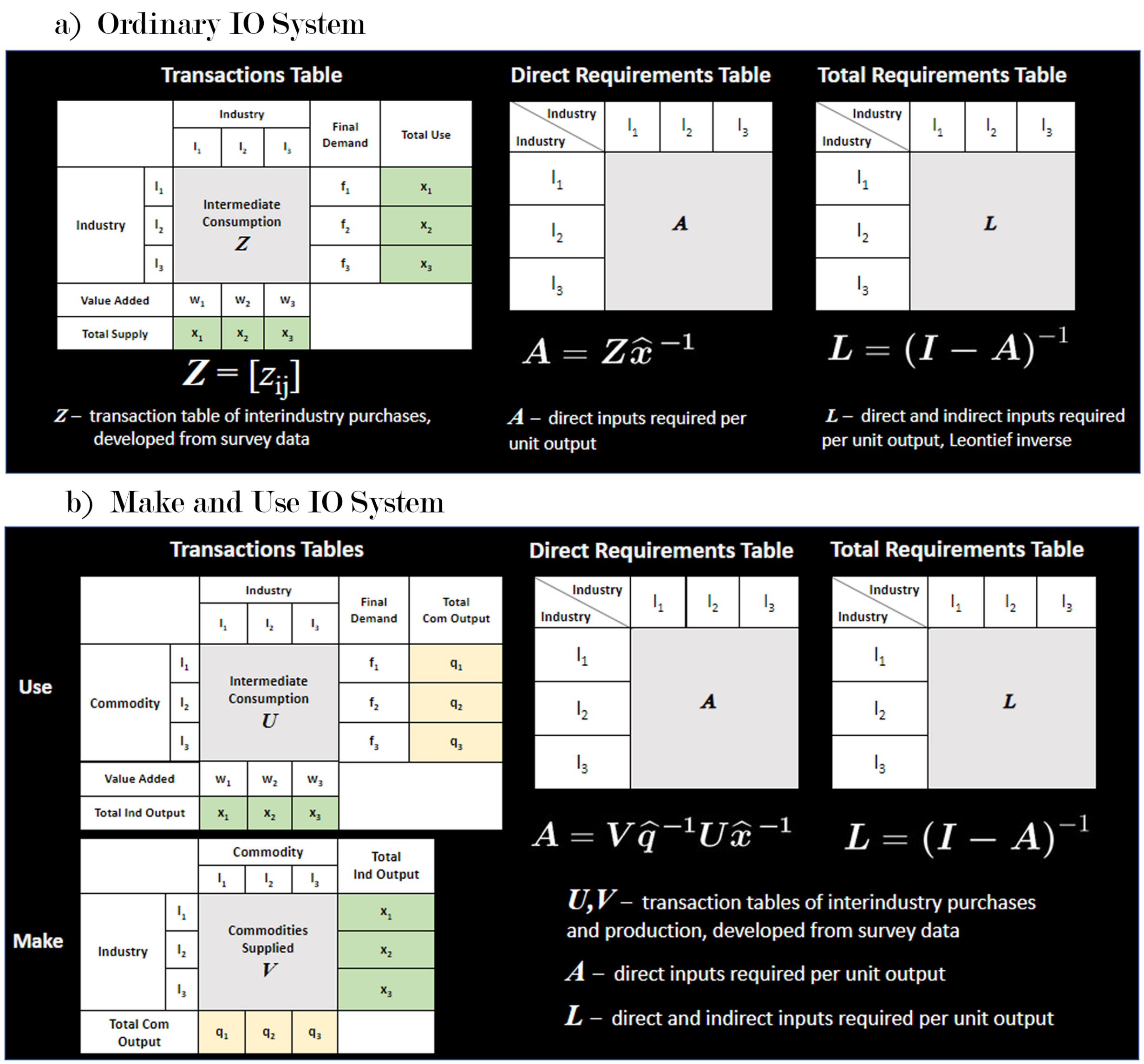


Figure 1.1. Economic input-output data structure. Ordinary IO assumes each industry produces one commodity. The Make and Use IO system accounts for the fact that many industries produce several types of commodities.

2. MRIO COBALT NETWORK DEVELOPMENT AND ANALYSIS

The multiregional input-output tables used in this study were generated with the Industrial Ecology Virtual Laboratory (IELab). The IELab is a cloud-based platform for rapid generation of MRIOs at customizable sectoral and regional aggregations [31], [32]; IELab MRIO models currently exist for several countries including Australia, China, Indonesia, Japan, Sweden, Switzerland, Taiwan, and the United States as does a Global MRIO Lab, which further builds on the virtual IO laboratory model and integrates Eora, EXIOBASE, and WIOD data [33], [34]. Although the US IELab can generate IO tables at the most detailed level of sectoral classification, critical materials and their derived products, whose supply chains are of interest to study using IO analysis, are still aggregated in the commodities that represent all of a sector's output in the IO models. Further disaggregating materials or products from the MRIO tables is then desirable in order to be able to distinguish between the exchange of products classified in the same IO sector but that have different trade structures than the one represented by the aggregated sector.

Disaggregating IO accounts requires additional data on the use of the target material or product in relation to the rest of the commodities contained in the aggregated sector. The electric power generation sector has been a good candidate for many IO disaggregation studies because there is ample data on the share of electricity generation by source that can be used to disaggregate the sector [35]–[37]. For tracking critical materials in IO tables, annual USGS data on material consumption is an annually updated and publicly available source of data that has been used for IO analysis of critical materials in the US [27]. However, for many materials, their applications are classified by the USGS into broad sector categories and therefore the data must be augmented with more detailed information on material use by industry in order to be mapped to detailed IO sectors for disaggregation. Empirical material flow data has previously been used to augment USGS data in the few studies taking an IO-based approach to critical material supply chain analysis in the US, but this material flow data is proprietary and like the national IO accounts themselves, not regularly updated due to the required resources for such effort.

A publicly available alternative data source worth investigating for this purpose is the EPA Toxic Release Inventory. The TRI includes substances that cause either cancer or other chronic human health effects, significant adverse acute human health effects, or significant adverse environmental effects [38]. There are seven hundred seventy individually listed chemicals and thirty-three chemical categories subject to reporting under the TRI [38] and many but not all US defined critical materials, including cobalt, are subject to TRI reporting. Facility reports on the use of regulated chemicals and compounds can be organized by the detailed industry classification, which is also used in the IO accounts. This makes the TRI a promising potential source of data on material use by sector and location that could be taken advantage of for application to IO analysis.

In an effort to contribute to advanced planning for the recovery of secondary cobalt materials, this research develops a method for identifying sectors and locations that are significant for a material's of interest supply chain in the US economy and applies it to the domestic supply chain of cobalt. There is no published literature that investigates cobalt use at the state- or subnational level, which is a necessary next step in evaluating how changes in the demand for cobalt may affect other industries in the economy and the regions they are located. Additionally, since the majority of cobalt is currently used in the US for non-battery applications, and the demand for these applications is also only expected to increase [15], investigating potential secondary sources of cobalt aside from just electric vehicle-derived batteries will be beneficial as the US expands its secondary material markets to help secure its supply of the material.

The purpose of this study was to elucidate the subnational trade structure of cobalt and identify significant subnetworks of cobalt-processing sectors.

2.1 Methods

2.1.1 Key Sector Determination and Cobalt Consumption Allocation

The proposed methodology for tracking specific metal flows in economy follows a top down approach of disaggregating certain economic sectors used in IO accounts into finer scale sectors that handle the material of interest. The disaggregation is carried out on economic IO tables but a combination of physical and economic data is used to determine how much value to separate and attribute to cobalt trade. The major cobalt processing sectors are identified for disaggregation from annually published and publicly available data, which are then mapped to sectors represented in economic IO tables. Network analysis is then used to investigate the structural significance of the identified major processing sectors and to try and identify additional sectors of secondary significance to the national cobalt supply chain. Figure 2.1 shows the overall workflow of the developed method. Each step of the approach is described in detail in the subsequent sections.

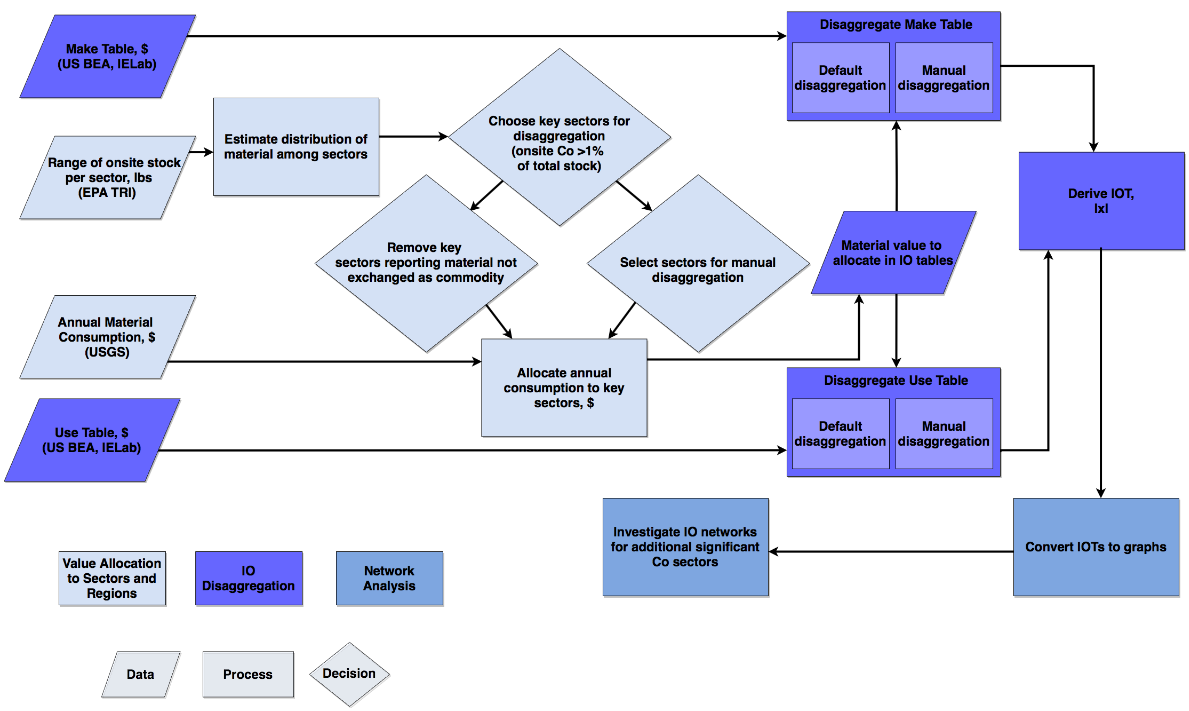


Figure 2.1. Flowchart of steps and data comprising the method.

Disaggregating cobalt value from sectors in Input-Output (IO) tables first required identifying which sectors exchange cobalt in the economy and how much of that sector's total value is associated with cobalt trade. Data on the total value of annual cobalt consumption were needed, as was information on the distribution of that value across sectors. Cobalt consumption data were compiled from the USGS Mineral Commodity Summaries 2013 (the earliest year reporting 2012 data) [39] and from the EPA 2012 Toxic Release Inventory (TRI)

[38]. The data used from the USGS included the monetary value of apparent consumption, which is defined as an estimate of primary and secondary domestic production + imports – exports ± adjustments to government and industry stock changes [40]. Note that apparent consumption does not include commodity quantities embodied in manufactured products, either imported or exported [41], so the value considered in this analysis is only that of cobalt that is in some way processed domestically and contained in a product upon importation. Despite this exclusion of embodied material, the cobalt accounted for by apparent consumption should correspond well to the material that is subject reporting in the TRI, and is the material being processed by the sectors we are interested in identifying – those who might be a potential supply source for secondary cobalt, or who risk being impacted by cobalt supply chain disruptions. The value of apparent consumption was sourced from USGS data while the EPA TRI data was used to identify which sectors to disaggregate and how to allocate total annual consumption between them. We were interested in exploring the TRI data's applicability to IO analysis because of its high level of sector and regional specificity, in addition to it being publicly available and updated annually. The steps taken to process consumption data from these sources is further described below.

Mapping NAICS codes reported in the TRI with BEA sector codes

The EPA TRI was used to identify which sectors to disaggregate in the national (single-region) and multiregional make and use tables and the proportions of annual cobalt consumption to allocate to each sector. First, the 6-digit NAICS codes used in the TRI were mapped to the corresponding sector codes in the national economic accounts. It was also necessary to reclassify the TRI sectors for use with the multiregional IELab tables, which were generated at the 4-digit NAICS level. The BEA national economic accounts sectoral classification system is a hybridized version of the NAICS system, hereafter referred to as BEA NAICS; this classification scheme contains some true 6-digit NAICS codes, while other 6-digit codes are aggregated. For example, the 6-digit NAICS code 331410 represents Nonferrous Metal Smelting and Refining. This code also exists in the BEA tables, so it could be matched exactly. However, 331491 represents Nonferrous Metal Rolling, Drawing, and Extruding — and 331492 represents Secondary Smelting, Refining, and Alloying of Nonferrous Metal. These two codes are aggregated under 331490 in the BEA accounts, so the data for facilities reporting under 331491 or 331492 were assigned to BEA sector 331490. From the TRI dataset, 159 unique 6-digit NAICS codes were aggregated to 117 unique BEA NAICS codes (the full mapping is available in appendix Table A.1).

Identification of key sectors for disaggregation

After sector reclassification, each sector's percentage of total reported cobalt use was estimated. The sum of onsite stock reported by each facility of a certain sector was used as a proxy for that sector's total cobalt use. Then the relative cobalt use per sector was calculated as the ratio of onsite cobalt stock for each sector relative to the total onsite stock across sectors. Each facility subject to TRI reporting reports a range of the maximum amount of chemical (MAOC) onsite at any time during the reporting year. The two smallest and largest ranges, in pounds, are [0 – 99]; [100 – 999]; [500,000,000 – 999,999,999]; ≥1 billion. The reporting options for MAOC are provided in Table 2.1. Exact quantities of a substance release to air, water, and land are included in the inventory, but because usage data can be sensitive information, no additional data on processed quantities or stock is reported aside from the MAOC. Given this data limitation, we used the midrange of the lower and upper bound of the reported MAOC range as a proxy, comparable across sectors, for annual cobalt use for each facility. This midrange is hereafter referred to as just 'MAOC'. The estimated onsite cobalt per facility was aggregated for each sector and the sectors whose cumulative MAOC was greater than one percent of the total MAOC for all sectors were designated as a key sector, $k \in K$, for disaggregation.

Pruning set of key sectors to include only those that process cobalt in a traceable form in the IO tables

TRI Data on cobalt use in each of the key sectors was then further investigated to determine whether the sector's use of cobalt would be captured by the IO data structure. Cobalt uses were deemed either structural, auxiliary, dissipative, or a combination based on the facility's reported uses of cobalt or cobalt compounds (examples of use type include formulation component, ancillary, byproduct, reactant, manufacturing impurity, etc.). The supply chain of cobalt with structural uses, where cobalt is an intentional product component, such as cobalt in alloys, may be tracked in the IO tables. Some auxiliary uses that result in cobalt being sent to other sectors, such as spent catalysts disposed of as waste, may also

Table 2.1.
Reporting code and corresponding weight ranges for Maximum Amount of the EPCRA Section 313 'Chemical Onsite at Any Time during the Calendar Year' (maximum amount of chemical - MAOC).

	Weight Range in Pounds	
Range Code	From	To
01	0	99
02	100	999
03	1000	9,999
04	10,000	99,999
05	100,000	999,999
06	1,000,000	9,999,999
07	10,000,000	49,999,999
08	50,000,000	99,999,999
09	100,000,000	499,999,999
10	500,000,000	999,999,999
11	1 billion	More than 1 billion

be tracked. Dissipative uses and cobalt that is reported as an unrecovered byproduct cannot be tracked in the economic IO tables. Key sectors who report most of their cobalt in these forms are excluded from further consideration. An exemplary excluded key sector was the Electric Utilities sector; this sector primarily reports cobalt air emissions from coal fired power plants. Since this cobalt would not be traceable in the IO tables, nor is included in the USGS annual apparent consumption estimates, the sector was excluded from further consideration.

Allocation of Cobalt Value to Key Sectors

The USGS monetary value of annual cobalt consumption was then allocated among the subset of key sectors, $J \subseteq K$, that remained after filtering. For the remaining key sectors j, where $j \in J$, the ratio of cumulative sector MAOC to total MAOC was normalized such that the use percentages for this subset sum to 100 percent. This normalization allows for 100 percent of annual cobalt value to be allocated and it is assumed the sectors with MAOC less than one percent of total MAOC use negligible amounts of cobalt. The use percentage for j is the ratio of estimated onsite cobalt for a sector and the sum of onsite cobalt for all key sectors. Let the dollar value of cobalt allocated to a key sector j be CA_{j}. CA_{j} was then calculated using Eq 2.1 as the product of the sector's normalized use percentage and the value of annual cobalt consumption from the USGS, V. An example calculation of CA_{j} for sector 331410 is shown below.

$$CA_{\mathrm{j}} = \frac{\sum MAOC_{\mathrm{j}}}{\sum MAOC_J} \cdot V \tag{2.1}$$

Table 2.2.
Data and calculation of the nonferrous metal smelting and refining sector's use of cobalt relative to other sectors reporting to the Toxic Release Inventory.

Sector: 331410 - Nonferrous metal smelting and refining					
Reported MAOC code[1]	3	4	5	6	Total
Average onsite stock per range (lbs)	5.5×10^3	5.5×10^4	5.5×10^5	5.5×10^6	
Number of facilities reporting range	1	3	1	1	6
Estimated onsite stock - MAOC (lbs)	$1(5.5\times10^3)$	$3(5.5\times10^4)$	$1(5.5\times10^5)$	$1(5.5\times10^6)$	6.2×10^6
Cumulative MAOC for sector (lbs)					6.2×10^6
Total MAOC for all sectors[2] (lbs)					2.4×10^8
Percent of total MAOC					3%

Cumulative MAOC >1% of total[3] $= \sum MAOC_J = 9.3 \times 10^7$ lbs

Value of cobalt consumption in 2012[4] = \$275 million

Cobalt value allocated to sector 331410 (CA_{331410}) $= \frac{6.2\times10^6\ lbs}{9.3\times10^7\ lbs} \times \$275$ million = \$18.41 million

The share of annual cobalt value allocated to each sector became the data used directly for disaggregating the make and use tables. To maintain balance of the disaggregated cobalt sections across the make and use tables, the same value of cobalt was disaggregated from a key sector's industry and commodity section in both tables, i.e., each disaggregated sector's total commodity output in the make table is equal to that in the use table, and likewise for total industry output.

[1]corresponds to a range in Table 2.1
[2]calculations for all sectors available in supporting information
[3]equals the sum of the cumulative MAOC for each key sector excluding pruned sectors like Electric Utilities
[4]from USGS

2.1.2 Input-Output (IO) Table Disaggregation

National IO Table Disaggregation

The inputs for the national-level disaggregated IO model were the detailed 2012 Benchmark make and use tables/After redefinitions, created by the US Bureau of Economic Analysis (BEA) [21], and the dataset of estimated cobalt consumption per sector generated from the 2012 TRI and USGS data. The value of cobalt consumption allocated to a key sector, CA_j, was disaggregated from that sector's industry and commodity outputs in the make and use tables. The BEA make and use tables used in this work are organized into 405 sectors, each corresponding to a 6-digit BEA NAICS code; the 6-digit BEA NAICS are the most detailed level of sectoral classification represented in the national input-output accounts. For the eleven key sectors identified from the EPA TRI (see Results section Table 2.5), CA_j was disaggregated from the superordinate/original/parent sector in both tables, resulting in disaggregated make and use tables each containing 416 commodities and 416 industries.

Disaggregation of a key sector was carried out across the interindustry transactions, value-added and final demand sections of the make tables so that the value-added and final demand sections, which contribute to table balance, would also contain the disaggregated subsectors and all IO table sections needed to simulate different final demand scenarios would be available in disaggregated form. Additional information on the contributions to domestic cobalt use from interindustry transactions compared with the final demand and value-added categories was unavailable for most sectors, so all sections of the use table were assumed to contribute in equal proportion to the generation of value associated with cobalt-containing products. If additional data on the relative contribution to total cobalt use from interindustry, value-added, and final demand categories becomes available, it could be used to perform a more accurate disaggregation of total industry or commodity output. The list of key sectors disaggregated and their descriptions is given in Table 2.5, along with the value of cobalt allocated to the sector and whether the sector was disaggregated using a default or manual procedure.

Default disaggregation

Disaggregating a row or column represents allocating a portion of the original sector's value to the segment of that sector associated with processing cobalt and the other portion to the remaining segment of the sector that does not process cobalt. In this case, disaggregation entails splitting a row or column into two new rows or columns. To do this, a portion of the value at each intersection with another row or column must be allocated to the corresponding new row or column associated with cobalt. The row or column containing the remaining, unallocated value can be thought of as the parent industry or commodity in which the cobalt value was originally aggregated. Most times there is insufficient information on the amount or value of cobalt that passes from one industry to another relative to the total magnitude of transaction between the industries to individually determine the value of cobalt to allocate from each interindustry intersection. Therefore, a default method of disaggregation was applied to those key sector rows and columns for which additional information on interindustry trade of cobalt within the sector was unavailable. In this default method, cobalt value is disaggregated in equal proportion from each interindustry element in a column or row. The default method was employed in the use table disaggregation for nine of the eleven key sectors described in Table 2.5. In the make table, cobalt value was only disaggregated from the table element representing the primary commodity of a given industry (diagonal table elements), which was considered a special case of manual disaggregation.

Manual disaggregation

In manual disaggregation, cobalt value is allocated from the original sector to a new disaggregated sector from only a selection of row or column intersections associated with cobalt trade. In the make table, cobalt value is only disaggregated from the main commodity of the key sector being disaggregated. In the use table, cobalt value is first disaggregated from value-added or final demand elements, and then the remaining value is disaggregated in equal proportion from the manually selected set of interindustry elements associated with cobalt trade.

Interpretation of disaggregated rows and columns in the make and use tables

An interpretation based on the make and use tables, each respectively organized in a commodity-by-industry and industry-by-commodity format, is offered as follows. Disaggregated rows in the use table represent the cobalt commodities or cobalt embodied in commodities of a particular industry. Each intersection with an industry column shows the value of cobalt contained in commodities (in the row) that is purchased by the industry (in the column). The row containing the remaining value after disaggregation represents the industry's commodities that do not contain cobalt.

Disaggregated columns in the use table represent the segment of an industry dedicated to manufacturing products containing cobalt. Each intersection with a commodity row shows the value of an interindustry purchase made to support the production of commodities containing cobalt by the sector.

Disaggregated rows in the make table represent the segment of a parent sector that makes commodities containing cobalt. The commodities produced by each cobalt-processing sector are assumed to only be aggregated in the main product of the parent sector, as opposed to assuming some commodities are aggregated in any of the secondary products also accounted for in the make table.

Disaggregated columns in the make table represent cobalt commodities and the cobalt embodied in commodities produced by the key industries; again, cobalt commodities are assumed to be produced by only the disaggregated cobalt industries.

Make table disaggregation

Each of the key sector rows and columns was replaced with either two new rows or two columns, one representing the part of the parent sector associated with cobalt products and the other representing the remaining portion of the superordinate sector's value. Disaggregation of the make table can be considered a special case of manual disaggregation because cobalt products made by a sector are assumed to be aggregated in that sector's primary commodity. Therefore, cobalt value was only disaggregated from one table element along a column or row such that cobalt value allocated to a key sector was only removed from the intersection of the parent sector with its main commodity. This resulted in cobalt commodity values only along the diagonal of the make table, in the section where disaggregated cobalt industry rows intersect with disaggregated cobalt commodity columns.

Use table disaggregation

Default disaggregation

The default disaggregation procedure will be described for only the use table columns, but the same procedure was applied to the rows. First, a weight, w_j, representing the share of a total sector's output associated with cobalt commodity production and used to separate the original column into two, was calculated using Eq 2.2. The value in the numerator comes from Table 2.5, which was calculated based on TRI and USGS data. The value in the denominator is the total industry output of sector j from the BEA IO accounts.

$$w_{\mathrm{j}} = \frac{Cobalt\, value\, allocated\, to\, sector\, \mathrm{j}}{Total\ output\ of\ sector\, \mathrm{j}} = \frac{CA_{\mathrm{j}}}{g_{\mathrm{j}}} \tag{2.2}$$

The disaggregated cobalt sector contains the product of this weight and the vector of inputs to sector j shown in Eq 2.3. The vector of inputs to sector j, defined as $\boldsymbol{u_j}$, contains the upstream supply chain and value-added transactions associated with the consumption of the allocated value of cobalt.

$$w_{\mathrm{j}}\boldsymbol{u}_{\mathrm{j}} \tag{2.3}$$

The remaining sector is the product of the vector of inputs to sector j and the remaining share of the sector's output for activities unrelated to processing cobalt given in Eq 2.4.

$$(1 - w_{\mathrm{j}})\boldsymbol{u}_{\mathrm{j}} \tag{2.4}$$

This procedure was then repeated for the same set of key sector rows. Nine of the eleven key sectors were disaggregated using this default method. The remaining two key sectors 324110 - Petroleum refineries and 562000 - Waste management and remediation services were disaggregated using a manual procedure because additional information on the specific uses of cobalt within these sectors was apparent.

Manual disaggregation

Once default disaggregation had been done for both rows and columns, the remaining sectors were disaggregated using a manual procedure. Again, the steps for disaggregating columns will be described but the same procedure was applied to the rows.

Manual disaggregation started with the same key sector weight, w_j, but the weight was not multiplied by each element in the column, i.e., cobalt value was not disaggregated blindly from each element in the column. To avoid having to manually disaggregate either the value-added or final demand sections, these sections were disaggregated in the same manner as in the default method, by taking the product of w_j and each element. The disaggregated value-added elements are calculated using Eq 2.5, where $\boldsymbol{u_{va_j}}$ is the vector of value-added inputs to sector j. The disaggregated final demand elements are calculated using Eq 2.6, where $\boldsymbol{u_{fd_i}}$ is the vector of final demand values for commodity i and w_i is the weight representing the share of total commodity output for a given sector that is attributed to cobalt contained in the commodity. The remaining value-added elements are calculated using Eq 2.7 and the remaining final demand elements are calculated similarly.

$$w_{\mathrm{j}} \boldsymbol{u}_{va_{\mathrm{j}}} \tag{2.5}$$

$$w_{\mathrm{i}} \boldsymbol{u}_{fd_{\mathrm{i}}} \tag{2.6}$$

$$(1 - w_{\mathrm{j}}) \boldsymbol{u}_{va_{\mathrm{j}}} \tag{2.7}$$

To start manual disaggregation of the interindustry values, the key sector weights w_j were multiplied by only a select number of interindustry column elements known to be involved in the trade of cobalt. For example, we assumed that all value associated with cobalt that is embedded in the Petroleum Refining sector is from the use of cobalt catalysts for desulphurization (Cobalt Institute, 2018). Therefore, the cobalt value disaggregated from this industry (column) is removed only from the intersection with the Inorganic Chemical Manufacturing commodity (row), which is assumed to be the form through which cobalt catalysts are supplied. With regards to the Petroleum Refining commodity (row), the cobalt value embedded in it is separated only from the row's intersection with the Waste Management industry, as any cobalt embedded in products leaving the Petroleum Refining industry (spent catalyst) is assumed to be 'used' only by waste management through disposal.

The Waste Management and Remediation Services (Waste Management) industry and commodity are both disaggregated by removing cobalt value from only the intersections with the other key sectors being disaggregated. This can be interpreted as Waste Management receiving waste containing cobalt from only the key sectors and only the key sectors generate waste containing cobalt. This assignment of the sectors generating waste containing cobalt may not be entirely accurate, but it provides a more reasonable estimation of the sources of cobalt waste than would the default disaggregation method. Applying the default disaggregation method to the Waste Management sector would have resulted in the inaccurate interpretation that nearly every sector generates some waste containing cobalt.

The disaggregation of a column or row takes place in two phases. In column disaggregation, multiplying w_j by a selection of interindustry table elements and the value-added section yielded intermediate disaggregated columns for both cobalt value and remaining sector value. Next, the leftover allocated value of cobalt was transferred from the sector of remaining value to the disaggregated cobalt sector. This was done by calculating a new weight from the total remaining value of cobalt to be disaggregated and the sum of the interindustry elements in the remaining sector column designated for disaggregation. The product of this new weight and the interindustry elements in the remaining sector designated for disaggregation yielded the share of the remaining cobalt value to be subtracted from the remaining sector and added to the disaggregated cobalt sector. Manual disaggregation can be mathematically represented as follows in equations 2.8 - 2.11.

Intermediate values are allocated to the disaggregated cobalt column; the values allocated to the disaggregated value-added section are calculated using Eq 2.5. The values allocated to the intermediate, disaggregated interindustry section are calculated using Eq 2.8, where $\boldsymbol{u_c}$ is the vector of commodity inputs to sector j known to contain cobalt.

$$w_{\mathrm{j}} \boldsymbol{u}_c \tag{2.8}$$

$$VA = \sum_{\mathrm{j}=1}^{s} w_{\mathrm{j}} \boldsymbol{u}_{va_{\mathrm{j}}} \tag{2.9}$$

$$M_1 = \sum_{c \in C} w_{\mathrm{j}} \boldsymbol{u}_c \tag{2.10}$$

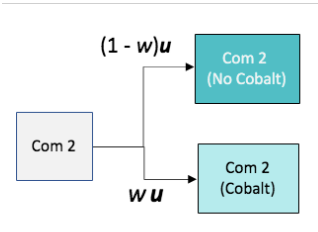
The cobalt value disaggregated from an industry column in the first phase of manual disaggregation is *M1+VA*. The remaining value of cobalt to be disaggregated in the second phase is the original value of cobalt to be allocated to sector j minus the amount disaggregated in the first phase: CA_j - (*M1+VA*).

In the second phase, a new weight is calculated based on the remaining value of cobalt to be allocated and the value of commodities in C, the set of commodity inputs to sector j known to contain cobalt, in the remaining parent sector. If *M1* is the total intermediate, disaggregated interindustry cobalt value than 1-*M1* is the leftover interindustry value in the parent sector from commodities that still correspond to cobalt in the sector being disaggregated. The new weight used to allocate the remaining cobalt value from the parent sector to the disaggregated sector is calculated as shown in Eq 2.11.

$$w'_{\mathrm{j}} = \frac{CA_{\mathrm{j}} - M_1 - VA}{1 - M_1} \tag{2.11}$$

The new weight, w'_j is then multiplied by each element in remaining industry column at the intersection with a commodity in C to yield the remaining value to add to the elements in the disaggregated cobalt column. Let *M2* be the total remaining cobalt value to transfer from the interindustry elements in the parent industry column to the disaggregated industry column. *M2* can be calculated using Eq 2.12 and *M1+M2* equals the original cobalt value to allocate to sector j less the value allocated to the value-added section. Figures 2.2 and 2.3 show a graphical example of default and manual disaggregation performed on the make and use tables.

$$M_2 = \sum_{c \in C} w'_{\mathrm{j}} (1 - w_{\mathrm{j}}) \boldsymbol{u}_c \tag{2.12}$$



C/I	Ind 1	Ind 2	Ind 3	Ind 4	FD	Total Com Output
Com 1	u_{11}		u_{13}			
Com 2	Com2 used by Ind 1	Com 2 used by Ind 2			FD for Com 2	Total output of Com2
Com 3						
Com 4	u_{41}		u_{43}			
VA						
Total Ind Output						

Original Use Table : Commodity by Industry

C/I	Ind 1	Ind 2 (No Cobalt)	Ind 3	Ind 4	Ind 2 (Cobalt)	FD	Total Com Output
Com 1							
Com 2 (No Cobalt)	Com 2 without cobalt used by Ind 1	Com 2 without cobalt used by portion of Ind 2 NOT making cobalt-based products			Com 2 without cobalt used by portion of Ind 2 making cobalt-based products		
Com 3							
Com 4							
Com 2 (Cobalt)	Com 2 with cobalt used by Ind 1	Com 2 with cobalt used by portion of Ind 2 NOT making cobalt-based products			Com 2 with cobalt used by portion of Ind 2 making cobalt-based products		
VA							
Total Ind Output							

Disaggregated Use Table: Commodity by Industry. Disaggregated commodity rows are color coded for emphasis. New commodity row represents flow of cobalt in commodities. New industry column represents share of that industry processing cobalt.

Figure 2.2. Graphical representation of the default disaggregation method. $\boldsymbol{u}$ is the vector of commodity outputs (row) or industry inputs (column) from the original use table. w is the disaggregation weight calculated based on TRI and USGS data, and total output. An analagous corresponding operation is applied for column disaggregation.

Conversion of disaggregated make and use tables to total requirements Tables

The disaggregated make and use tables were then converted to an industry by industry total requirements matrix following BEA guidelines described below [42].

$\boldsymbol{q}$ = a column vector in which each entry shows the total amount of each commodity's output.

$\boldsymbol{g}$ = a column vector in which each entry shows the total amount of each industry's output.

$\boldsymbol{U}$ = interindustry portion of the use table; this is a commodity-by-industry matrix.

$\boldsymbol{V}$ = make matrix; this is an industry-by-commodity matrix.

$\boldsymbol{A}$ = Direct requirements matrix = $V\hat{q}^{-1}U\hat{g}^{-1}$

$\boldsymbol{L}$ = industry-by-industry total requirements matrix = $(I - A)^{-1}$

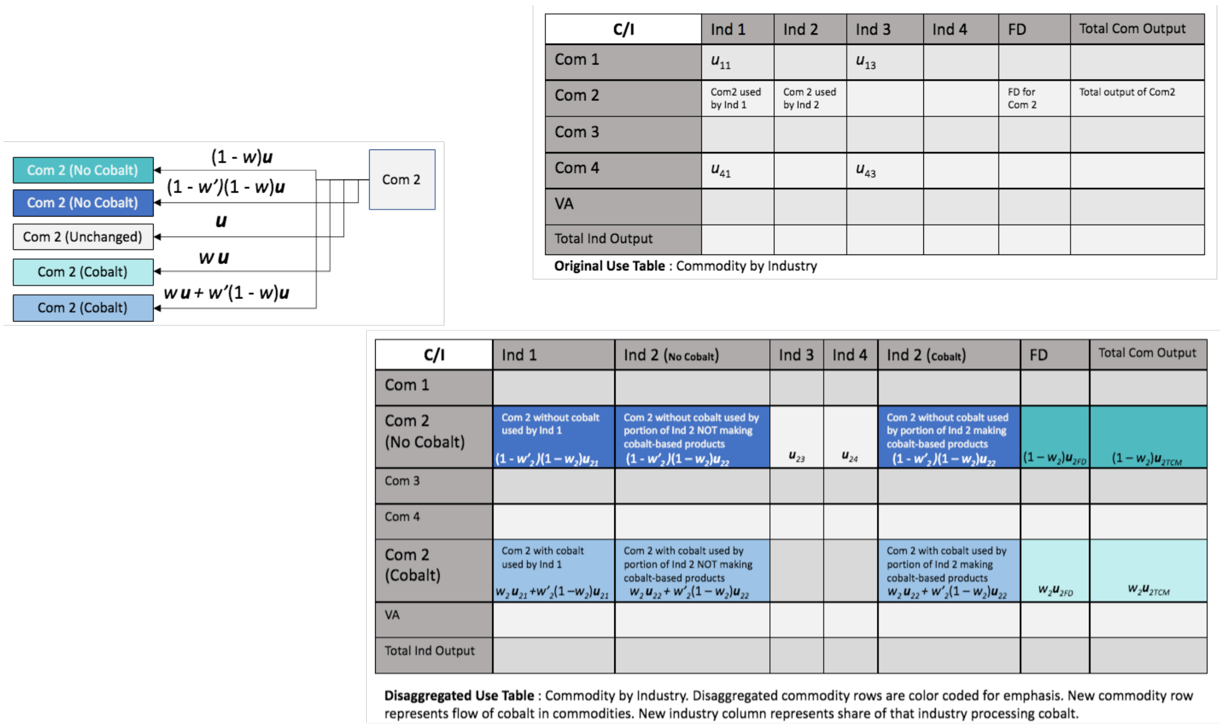


Figure 2.3. Graphical representation of the manual disaggregation method. $\boldsymbol{u}$ is the vector of commodity outputs (row) or industry inputs (column) from original use table w is the initial disaggregation weight calculated based on TRI and USGS data. w' a secondary weight calculated based on the remaining cobalt value to be allocated after the initial share is removed from select column elements and the FD section.

Multiregional IO (MRIO) Table Disaggregation

The same determination of key sectors used in the national table disaggregation was also used to disaggregate the multiregional supply and use tables. However, the national tables were organized by 6-digit BEA NAICS code while the MRIO tables were organized by 4-digit NAICS code. The list of 6-digit key sector codes and their descriptions is given in Table 2.5 in addition to the value of cobalt allocated to the sector and whether the sector was disaggregated using the default or manual procedure. The key sectors identified at the 6-digit NAICS level were mapped to the 4-digit level and the value assigned to each sector was aggregated accordingly. In one case, the sector, 562000 – Waste management and remediation services was further disaggregated into two separate 4-digit NAICS waste-related sectors in the MRIO tables. The mapping of 6-digit sectors used for the national level table disaggregation to their encompassing 4-digit sectors for disaggregation of the MRIO is shown in Table 2.6 in the Results section.

The inputs for disaggregating the multiregional IO model were MRIO supply and use tables (SUTs) for 2012, generated by the Industrial Ecology Virtual Laboratory (IELab) for the US [43] and the dataset of estimated cobalt consumption per sector and region generated from the TRI and USGS data. The US IELab was used to generate a 312 sector, 52 region MRIO model using the national IO accounts and data sources such as state-level GDP and commodity flow surveys to constrain the specified regional and sectoral disaggregation. Flegg's location quotient was used to create the initial regionalization and the data used to further constrain the tables to the desired regional and sectoral classification are listed in Table 2.3.

Table 2.3.
Datasets used to constrain the MRIO model in the US IELab.

USLab Constraints	**Issuing Agency**
Commodity Flow Survey	Bureau of Transportation Statistics
Export Import Data	Census Bureau
State GDP	Bureau of Economic Analysis
Personal Consumption Expenditures	Bureau of Economic Analysis
Make and Use tables, detailed level	Bureau of Economic Analysis
Make and Use tables, summary level	Bureau of Economic Analysis

In contrast to the national make and use tables, the MRIO supply and use tables were generated with sector disaggregation at the 4-digit NAICS code level and regional disaggregation at the US state-level (including Washington, DC and Puerto Rico). MRIO data on the supply of commodities from different industries to each region formed the total supply from which cobalt value was disaggregated, analogous to the disaggregation from the make table at the national level. MRIO data on the use of commodities by different industries in each region, value added, imports by regionalized sector, exports by region, and final demand were aggregated to form the total demand from which cobalt value was disaggregated, analogous to the disaggregation from the use table at the national level.

A similar procedure as before was followed to split the key sectors into a subsector processing cobalt and a remaining portion using a default or manual procudure. The 4-digit sectors corresponding to the 6-digit sectors disaggregated with the manual procedure in the national-level tables were also disaggregated with the manual procedure in the MRIO tables. The main difference between disaggregating the single-region and multiregional IO tables was that the cobalt value disaggregated from key sectors in the multiregional tables was also allocated across regions. Cobalt value was allocated across regions based on the sector's percentage of national output coming from each region. Figure 2.4 shows how cobalt value was allocated to key sectors and across regions in the MRIO tables based on a region's contribution to total sector output.

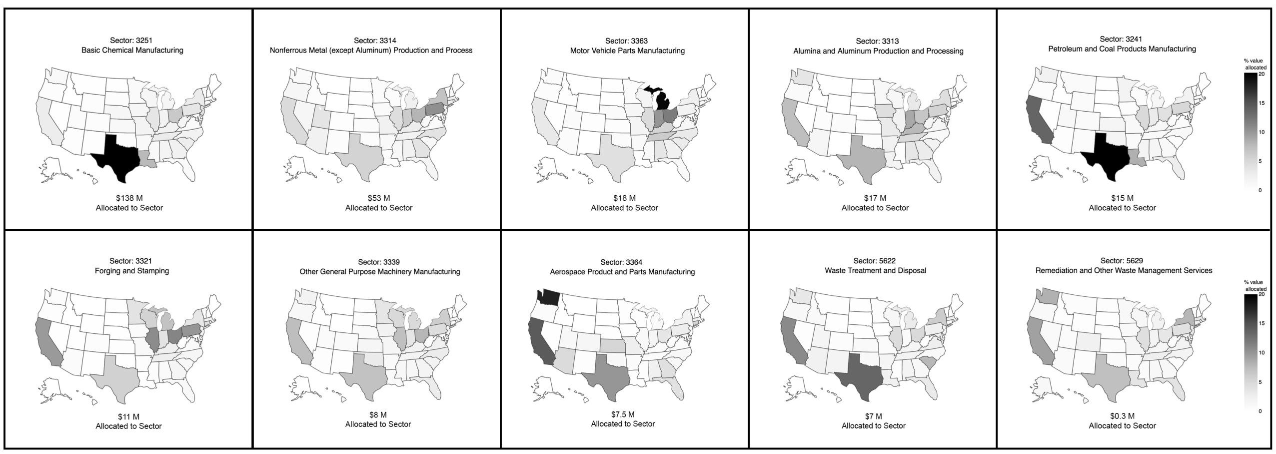


Figure 2.4. Allocation of cobalt value across regions in the MRIO tables.

Supply table disaggregation

As in the disaggregation of the national make table, disaggregation of the supply matrices was considered a special case of manual disaggregation because cobalt products supplied by a sector were disaggregated only from that sector's primary commodity. The amount of cobalt to disaggregate from a key sector in a region was calculated by multiplying two percentages, or weights, by the monetary value of cobalt allocated to the entire sector from Table 2.6. The first weight used is $w_{j'}$, a similar version of the weight used in the national level disaggregation, Eq 2.2, and represents the share of a sector's total output that can be allocated to cobalt flows. An approximation of total sector *j'* output is taken to be the value of commodity s supplied by the sectors whose primary product is s. This is a reasonable approximation of the total domestic supply of a commodity because the vast majority of any commodity is supplied by the sector that produces it as its primary product. For regional disaggregation, weight $w_{j'}$ was calculated using Eq 2.13. The value in the numerator comes from Table2.6, which was calculated based on TRI data and USGS data. The value in the denominator is the total primary output of commodity s calculated from the MRIO matrices.

$$w_s = \frac{Cobalt\, value\, allocated\, to\, sector\, \mathrm{j}'\ (CA_{\mathrm{j}'})}{Total\, primary\, output\, of\ s\ from\, \mathrm{j}'} \tag{2.13}$$

The second weight used, $w_{j'r}$, represents the share of the total supply of a disaggregated cobalt commodity provided by a particular region. This value could either be determined using economic allocation based solely on MRIO data or with a mass-based allocation using TRI data, which is linked to facility location. Using data from the MRIO to calculate the regional weights allows for separate sets of regional weights to be calculated for supply and use disaggregation as well as separate weights for industry inputs and use of commodities in the use tables. A key sector's allocated value was further distributed to states r using Eq 2.14.

As the economic allocation approach was preferred for initial testing, or had industry location data not been available, value can be distributed among regions based on a region's share of national supply for the key sectors under consideration. Let each region's supply table be $\boldsymbol{S_r}$. A regional supply weight w_{rs}, described in Eq 2.14, would be calculated for each region in which a key sector operates to determine the portion of total cobalt value allocated to *j'* to disaggregate from the regional supply of s in $\boldsymbol{S_r}$.

$$w_{rs} = \frac{Primary\, output\, of\, commodity\, s\, in\, region\, r}{Total\, primary\, supply\, of\ s\ from\, \mathrm{j}'} \tag{2.14}$$

Again, for allocation purposes, total supply was approximated as the value of commodity s provided by its primary producing sector. Total primary supply of any s then equals the sum of corresponding diagonal entries in each $\boldsymbol{S_r}$, with diagonal elements represented as $\boldsymbol{S_{r_{ss}}}$, shown in Eq 2.15.

$$Primary\ output\ of\ commodity\ s = \sum_{r=1}^{52} S_{r_{ss}} \tag{2.15}$$

The row and column in $\boldsymbol{S_r}$, corresponding to a key sector and its main commodity were separated into two parts as was done in the national level disaggregation. The cobalt value disaggregated from domestic supply was calculated using Eq 2.16. The remaining value of a commodity supplied for domestic use by region r was calculated using Eq 2.17.

$$w_{\mathrm{j}'} w_{rs} S_{r_{ss}} \tag{2.16}$$

$$(1 - w_{\mathrm{j}'})(1 - w_{rs}) S_{r_{ss}} \tag{2.17}$$

Use table disaggregation

After the supply tables were disaggregated, cobalt value was disaggregated from the use tables whose sections include interindustry matrices, value-added, imports, exports, and final demand. As in the disaggregation of the supply tables, two weights (a sector and region weight) are used to separate use table elements for a key sector into a portion representing the commodities consumed that contain cobalt and another portion of cobalt-free commodities. The sector weight used is w_s, representing the share of a total sector's output attributable to cobalt consumption and was calculated using Eq 2.18. C_s is the total industry or commodity output for a key sector, depending on whether the weight is used for row or column disaggregation. Since the use tables are organized commodity by industry. for row disaggregation, C_s is calculated using Eq 2.19 and Eq 2.20 is used for column disaggregation.

$$w_s = \frac{CA_{\mathrm{j}'}}{C_s} \tag{2.18}$$

$$C_{s,com} = total\, interindustry\, outputs\, +\, total\, exports\, +\, total\, imports\, +\, total\, final\, demand \tag{2.19}$$

$$C_{s,\text{ind}} = total\, interindustry\, inputs\, + total\, imports\, by\, ind.\, + (value - added) \tag{2.20}$$

Imports are added instead of subtracted in the calculation of $C_{s,com}$ because imports are recorded in the MRIO as if they are separate commodities. We do not distinguish between imported supply and domestic supply in this work, though the majority of cobalt is imported, so the value of imported commodities from industry type *j'* was added to the value of that sector's domestic commodities to yield the total consumption of commodity s from which to disaggregate cobalt value.

Conversion of disaggregated supply and use tables to total requirements table

The BEA method for converting make and use tables to total requirements tables is nearly identical to the method for the supply and use framework. Once the multiregional supply and use matrices were disaggregated an industry-by-industry total requirements matrix was derived using the Eurostat Model D method [44], modified for multiregional SUTs. Coefficient matrices were created using equations 2.21 and 2.21. The market share coefficient matrices, D_r, derived from the supply tables were calculated $D_r = V_r \hat{q}_r^{-1}$ where V_r is the single supply table for a region r and q_r is the vector of total commodity output from that region. The direct requirements coefficient matrices, B_{tr}, derived from the use tables were calculated $B_{tr} = U_{tr} \hat{g}_r^{-1}$ where U_{tr} is the use table of commodities used by region r from region t and g_r is the vector of total industry outputs from r. The market share matrix and direct requirements matrices for each region are then converted to the regions' transformation matrices A_{tr} through Eq 2.23.

$$D_r = V_r \hat{q}_r^{-1} \tag{2.21}$$

$$B_{tr} = U_{tr}\hat{g}_r^{-1} \tag{2.22}$$

$$A_{tr} = D_r B_{tr} \tag{2.23}$$

$$A = [A_{tr}] \tag{2.24}$$

Transformation matrix A was organized as in Eq 2.24 and converted to a compound total requirements matrix using the Leontief model:

$$L = (I - A)^{-1} \tag{2.25}$$

2.1.3 Disaggregated IO Network Analysis

The disaggregated total requirements tables at the national and state-level were then converted to a total requirements matrix, which formed the basis of the IO network, disaggregated for cobalt. Several input-output and graph theory-based metrics that have been deemed suitable for analysis of dense, weighted, and directed networks ([45]–[48]) were calculated using the national and multiregional IO networks to try to determine the significance of the disaggregated sectors relative to each other and identify additional sectors of importance to the domestic cobalt trade network. The total requirements matrix (Leontief inverse) was used for network analysis to capture the direct and indirect connections between sectors at all levels of the supply chain. In graph representation of the IO network, industries correspond to nodes and economic transactions correspond to edges, i.e., the links between nodes. Unless otherwise stated, edges represent direct or indirect economic connections between sectors. A summary of the metrics used to identify significant sectors is show in Table B.5 and are further described below.

Eigenvector Centrality (EC)

The eigenvector centrality of a node is the sum of the eigenvector centralities of all of its connecting nodes divided by the largest eigenvalue of the adjacency matrix of the graph.

Table 2.4.
Metrics tested for identifying significant sectors in the disaggregated cobalt network and the Python package used to calculate the metric.

Network Analysis Metric	Description	Package
In/Out-Degree	Number of incoming/outgoing connections to a node	networkx
Eigenvector Centrality	Indicates node significance based on the incoming or outgoing connections to either many nodes or to other highly important nodes	networkx
PageRank	Indicates node significance based on the the incoming (upstream) connections to either many sectors or to other highly important sectors	networkx
Authority Score	Ranks significance of nodes with many incoming links, calculated in tandem with hub score	networkx
Hub Score	Ranks significance of nodes with many outgoing links, calculated in tandem with authority score	networkx
Closeness Centrality	Proportional to the sum of shortest paths between a node and its direct and indirect connections	igraph
Betweenness Centrality	Proportional to the number of shortest paths between two nodes that pass through the node of interest	igraph
Clustering using k-means	Partitions data into groups by minimizing the sum of squared error between a data point and cluster centroid	sklearn
Backward/ Forward Linkage	Indicates magnitude of impact on other upstream or downstream sectors that would occur due to a change in final demand for a sector	pandas
Diffusion	Identify sectors that may distribute the effect of a change in final demand widely across many other sectors versus to a concentrated few	pandas

It is calculated recursively, whereby a relative score is assigned to each node and at each iteration a node's score then becomes influenced by the scores of the connecting nodes.

PageRank (PR)

PageRank is a modified measures the importance of a node based on the structure of its incoming connections.

The PageRank of a node v is the sum of a) the normalized sum of the pageranks of all other nodes that link to v, divided by the number of outgoing edges from those nodes, multiplied by a damping factor and b) the probability of linking to any other node at random.

Pagerank is also calculated recursively; each node's relative assigned score is modified at each iteration based on the scores of the connecting nodes.

The pagerank of sector v depends on the pageranks of all other sectors that link to sector v, divided by the number of outgoing edges (L) from each sector linked to v.

Hub and Authority Score (HS/AS)

As interdependent centrality measures, hub and authority scores are also calculated recursively.

Closeness Centrality (CC)

Closeness centrality measures the average shortest distance between a node and all other nodes n that connect to it [49]. Closeness centrality for a node v is calculated using 2.26 where $\sigma(u, v)$ is the shortest distance (geodesic path) between nodes u and v.

$$c_C(v) = \frac{n-1}{\sum_{\mathrm{i}=1}^{n} \sigma(u_{\mathrm{i}}, v)} \tag{2.26}$$

In the weighted IO network, the edge weight or magnitude of exchange between two sectors is treated as the inverse of the distance between them, so the larger the exchange, the closer the two nodes are to each other.

Betweenness Centrality (BC)

Betweenness centrality measures the extent to which a node lies on the shortest paths between other nodes in the network. In weighted networks, edge weight is incorporated into the length of the path [50]. In the context of IO networks, this measure has been interpreted to highlight sectors that may act as bottlenecks in the supply chain [48], [51]. Sectors with higher betweenness are more likely to cause disruptions to the flow of resources dependent on passage through them. Betweenness centrality for a node $v \in V$ is calculated as follows in 2.27 where $\sigma(s, t)$ is the number of shortest or geodesic paths between pairs of nodes (s,t) in the network and $\sigma(s, t|v)$ is the number of shortest paths that pass through v.

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s, t|v)}{\sigma(s, t)} \tag{2.27}$$

Important to note is that the reciprocal of edge weight was used as the 'weight' attribute in calculating weighted betweenness of the IO networks. For weighted networks, weight can be used as a proxy for distance but in the betweenness algorithm, shortest paths with greater distance that are intercepted by a note would yield a smaller centrality for the intercepting node [52]. Since it is desirable for the weight associated with the shortest path to be proportional to the centrality score, the reciprocal of edge weight (strength of economic connection between sectors) was used as the attribute to calculate weighted betweenness centrality.

Clustering for Community Detection

The K-means algorithm in the scikit learn Python library was used to divide the disaggregated IO networks into clusters. The algorithm divides the data into k clusters, specified by the user, by minimizing the sum of squared distances between the samples in a cluster and the mean of the samples in the cluster, also called the centroid [53]. The total sum of squared distances for the entire dataset is called the inertia or distortion score and this quantity can be automatically returned after clustering.

The 'elbow method' was used for choosing the most appropriate number of clusters to separate the IO network into. This graphical analysis technique involves plotting the inertia vs. clusters to find the number of clusters at which diminishing returns on decreased inertia begin. The number of clusters thought to best fit the model is and the point in the graph where there are noticeable diminishing returns in the decrease in inertia with additional cluster added, in other words, at the elbow of the chart. In Figure 2.5, the number of clusters that would minimize inertia while requiring the least amount of computational power is three. The following documentation further describes the elbow method [53], but the Yellowbrick Python package was not used for calculation. Instead, inertia was plotted against a range of cluster quantities.

Linkage (BL/FL)

Traditional input-output analysis measures of linkage were also used to try to pick out significant sectors in the IO network. Sectors with high backward or forward linkage (BL or FL) have a stronger technical connection to either their upstream or downstream supply chains [55]. The supply chain of a sector with an above average linkage will be more heavily affected by impacts to sectors in its supply chain, especially by those that also have high linkage. Whether a sector has a high or low linkage is determined by examining the average linkage compared to others. Average or normalized backward [$\bar{\mathbf{b}}(t)$] and forward [$\bar{\mathbf{f}}(t)$] linkage is calculated as the total linkage (equations 2.28 and 2.29) in either direction divided by the simple average of all sectors' linkage values in that direction [20], [55].

$$BL(total)_{\mathrm{j}} = \sum_{\mathrm{i}=1}^{n} l_{\mathrm{ij}} \tag{2.28}$$

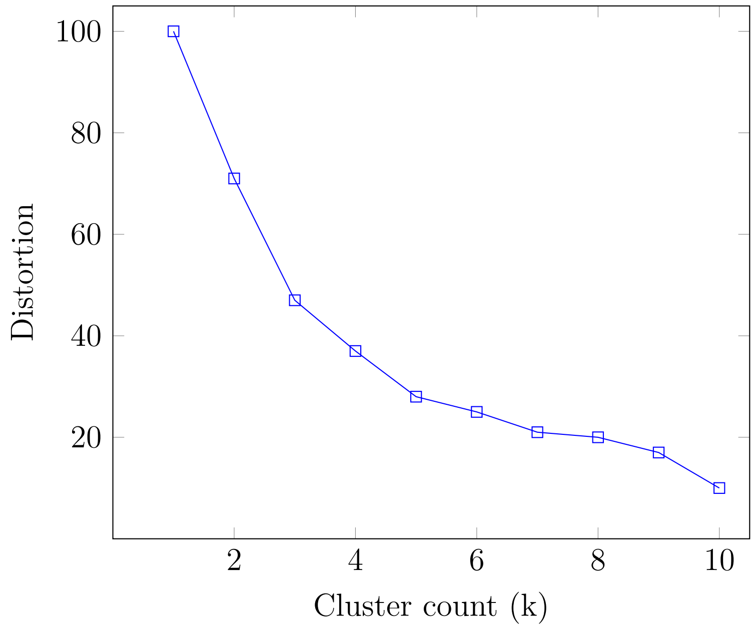


Figure 2.5. A typical elbow method plot of distortion (inertia) vs. cluster count used to determine an appropriate number of clusters in a dataset, adapted from [54].

$$FL(total)_{\mathrm{i}} = \sum_{\mathrm{j}=1}^{n} l_{\mathrm{ij}} \tag{2.29}$$

Diffusion (DF)

A diffusion metric, proposed by (Alatriste-Contreras, 2012), is used to identify sectors that may widely distribute the effect of an economic shock to its final demand among many other sectors versus a concentrated few [16]. Diffusion is defined in equations 2.30 and 2.31 where s is the proportion of economic effect absorbed by sector i. Ranking sectors based on their diffusion could aid in designing policies that maximize the effect of a stimulus throughout the economy, or those that seek to limit the spread of a negative shock to final demand [16]. A higher diffusion score d_{i}, as calculated in Eq 2.31, indicates a sector i has good diffusion properties and the effects of a shock to its final demand will be distributed more evenly throughout the IO network.

$$H_{\mathrm{i}} = \sum_{\mathrm{i}=1}^{n} s_{\mathrm{i}}^2 = \sum_{\mathrm{j}=1}^{n} (l_{\mathrm{ji}} / \sum_{\mathrm{j}=1}^{n} l_{\mathrm{ji}})^2 \tag{2.30}$$

$$d_{\mathrm{i}} = 1 - H_{\mathrm{i}} \tag{2.31}$$

The above network metrics were used to elucidate the ways in which key sectors may be important in the economy aside from having been identified as important to domestic cobalt use based on how much cobalt they process relative to other sectors. A combination of community detection and comparison of metric scores were used to identify additional sectors of significance to the disaggregated IO networks. The k-means clustering algorithm was used to detect communities of sectors. The network metric scores of sectors in community with previously identified key cobalt processing sectors were further explored for insights on the relative importance of neighboring sectors, and locations in the MRIO model, based on the criteria measured by each metric.

2.2 Results

2.2.1 Sectors Identified for Disaggregation in IO Model

One hundred fifty-nine NAICS industries reported manufacturing or processing at least 25,000 pounds, or otherwise using at least 10,000 pounds of cobalt or cobalt compounds in the 2012 Toxic Release inventory. These industries correspond to one hundred seventeen BEA NAICS sectors; of these sectors, eleven were determined to be key sectors and had cobalt value disaggregated from them in the national make and use tables. Table 2.5 shows which sectors were disaggregated from the national IO tables and Table 2.6 shows which analagous sectors were disaggregated from the MRIO tables.

Table 2.5.
Key sectors from which cobalt value was disaggregated in the make and use tables. The value of annual cobalt consumption in 2012 was distributed among the key sectors based on each sector's cobalt use relative to other sectors estimated from TRI data.

Key Sector Code	Sector Description	Co value allocated to sector (in million USD)	Disaggregation Method
325180	Other basic inorganic chemical mfg.	30.30	Default
325190	Other basic organic chemical mfg.	107.74	Default
331313	Alumina refining and primary production	16.61	Default
331410	Nonferrous metal smelting and refining	18.42	Default
331490	Nonferrous metal rolling, drawing, extruding, alloying	34.72	Default
333920	Material handling equipment mfg.	8.30	Default
336370	Motor vehicle metal stamping	17.94	Default
336412	Aircraft engine and engine parts mfg.	7.51	Default
33211A	All other forging, stamping, and sintering	11.17	Default
324110	Petroleum refineries	14.94	Manual
562000	Waste management and remediation services	7.34	Manual

2.2.2 Network Analysis Results

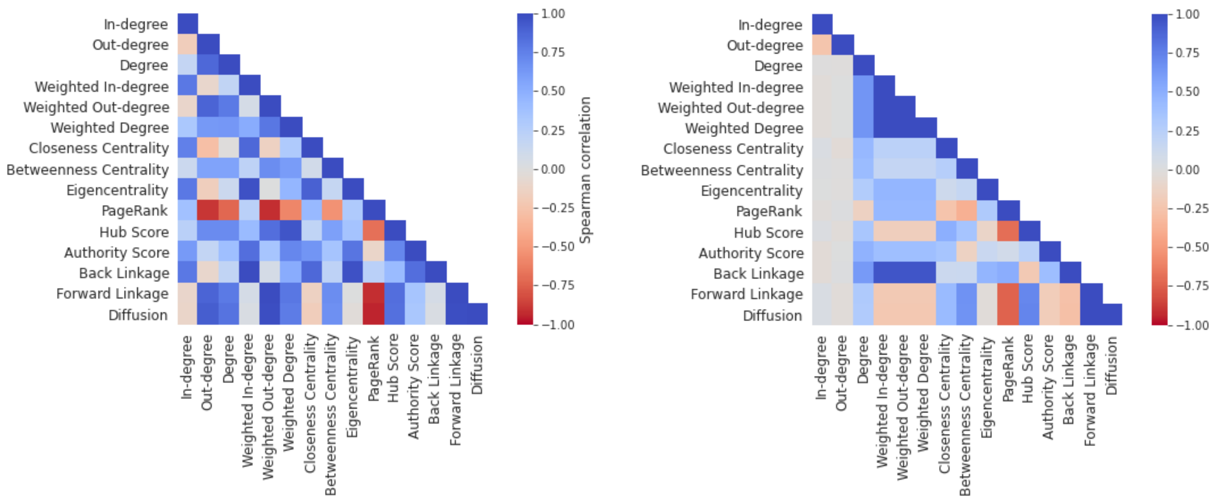
Both the national and state-level IO networks of direct and indirect connections were filtered to exclude intersectoral dependencies (network edges) equivalent to less than one hundred dollars. This was necessary to process the state-level network due to computer memory limitations encountered using both the networkx package in Python and igraph in R (a node with memory of 96GB was used). Before filtering, the national IO network had 416 nodes, 164,790 edges, and a density of 95 percent; the MRIO network had 16,744 nodes, 279,942,961 edges, and a density of 99.9 percent. After filtering edges representing economic flows of less than 100 dollars, the national IO network had 416 nodes, 108,715 edges, and a density of 63 percent; the MRIO network had 16,744 nodes, 2,183,716 edges, and a density of 0.8 percent.

Spearman's correlation coefficient was used to detect any monotonic relationships between network metrics that may not be linear in nature. The correlation between metrics in the national and multiregional networks is illustrated by the heatmaps in Figure 2.6. More than any other sector pairs, forward linkage and diffusion were strongly positively correlated and shared an equal degree of correlation with other sectors. Based on the Spearman cor-

Table 2.6.
Mapping of 6-digit BEA NAICS sectors to 4-digit NAICS sectors and cobalt value allocated to each 4-digit key sector.

6-Digit Key Sector	4-Digit Key Sector	Sector Description	Co value allocated (in million USD)
324110	3241	Petroleum and Coal Products Manufacturing	14.94
325180	3251	Basic Chemical Manufacturing	138.04
325190			
331313	3313	Alumina and Aluminum Production and Processing	16.61
331410	3314	Nonferrous Metal Production and Processing	53.13
331490			
333920	3339	Other General Purpose Machinery Manufacturing	8.30
336370	3363	Motor Vehicle Parts Manufacturing	17.94
336412	3364	Aerospace Product and Parts Manufacturing	7.51
562000	5622	Waste Treatment and Disposal	7.01
	5629	Remediation and Other Waste Management Services	0.34
33211A	3321	Forging and Stamping	11.17

relation coefficient, the strength of a measure appears to be influenced by one of two main factors, upstream connections or downstream connections. Closeness centrality, eigenvector centrality, backward linkage, and to a lesser extent authority score were all positively and somewhat strongly correlated with in-degree and weighted in-degree. Forward linkage, diffusion, and hub score were all positively and somewhat strongly correlated with out-degree and weighted out-degree. Previous interpretations of hub scores representing important suppliers in IO networks and authority scores representing important buyers [16] are supported by these results because it is expected for important suppliers to exhibit significance as it relates to their outgoing connections and vice versa for significant buyers. In contrast to the metrics positively correlated with strong outbound connections, PageRank showed a strong, negative correlation with out-degree, weighted out-degree and forward linkage/diffusion; it was the only metric to have a strong negative correlation with other metrics. This suggests that those sectors with high PageRank would have a smaller than average effect on their downstream sectors and an if there were shocks to the sector, a few downstream sectors would absorb most of the impact. The negative correlation with hub score further supports the interpretation that sectors highlighted by PageRank are not significant because they are strong suppliers. See appendix Tables B.1 - B.6 for exact Spearman correlation coefficients and associated p-values. Key disaggregated sectors with the largest network metric scores at both the national and multiregional level are presented in Table 2.7 and are discussed further below.



(a) National IO network

(b) MRIO network

Figure 2.6. Heatmap of spearman correlation coefficient for each network metric pair in the national and MRIO networks.

Centrality

Centrality measures quantify a sector's importance on a macro scale. The centrality-based measures applied to the IO networks included closeness centrality, betweenness centrality, eigenvector centrality, PageRank, and hub and authority scores. In the network as a whole, there is a strong, positive correlation between closeness centrality, and eigenvector centrality.

Betweenness centrality is zero for six of the disaggregated cobalt sectors in the national IO network and for all of the disaggregated cobalt sectors in the MRIO network. A betweenness centrality of zero for these sectors means that they are not in the middle of any shortest paths. In a physical network this would indicate there are other routes cobalt could take in order to be incorporated into a final product.

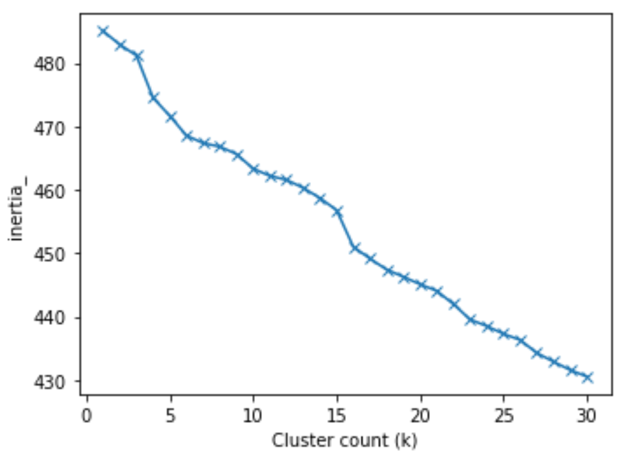
Closeness and betweenness centrality for disaggregated sectors was not estimated well with the filtered network because so many of the smaller flows have been removed. An estimate based on a more dense version of the network may provide a better indicator of path-based centrality, provided the computational power to support processing a network of this size is available. In terms of the petroleum refineries and waste management sectors being the only two manually disaggregated sectors with betweenness centrality greater than zero this could be because the other sectors share all the same shortest paths with their superordinate sectors. Since the superordinate sectors have higher edge weight, the weighted betweenness for them will be greater than for the disaggregated counterparts, therefore giving the superordinate sectors a shorter, weighted shortest path, preventing the default disaggregated sectors from intersecting any shortest paths.

There was a difference in which disaggregated key sectors had the highest centrality scores in the national and multiregional IO networks. The key disaggregated sectors with highest scores for each measure are shown in Table 2.7. In the national network, the Inorganic chemical manufacturing sector had the highest eigenvector centrality (EC), PageRank (PR), Hub (HS), and Authority scores (AS). In the multiregional network, the sector with the highest centrality score varies between each metric, but Basic chemical manufacturing, the sector in which Inorganic chemical manufacturing is aggregated, only has the highest PageRank. In the national network, the following three sectors are ranked in the top five for each centrality measure but the specific ranking withing the top five varies between measures: Waste management and remediation services, Nonferrous metal (except Al) smelting and refining, and Material handling equipment maufacturing. In the multiregional network, the Alumina and aluminum production and processing sector has by far the highest eigenvector centrality, with this sector in almost every state having among the highest EC scores of all the disaggregated sectors. Motor vehicle parts manufacturing sectors in different states have a higher rank in general in the multiregional network than in the national network. The disaggregated sectors highlighted by the hub score and authority score in both the national and multiregional network were the same, so HS and AS are included in the same group in

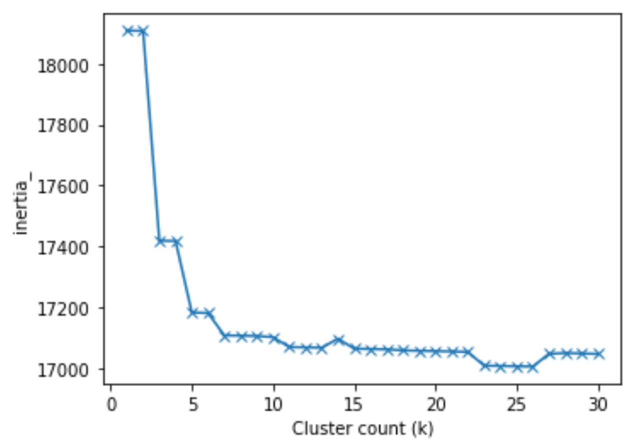
Table 2.7. Hub score measures the importance of a note based on its connections to either many or significant sectors, so sectors with high hub scores have been interpreted as good ”suppliers” in the IO network [16].

Community Detection

Figure 2.7 shows the results of the elbow method applied to the disaggregated cobalt networks. The optimal number of clusters to group the data into is not as clear with the IO data as it was in the example plot in Figure 2.5. However, in both the national and multiregional networks, it appears that approximately six or fifteen is an appropriate number of groups for K-means clustering. There are also decreasing returns on inertia reduction around a cluster sizes of approximately twenty-three.



(a) National IO network



(b) MRIO network

Figure 2.7. The elbow method applied to the disaggregated IO networks.

Table 2.8 provides information on the disaggregated sectors that were clustered together using K-means in the national table. When the MRIO network was grouped into fifteen clusters, over ninety-nine percent of all regionalized sectors were grouped in the same number

Table 2.7.

Comparison of key sectors in the national and MRIO networks with the five highest metric rankings and the states associated with the highest scoring sectors. Sectors are listed in descending order for each metric. Sectors highlighted by hub and authority score are grouped because the same top sectors were identified by both metrics. Sectors in parentheses were the next highest ranked sectors for a metric, though the highest ranked sector held top ranking for nearly all states. Italicized sectors highlighted by linkage are those that had highest regional instead of total linkage.

Metric	Disaggregated sectors highlighted in national IO network	Disaggregated sectors highlighted in MRIO network	Dominant states
Eigenvector Centrality	Inorganic Chemical Manufacturing	Alumina and Aluminum Production and Processing	FL, CA, GA, MN, IL
	Material Handling Equipment Manufacturing	(Waste Treatment and Disposal)	(FL)
	Nonferrous Metal Smelting and Refining	(Remediation and Other Waste Management Services)	(FL)
	Waste Mgmt. and Remediation Services		
	Aircraft Engine Manufacturing		
PageRank	Inorganic Chemical Manufacturing	Basic Chemical Manufacturing	NH, MT, ID, HI
	Waste Mgmt. and Remediation Services	Motor Vehicle Parts Manufacturing	CT
	Material Handling Equipment Manufacturing	(Alumina and Aluminum Production and Processing)	(SD, NH, VA)
	Nonferrous Metal Smelting and Refining	(Nonferrous Metal (except Al) Production and Processing)	(SD, VT)
	Aircraft Engine Manufacturing		
Hub Score, Authority Score	Inorganic Chemical Manufacturing	Petroleum and Coal Products Manufacturing	DC
	Material Handling Equipment Manufacturing	Alumina and Aluminum Production and Processing	HI
	Waste Mgmt. and Remediation Services	Nonferrous Metal (except Al) Production and Processing	HI, WY
	Petroleum Refineries	Motor Vehicle Parts Manufacturing	DC
	Nonferrous Metal Smelting and Refining		
Backward Linkage	Inorganic Chemical Manufacturing	Motor Vehicle Parts Manufacturing	CA, TX, IL
	Material Handling Equipment Manufacturing	Other General Purpose Machinery Manufacturing	CA
	Waste Mgmt. and Remediation Services	*Forging and Stamping (and Sintering)*	*TX*
	Nonferrous Metal Smelting and Refining	*Basic Chemical Manufacturing*	*CA*
	Petroleum Refineries		
Forward Linkage/Diffusion	Petroleum Refineries	Basic Chemical Manufacturing	LA, NJ, IL
	Inorganic Chemical Manufacturing	Nonferrous Metal Production and Processing	IN
	Primary Aluminum Production	Motor Vehicle Parts Manufacturing	MI
	Nonferrous Metal Smelting and Refining	*Basic Chemical Manufacturing*	*TX, LA, OH, PA*
	Organic Chemical Manufacturing	*Nonferrous Metal (except Al) Production and Processing*	*PA, OH*

Table 2.8.

Communities from K-means clustering containing key cobalt sectors in the national-level network and the percentage of all sectors they include. A selection of non-key sectors in the same cluster and their relative ranking for eigenvector centrality (EC), PageRank (PR), backward linkage (BL), and forward linkage (FL). The number under each metric is the ranking out of 416 sectors. Italic font in linkages indicates and an above average, i.e., high linkage. Italic font in list of non-key sectors differentiates sectors without highest metrics, included for their relevance or to illustrate the range of sectors in this cluster.

			National			
Cluster's inclusion of all sectors (%)	Sector description	Sectors in same community with highest scores, and selected sectors	EC	PR	BL	FL
69%	Organic Chemical Mfg.	Poultry processing	5	28	*8*	218
	Primary Aluminum Production	Motor home manufacturing	9	1	21	382
	Nonferrous Metal Smelting and Refining	State and local government passenger transit	8	88	*3*	293
	Nonferrous Metal Processing	Commercial and industrial machinery and equipment rental and leasing	326	364	321	*59*
	Material Handling Equipment Mfg.	Light truck and utility vehicle manufacturing	16	4	*17*	372
	Motor Vehicle Metal Stamping	*Storage Battery Manufacturing*	111	195	*143*	261
	Aircraft Engine Mfg.	*Ball and Roller*	179	288	208	134
	All other forging, stamping, sintering	*Other Crop Farming*	229	309	236	125
6%	Petroleum Refineries	Aluminum product manufacturing from purchased aluminum	40	297	*37*	*47*
	Inorganic Chemical Mfg.	Satellite, telecommunications resellers, and all other	280	250	217	183
		Electric power generation, transmission, and distribution	322	413	315	*7*
		All other chemical product and preparation manufacturing	99	328	*89*	*63*
0.48%	Waste Mgmt. and Remediation Services	Inorganic Chemical Manufacturing (non-cobalt)	204	379	200	*24*

Table 2.9.

Communities from Gephi Modularity clustering containing key cobalt sectors in the national-level network and the percentage of all sectors they include. A selection of non-key sectors in the same cluster with their relative ranking for eigenvector centrality (EC), PageRank (PR), backward linkage (BL), and forward linkage (FL). The number under each metric is the ranking out of 416 sectors. Italic font in linkages indicates and an above average, i.e., high linkage.

			National			
Cluster's inclusion of all sectors (%)	Sector description	Sectors in same community with highest scores	EC	PR	BL	FL
15%	Material Handling Equipment Mfg.	Other nonresidential structures	194	21	201	408
	Nonferrous Metal Smelting and Refining	Copper rolling, drawing, extruding and alloying	7	334	*13*	*27*
	Aircraft Engine Mfg.	Iron and steel mills and ferroalloy manufacturing	85	366	58	5
	Primary Aluminum Production	Communication and energy wire and cable manufacturing	15	278	*41*	120
	Nonferrous Metal Processing	Custom roll forming	36	260	*29*	168
4%	Inorganic Chemical Mfg.	Other furniture related product manufacturing	89	20	*83*	345
	Petroleum Refineries	Plastics bottle manufacturing	28	245	*33*	181
	Waste Mgmt. and Remediation Services	Petroleum refineries	209	407	*121*	*1*
	Organic Chemical Mfg.	Laminated plastics plate, sheet (except packaging), and shape mfg.	75	203	*110*	233
		Printing ink manufacturing	94	150	*68*	255
1%	Motor Vehicle Metal Stamping	Aircraft manufacturing	202	63	223	286
		Other aircraft parts and auxiliary equipment manufacturing	183	190	213	180
		Aircraft engine and engine parts manufacturing (non-cobalt)	215	219	220	124
0.5%	All Other Forging, Stamping, Sintering	Waste Mgmt. and Remediation Services (non-cobalt)	245	335	251	*60*

of clusters. Therefore, using the K-means method for community detection, national table clustering provided more insight into how the key sectors could be partitioned and which non-key sectors are densely connected in the same community.

For comparison, the IO networks were also partitioned using the Gephi network analysis software's modularity algorithm. K-means is a common network clustering technique, but there has been evidence that K-means sometimes mis-partitions data sets into different clusters than those known to exist within the dataset [56]. K-means identifies related nodes by minimizing SSE, while Gephi uses an optimization algorithm to minimize the modularity of clusters (a measure of the density of connections within the cluster compared to the density of connections between clusters). Partitioning the national IO network into fifteen clusters using Gephi resulted in groupings containing key sectors shown in Table 2.9. The MRIO network was then used to identify regionally-specific versions of these sectors that stood out based their ranking for selected network measures. The locations of these sectors and whether they also reported cobalt use in the 2012 TRI is described in Table 2.12. The K-means algorithm was also used to partition the national-level, coefficient A matrix into clusters. It was expected that the sectors in communities derived from the A matrix would be more recognizably similar in function due to only direct connections being represented. However, all disaggregated key cobalt sectors were grouped in the same cluster, with the majority of other sectors, so no additional information was gleaned from using the A instead of the L matrix for clustering with K-means.

Linkages

The significance of the IO sectors was also evaluated based on the sector's linkage measure. Disaggregated sectors and their superordinate counterparts at the national level are classified by linkage measures in tables 2.10 and 2.11. All but four disaggregated key sectors in the national network had higher than average back linkage (BL) measures. Of the disaggregated sectors, the following had the top five highest BL measures out of all sectors, disaggregated or not, in order of decreasing magnitude: Inorganic Chemical Mfg. (325180), Material Handling Equipment Mfg. (333920), Waste Mgmt. and Remediation Services (562000), and

Nonferrous Metal Smelting and Refining (331410). The superordinate sector counterparts from which cobalt value was disaggregated were not also among the highest ranked sectors in the disaggregated network and in the original network, Inorganic Chemical Mfg. and Waste Mgmt. and Remediation Services do not display higher than average BL. This suggests that the disaggregation method has highlighted these four cobalt sectors as having a connection to their upstream supply chains that is distinctly stronger than that of the sector in which they were aggregated and that they are significant among the key sectors based on the BL metric. No disaggregated sectors in either the national or MRIO network had a higher than average forward linkage (FL). This may be, in part, be because many of the outgoing edges from these sectors represented transactions less than one hundred dollars and were therefore filtered from the network. Some key sectors may have had higher than average linkage measures if the full network was considered. However, small incoming edges were also filtered, showing there were larger transactions between industries in the upstream supply chains of the disagregated sectors compared to these sector's downstream exchanges.

Table 2.10.
Classification of linkage results, National IO key cobalt disaggregated sectors

		Total [$\bar{\mathbf{f}}(t)$] Forward Linkage	
		Low (<1)	High (>1)
Total [$\bar{\mathbf{b}}(t)$] Backward Linkage	Low (<1)	All other forging, stamping, sintering (33211A) Motor Vehicle Metal Stamping (336370) Nonferrous Metal Processing (331490) Organic Chemical Mfg. (325190)	—
	High (>1)	Inorganic Chemical Mfg. (325180) Material Handling Equipment Mfg. (333920) Waste Mgmt. and Remediation Services (562000) Nonferrous Metal Smelting and Refining (331410) Petroleum Refineries (324110) Aircraft Engine Mfg. (336412) Primary Aluminum Production (331313)	—

As can be seen in Figure 2.6, there is a nearly one to one positive correlation between forward linkage and diffusion, diffusion being an indicator of how well a sector can buffer economic shocks [16]. Accordingly, in the national-level table the disagregated sectors are ranked in the same order using either of these two metrics and the rankings are nearly identical in the MRIO network. However, all disaggregated sectors at the national level have low forward linkages compared to backwards linkage and according to the criteria generally used for defining high linkage values as being greater than one when normalized.

Table 2.11.

Classification of linkage results, National IO key cobalt parent sectors

		Total $[\bar{\mathbf{f}}(t)]$ Forward Linkage	
		Low (<1)	High (>1)
Total $[\bar{\mathbf{b}}(t)]$ Backward Linkage	Low (<1)	Aircraft Engine Mfg. (336412)	Inorganic Chemical Mfg. (325180) Waste Mgmt. and Remediation Services (562000)
	High (>1)	Motor Vehicle Metal Stamping (336370) Material Handling Equipment Mfg. (333920)	Petroleum Refineries (324110) Organic Chemical Mfg. (325190) Nonferrous Metal Processing (331490) Nonferrous Metal Smelting and Refining (331410) All other forging, stamping, sintering (33211A) Primary Aluminum Production (331313)

Diffusion

All the disaggregated cobalt sectors have a very low diffusion capacity, which can be interpreted as impacts to these sectors would have a stronger relative effect on their downstream industries. Cobalt sectors with lowest diffusion would therefore pose a greater risk to supply chain continuity if they were disrupted. If a sector is strongly linked to its entire direct and indirect downstream supply chain, as measured by forward linkage, the effect of an impact to that sector can be more evenly distributed across the supply chain.

2.3 Discussion

At the national level, the chemical manufacturing sectors and in particular inorganic chemical manufacturing was a disaggregated cobalt sector that was consistently highlighted as one of the most significant sectors across all metrics. Waste management also had a consistently high ranking using all measures except forward linkage. The most cobalt value was allocated to the organic chemical manufacturing sector, based on analysis of TRI data, so the significance of inorganic chemical manufacturing and waste management was not due to these sectors have a large portion of total cobalt value allocated to them from the start. Nonferrous metal smelting and refining is also highlighted as significant in the national IO network but to a less extent than chemical manufacturing and waste management. However, in the MRIO, sectors that rely on nonferrous metal smelting and refining, i.e., sectors using cobalt alloys, show higher significance than they did in the national network.

Regarding the approach chosen for allocation of cobalt value to states in the MRIO table, cobalt value was allocated across regions based on the sector's percentage of national output coming from each region. This economic-based approach was chosen to allow for differentiation between the regional allocation of cobalt supply and use. An alternative approach to calculating the regional weights for disaggregation could be to use the facility location data included in the TRI to determine where to allocate cobalt value. This could be considered a mass-based regional allocation approach because the disaggregation weight would be calulated based on the share of total onsite stock in different regions. In this approach the share of a key sector's allocated value would be further allocated to states r using equations

Table 2.12.

Major locations of secondary sectors of significance based on national IO network community detection.

MRIO Sector	National IO Sector	Non-cobalt sectors with highest scores in clusters containing disaggregated sectors	Highest Ranking Metric(s)	Sector (6-digit) in 2012 Co TRI	Dominant states based on highest ranking metric(s)
2362	2332D0	Other nonresidential structures	PR	N	NC, TN, SC, AR, OR
3314	331420	Copper rolling, drawing, extruding and alloying	EC / BL	Y	**CA, TX, FL, VA / HI, WY, DC, DE, AK**
3311	331110	Iron and steel mills and ferroalloy manufacturing	FL	Y	**IN, PA, OH, MI, AL, IL**
3359	335920	Communication and energy wire and cable manufacturing	EC / PR	N	SD, FL, CA, TX, HI / SD, HI, ND, ME, NM
3321	332114	Custom roll forming	PR / BL	N	FL, KS, NC, AZ, NJ / RI, MT, ID, HI, DC
3379	337900	Other furniture related product manufacturing	PR	N	OK, KY, CT, TN, WA
3261	326160	Plastics bottle manufacturing	EC, BL	N	FL, CA, TX, NY, PR / SD, MT, VT, HI, WA
3241	324110	Petroleum refineries	FL	Y	**TX, LA, CA, PA, IL**
3261	326130	Laminated plastics plate, sheet (except packaging), and shape mfg.	EC, PR	N	FL, CA, TX, NY, PR / NM, DC, HI, AK, MT
3259	325910	Printing ink manufacturing	PR / BL	Y	**UT, VT, NM, MT, ME / MT, VT, NH, NM, SD**
3364	336411	Aircraft manufacturing	PR	N	OR, VT, NH, OK, KY
3364	336413	Other aircraft parts and auxiliary equipment manufacturing	EC / BL	Y	**FL, RI, TX, OR, PR / RI, PR, DC, OR, OK**
3364	336412	Aircraft engine and engine parts manufacturing (non-cobalt)	FL	Y	**WA, CA, KS, CT, TX**
5622	562000	Waste Mgmt. and Remediation Services	PR / FL	Y	**IA, NC, MO, VA, OK / TX, CA, SC, NY, OH, IL**

2.32 - 2.34. Figure 2.8 shows how cobalt value was allocated based on the economic strength of sectors in a region in comparison to how it would would be allocated using a regional distribution determined from the TRI.

$$S_{\mathrm{j}'r} = \sum_{\mathrm{i}=1}^{10} s_{\mathrm{i}} f_{\mathrm{i}r} \tag{2.32}$$

$$S_{\mathrm{j}'} = \sum_{r=1}^{n} S_{\mathrm{j}'r} \tag{2.33}$$

$$w_{\mathrm{j}'r} = \frac{S_{\mathrm{j}'r}}{S_{\mathrm{j}'}} \tag{2.34}$$

j' is a key sector to which cobalt value is allocated in the multiregional make/use tables.

n is the number of regions with facilities reporting under sector *j'*.

s_i is the assumed average onsite stock for a reported MAOC range i.

f_{ir} is the number of facilities in region r reporting range i.

$S_{j'r}$ is the estimated total average MAOC for facilities reporting under *j'* in region r.

$w_{j'r}$ is the weight or share of sector *j'* value to allocate to region r.

$CA_{j'r}$ is the cobalt value allocated to *j'* in r.

Use of TRI data for IO analysis

The TRI was used to estimate the relative magnitude of cobalt use among sectors, but it could also be used to calculate the regional weights for disaggregation of the multiregional IO tables instead of the ratio of regional output to national output. The average onsite stock (MAOC) linked to facility location could be used to determine the key sectors for disaggregation and the distribution of key sector value across regions. TRI data provides exceptional data in terms of location and industry classification, but the uncertainty around relative use quantities, which are understandably in place to protect sensitive production information, also limits its usefulness for material flow accounting. Apart from including more specific data on facility throughput, this uncertainty could be better addressed with uncertainty analysis of TRI data.

Considering the best potential applications of the TRI data to MRIO analysis, it perhaps the most ideal data source available estimating the largest national processors of cobalt or other regulated toxic substances. In using the TRI for traditional IO analysis it could be used primarily to determine the sectors and locations to focus simulated economic shocks. The MRIO and national IO tables could then be used to simulate the potential impact to the rest of the economy that would occur from shocks to the largest industries processing cobalt in specific regions.

Future studies that analyze similarly sized MRIO networks would benefit from exploration of other graph analysis packages designed for large networks and multiprocessing techniques to compute graph algorithms in order to allow for the full IO network to be considered. Filtering the network affects its structure, which in turn likely alters the metrics based on a filtered versus a complete network.

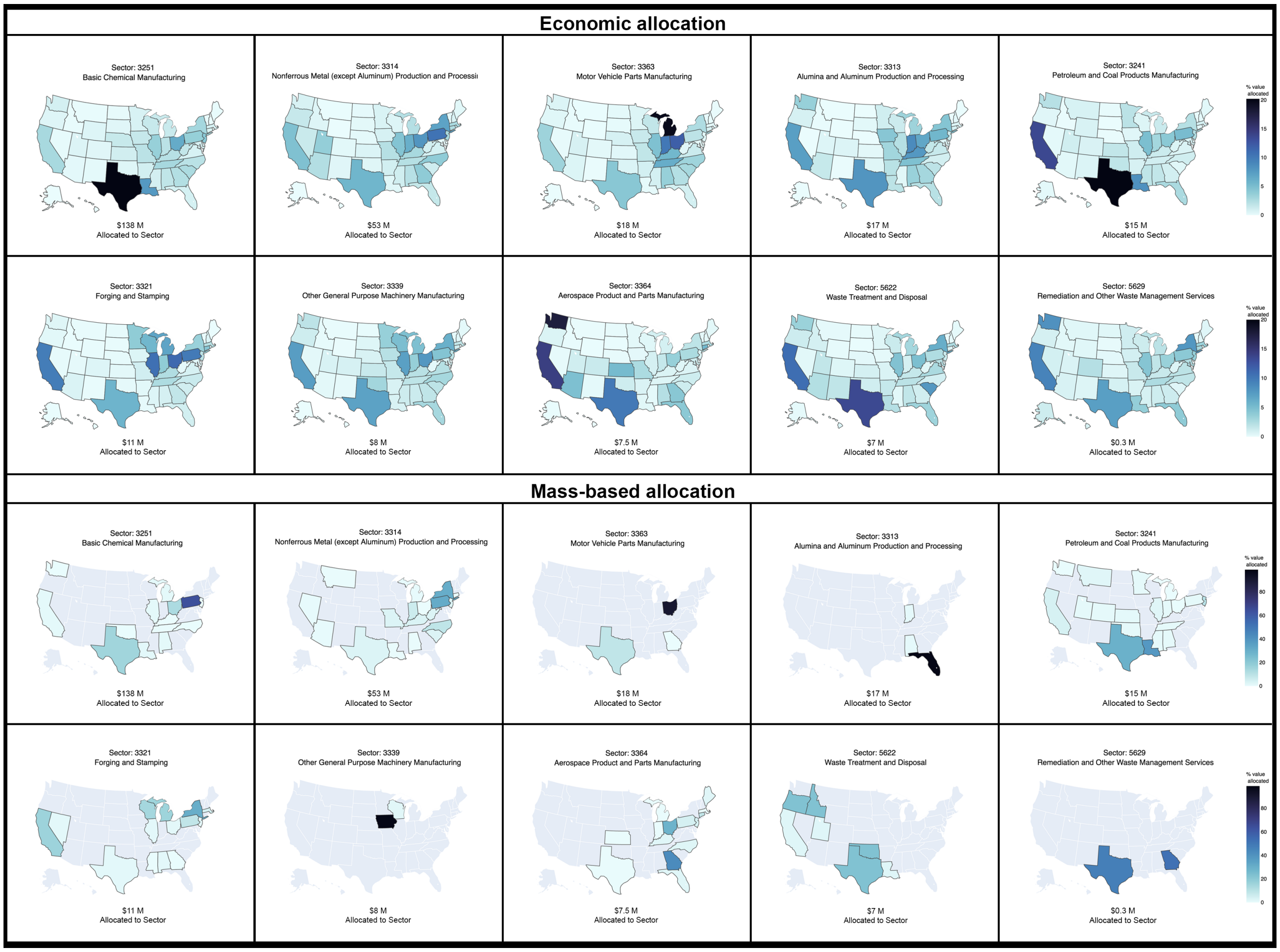


Figure 2.8. Comparison of economic and mass-based allocation of cobalt value across regions in the MRIO tables. Using economic allocation, value was distributed among states based on the state's share of national output or use of the key sector from which cobalt was being disaggregated. In mass-based allocation, average onsite stock as reported in the EPA TRI would be used to determine the distribution of key sector value across states. Note the difference in color scale ranges between economic and mass-based allocation.

3. CONCLUSIONS AND FUTURE WORK

3.1 Conclusions

The key sectors identified and sectors that are densely connected to them are those whose impact from disruptions to imported Cobalt supply may result in the largest economy-wide impacts. The locations highlighted by analysis of the network structure are places where it may be prudent to put buffers in place to mitigate disruptions.

The future supply of cobalt for lithium-ion batteries is of greatest concern because this will be the primary driver of this material's increased demand. However, as growth in all sectors where cobalt is used is also expected to continue and since these are many of the sectors in the US currently reliant on cobalt supplies, securing these sectors again supply risks is not something that should be overlooked.

A limitation of this study is that it does not capture the exchange of cobalt in imported products, only products that required the processing of the material domestically. This means effectively all electric vehicle batteries are not explicitly considered in the year of investigation because they were not produced at a large scale domestically. A limitation of this project's current analysis but not the method is that it does not currently make visible the battery manufacturing industry's economic activity. This is because the analysis is based on 2012 data when there was much less battery production, but still, there is not sufficient large format lithium-ion battery manufacturing occurring in the US for this sector to be a major processor of cobalt based on their reporting to other sectors in the TRI Inventory. For example, as of 2019, notable electric vehicle manufacturers like TESLA, who are beginning to produce their own batteries, were not processing enough to warrant reporting it to the TRI. As electric vehicle and other large format Lithium ion battery makers increase domestic production to expected levels, it will be capture and likely highlighted by the analysis of TRI data proposed in this work.

The approach presented in this work were intended to enable a relatively quick screen of the IO network to identify unknown sectors of significance to a material, but pursuing additional data on interindustry transactions could be used to manually disaggregate more key sectors or used to filter the resulting network of nonphysical flows similar to in the

WIO-MFA method. Provided this level of detailed data is available, WIO-MFA would be another feasible approach for constructing the network if analysis on a physical network is preferred. Implementation of WIO-MFA or manually disaggregating more sectors with the method used in this work would require more readily accessible data on at least the input quantities, preferably physical, of the material of interest to processing industries.

Supply chain data is increasingly being sought for ESG reporting purposes. As many companies look to make their supply chain operations more transparent and suppliers at all levels are held to higher expectations, desired data on producer's manufacturing and operational conditions is being sought and in cases, required. Expanding readily available supply chain data on physical inputs (but necessarily not product formulations or processes) and production conditions at a more detailed level, would greatly benefit economy-wide and individual companies' supply chain management efforts.

3.1.1 Directions for Future Research

Improvements to the disaggregation methods used in this study would include conducting a sensitivity analysis on the range of values used as proxy consumption data from the TRI for each sector.

Identifying clusters of connected sectors in IO networks would be another area for additional research. Kmeans was the primary clustering approach used in this study, but other community detection algorithms may be better suited for IO networks [47]. This will require additional consideration into best practices for navigating the computational intensity of network analysis on large graphs.

An intended direct application of this work is to inform the development of physical input-output tables (PIOTs) for cobalt-based products. The key sectors identified in this study would be the most prioritized industries to include in process-model based PIOTs [57], [58]. Planning future reuse and recycling supply chains for critical materials would be better done based on physical flow analysis instead of monetary flow analysis, which is already being pursued by research such as WIO-MFA and buiding PIOTS from process models. The latter being directly meant to address the long-standing concern that PIOTs derived from MIOTs are unlikely to reflect the actual physical flows they approximate [59].

Disaggregated IO networks for other critical materials are also being developed with this approach. The focus of this study and its immediate extensions is critical materials for energy storage, but applying the use of TRI data to estimate relative sector consumption could potentially be applied to a diverse set of regulated chemicals and compounds.

Using the disaggregated, monetary MRIO network for traditional IO analysis is another area of interest for future work. Modeling policy scenarios that incentivize regenerative use of critical materials, simulate implementation of technology solutions, as well as modeling possible disruptions to key sectors could also stem from this work.

REFERENCES

[1] The World Bank, “Minerals for Climate Action: The Mineral Intensity of the Clean Energy Transition,” Tech. Rep., 2020. [Online]. Available: https://www.worldbank.org/en/topic/extractiveindustries/brief/climate-smart-mining-minerals-for-climate-action.

[2] IPCC, “Climate Change 2014: Synthesis Report,” Tech. Rep., 2014, IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

[3] K. J. Schulz, J. H. DeYoung Jr., R. R. Seal II, and D. C. Bradley, “Critical mineral resources of the United States—An introduction,” English, Reston, VA, Report 1802A, 2017, p. 22. DOI: 10.3133/pp1802A. [Online]. Available: http://pubs.er.usgs.gov/publication/pp1802A.

[4] The White House, “Building resilient supply chains, revitalizing American manufacturing, and fostering broad-based growth,” Tech. Rep., Jun. 2021. [Online]. Available: https://www.whitehouse.gov/wp-content/uploads/2021/06/100-day-supply-chain-review-report.pdf.

[5] Y. Shen, R. Moomy, and R. G. Eggert, “China’s public policies toward rare earths, 1975–2018,” en, *Mineral Economics*, vol. 33, no. 1, pp. 127–151, Jul. 2020, ISSN: 2191-2211. DOI: 10.1007/s13563-019-00214-2. [Online]. Available: https://doi.org/10.1007/s13563-019-00214-2.

[6] S. M. Fortier, N. T. Nassar, G. W. Lederer, J. Brainard, J. Gambogi, and E. A. McCullough, “Draft critical mineral list—Summary of methodology and background information—U.S. Geological Survey technical input document in response to Secretarial Order No. 3359,” U.S. Geological Survey, Reston, VA, USGS Numbered Series 2018-1021, 2018, p. 26. DOI: 10.3133/ofr20181021. [Online]. Available: http://pubs.er.usgs.gov/publication/ofr20181021.

[7] Commonwealth of Australia, “Australia’s Critical Minerals Strategy 2019,” en, p. 22, 2019. [Online]. Available: https://www.industry.gov.au/sites/default/files/2019-03/australias-critical-minerals-strategy-2019.pdf.

[8] H. Hatayama and K. Tahara, “Criticality Assessment of Metals for Japan’s Resource Strategy,” en, *MATERIALS TRANSACTIONS*, vol. 56, no. 2, pp. 229–235, 2015, ISSN: 1345-9678, 1347-5320. DOI: 10.2320/matertrans.M2014380. [Online]. Available: https://www.jstage.jst.go.jp/article/matertrans/56/2/56_M2014380/_article.

[9] European Commission, “Critical materials for strategic technologies and sectors in the EU - a foresight study,” Tech. Rep., 2020. [Online]. Available: https://rmis.jrc.ec.europa.eu/uploads/CRMs_for_Strategic_Technologies_and_Sectors_in_the_EU_2020.pdf.

[10] T. E. Graedel, E. M. Harper, N. T. Nassar, P. Nuss, and B. K. Reck, “Criticality of metals and metalloids,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 112, no. 14, pp. 4257–4262, 2015, ISSN: 0027-8424. [Online]. Available: https://www.jstor.org/stable/26462476.

[11] N. T. Nassar, T. E. Graedel, and E. M. Harper, “By-product metals are technologically essential but have problematic supply,” *Science Advances*, vol. 1, no. 3, Apr. 2015, ISSN: 2375-2548. DOI: 10.1126/sciadv.1400180. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4640630/.

[12] P. Nuss and M. J. Eckelman, “Life Cycle Assessment of Metals: A Scientific Synthesis,” English, *PLoS One; San Francisco*, vol. 9, no. 7, e101298, Jul. 2014. DOI: http://dx.doi.org/10.1371/journal.pone.0101298. [Online]. Available: https://search.proquest.com/docview/2013254520/abstract/A7CF683628774A68PQ/1.

[13] J. Dewulf, G. A. Blengini, D. Pennington, P. Nuss, and N. T. Nassar, “Criticality on the international scene: Quo vadis?” en, *Resources Policy*, vol. 50, pp. 169–176, Dec. 2016, ISSN: 0301-4207. DOI: 10.1016/j.resourpol.2016.09.008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301420716301556.

[14] USGS (U.S. Geological Survey), “Mineral Commodity Summaries 2019,” Washington, DC: U.S., Tech. Rep., 2019. [Online]. Available: https://www.usgs.gov/centers/nmic/mineral-commodity-summaries.

[15] X. Fu, D. N. Beatty, G. G. Gaustad, G. Ceder, R. Roth, R. E. Kirchain, M. Bustamante, C. Babbitt, and E. A. Olivetti, “Perspectives on Cobalt Supply through 2030 in the Face of Changing Demand,” en, *Environmental Science & Technology*, vol. 54, no. 5, pp. 2985–2993, Mar. 2020, ISSN: 0013-936X, 1520-5851. DOI: 10.1021/acs.est.9b04975. [Online]. Available: https://pubs.acs.org/doi/10.1021/acs.est.9b04975.

[16] M. Alatriste Contreras, “Detecting diffusion properties of sectors in the Mexican economy, 2012,” *Investigación Económica*, vol. 79, p. 110, Dec. 2019. DOI: 10.22201/fe.01851667p.2020.311.72438.

[17] K. B. Shedd, E. A. McCullough, and D. I. Bleiwas, “Global trends affecting the supply security of cobalt,” English, *Mining Engineering; Littleton*, vol. 69, no. 12, pp. 37–42, Dec. 2017, ISSN: 00265187. [Online]. Available: https://search.proquest.com/docview/1980030642/abstract/23DD9D316DA04EA8PQ/1.

[18] Ellen MacArthur Foundation, *What is a Circular Economy? | Ellen MacArthur Foundation*, 2021. [Online]. Available: https://www.ellenmacarthurfoundation.org/circular-economy/concept.

[19] P. A. Dias, D. Blagoeva, C. Pavel, N. Arvanitidis, European Commission, and Joint Research Centre, *Cobalt: demand-supply balances in the transition to electric mobility.* en. 2018, OCLC: 1111129660, ISBN: 978-92-79-94311-9. [Online]. Available: http://publications.europa.eu/publication/manifestation_identifier/PUB_KJNA29381ENN.

[20] R. E. Miller, *Input-output analysis foundations and extensions*, 2nd ed., P. D. Blair, Ed. Cambridge: Cambridge University Press, 2009.

[21] BEA (Bureau of Economic Analysis), "2012 Input-Output Accounts Data," U.S. Department of Commerce, Tech. Rep., 2012. [Online]. Available: https://www.bea.gov/industry/input-output-accounts-data.

[22] A. M. Wolsky, "Disaggregating Input-Output Models," *The Review of Economics and Statistics*, vol. 66, no. 2, pp. 283–291, 1984, Publisher: The MIT Press, ISSN: 00346535, 15309142. DOI: 10.2307/1925829. [Online]. Available: http://www.jstor.org/stable/1925829.

[23] M. Lenzen, "AGGREGATION VERSUS DISAGGREGATION IN INPUT–OUTPUT ANALYSIS OF THE ENVIRONMENT," *Economic Systems Research*, vol. 23, no. 1, pp. 73–89, Mar. 2011, Publisher: Routledge, ISSN: 0953-5314. DOI: 10.1080/09535314.2010.548793. [Online]. Available: https://doi.org/10.1080/09535314.2010.548793.

[24] S. Nakamura and K. Nakajima, "Waste Input–Output Material Flow Analysis of Metals in the Japanese Economy," en, *MATERIALS TRANSACTIONS*, vol. 46, no. 12, pp. 2550–2553, 2005, ISSN: 1345-9678, 1347-5320. DOI: 10.2320/matertrans.46.2550. [Online]. Available: https://www.jstage.jst.go.jp/article/matertrans/46/12/46_12_2550/_article.

[25] S. Nakamura and Y. Kondo, "Input-Output Analysis of Waste Management," en, *Journal of Industrial Ecology*, vol. 6, no. 1, pp. 39–63, 2002, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1162/108819802320971632, ISSN: 1530-9290. DOI: 10.1162/108819802320971632. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1162/108819802320971632.

[26] W.-Q. Chen, T. E. Graedel, P. Nuss, and H. Ohno, "Building the Material Flow Networks of Aluminum in the 2007 U.S. Economy," *Environmental Science & Technology*, vol. 50, no. 7, pp. 3905–3912, Apr. 2016, Publisher: American Chemical Society, ISSN: 0013-936X. DOI: 10.1021/acs.est.5b05095. [Online]. Available: https://doi.org/10.1021/acs.est.5b05095.

[27] H. Ohno, P. Nuss, W.-Q. Chen, and T. E. Graedel, "Deriving the Metal and Alloy Networks of Modern Technology," *Environmental Science & Technology*, vol. 50, no. 7, pp. 4082–4090, Apr. 2016, Publisher: American Chemical Society. DOI: 10.1021/acs.est.5b05093. [Online]. Available: https://doi.org/10.1021/acs.est.5b05093.

[28] W.-Q. Chen, T. E. Graedel, P. Nuss, and H. Ohno, “Building the Material Flow Networks of Aluminum in the 2007 U.S. Economy,” *Environmental Science & Technology*, vol. 50, no. 7, pp. 3905–3912, Apr. 2016, Publisher: American Chemical Society, ISSN: 0013-936X. DOI: 10.1021/acs.est.5b05095. [Online]. Available: https://doi.org/10.1021/acs.est.5b05095.

[29] A. Tisserant and S. Pauliuk, “Matching global cobalt demand under different scenarios for co-production and mining attractiveness,” en, *Journal of Economic Structures*, vol. 5, no. 1, p. 4, Feb. 2016, ISSN: 2193-2409. DOI: 10.1186/s40008-016-0035-x. [Online]. Available: https://doi.org/10.1186/s40008-016-0035-x.

[30] X. Sun, H. Hao, F. Zhao, and Z. Liu, “Tracing global lithium flow: A trade-linked material flow analysis,” en, *Resources, Conservation and Recycling*, vol. 124, pp. 50–61, Sep. 2017, ISSN: 0921-3449. DOI: 10.1016/j.resconrec.2017.04.012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921344917301118.

[31] A. Geschke and M. Hadjikakou, “Virtual laboratories and MRIO analysis – an introduction,” *Economic Systems Research*, vol. 29, no. 2, pp. 143–157, 2017, Publisher: Routledge _eprint: https://doi.org/10.1080/09535314.2017.1318828. DOI: 10.1080/09535314.2017.1318828. [Online]. Available: https://doi.org/10.1080/09535314.2017.1318828.

[32] M. Lenzen, A. Geschke, T. Wiedmann, J. Lane, N. Anderson, T. Baynes, J. Boland, P. Daniels, C. Dey, J. Fry, M. Hadjikakou, S. Kenway, A. Malik, D. Moran, J. Murray, S. Nettleton, L. Poruschi, C. Reynolds, H. Rowley, J. Ugon, D. Webb, and J. West, “Compiling and using input–output frameworks through collaborative virtual laboratories,” *Science of The Total Environment*, vol. 485-486, pp. 241–251, Jul. 2014, ISSN: 0048-9697. DOI: 10.1016/j.scitotenv.2014.03.062. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0048969714003921.

[33] M. Lenzen, A. Geschke, M. D. Abd Rahman, Y. Xiao, J. Fry, R. Reyes, E. Dietzenbacher, S. Inomata, K. Kanemoto, B. Los, D. Moran, H. Schulte in den Bäumen, A. Tukker, T. Walmsley, T. Wiedmann, R. Wood, and N. Yamano, “The Global MRIO Lab – charting the world economy,” *Economic Systems Research*, vol. 29, no. 2, pp. 158–186, Apr. 2017, Publisher: Routledge, ISSN: 0953-5314. DOI: 10.1080/09535314.2017.1301887. [Online]. Available: https://doi.org/10.1080/09535314.2017.1301887.

[34] T. Wiedmann, “An input–output virtual laboratory in practice – survey of uptake, usage and applications of the first operational IELab,” *Economic Systems Research*, vol. 29, no. 2, pp. 296–312, Apr. 2017, Publisher: Routledge, ISSN: 0953-5314. DOI: 10.1080/09535314.2017.1283295. [Online]. Available: https://doi.org/10.1080/09535314.2017.1283295.

[35] J. V. Algarin, T. R. Hawkins, J. Marriott, H. S. Matthews, and V. Khanna, “Disaggregating the Power Generation Sector for Input-Output Life Cycle Assessment,” en, *Journal of Industrial Ecology*, vol. 19, no. 4, pp. 666–675, 2015, ISSN: 1530-9290. DOI: 10.1111/jiec.12207. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/jiec.12207.

[36] C.-H. Liu, M. Lenzen, and J. Murray, "A disaggregated emissions inventory for Taiwan with uses in hybrid input-output life cycle analysis (IO-LCA)," en, *Natural Resources Forum*, vol. 36, no. 2, pp. 123–141, 2012, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1477-8947.2012.01439.x, ISSN: 1477-8947. DOI: 10.1111/j.1477-8947.2012.01439.x. [Online]. Available: https://www.onlinelibrary.wiley.com/doi/abs/10.1111/j.1477-8947.2012.01439.x.

[37] S. Lindner, J. Legault, and D. Guan, "Disaggregating the Electricity Sector of China's Input–Output Table for Improved Environmental Life-Cycle Assessment," *Economic Systems Research*, vol. 25, no. 3, pp. 300–320, Sep. 2013, Publisher: Routledge _eprint: https://doi.org/10.1080/ ISSN: 0953-5314. DOI: 10.1080/09535314.2012.746646. [Online]. Available: https://doi.org/10.1080/09535314.2012.746646.

[38] US EPA, "Toxic Release Inventory," Tech. Rep., 2012. [Online]. Available: https://www.epa.gov/toxics-release-inventory-tri-program.

[39] USGS (U.S. Geological Survey), "Mineral Commodity Summaries 2013," Washington, DC: U.S., Tech. Rep., 2013. [Online]. Available: https://www.usgs.gov/centers/nmic/mineral-commodity-summaries.

[40] Kelly, T.D. and Matos, G.R., "General Notes on Historical statistics for mineral and material commodities in the United States (2016 version): U.S. Geological Survey Data Series 140," Tech. Rep., 2016. [Online]. Available: https://www.usgs.gov/centers/nmic/historical-statistics-mineral-and-material-commodities-united-states.

[41] D. R. Wilburn and Buckingham, David A., "Apparent consumption vs. total consumption—A lead-acid battery case study: U.S. Geological Survey Scientific Investigations Report 2006–5155," U.S. Geological Survey, Tech. Rep. 5155, 2006. [Online]. Available: https://pubs.er.usgs.gov/publication/sir20065155.

[42] BEA (Bureau of Economic Analysis), "Concepts and Methods of the U.S. Input-Output Accounts," Tech. Rep., 2009. [Online]. Available: https://www.bea.gov/sites/default/files/methodologies/IOmanual_092906.pdf.

[43] F. Faturay, V. S. G. Vunnava, M. Lenzen, and S. Singh, "Using a new USA multi-region input output (MRIO) model for assessing economic and energy impacts of wind energy expansion in USA," en, *Applied Energy*, vol. 261, p. 114 141, Mar. 2020, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.114141. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919318288.

[44] Eurostat, "Eurostat Manual of Supply, Use and Input-Output Tables," Office for Official Publications of the European Communities, Luxembourg, Tech. Rep., 2008.

[45] F. Blöchl, F. J. Theis, F. Vega-Redondo, and E. O. Fisher, "Vertex centralities in input-output networks reveal the structure of modern economies," *Phys Rev E Stat Nonlin Soft Matter Phys*, vol. 83, no. 4 Pt 2, pp. 046 127–046 127, 2011, Place: United States Publisher: United States, ISSN: 1539-3755. DOI: 10.1103/PhysRevE.83.046127.

[46] F. DePaolis, P. Murphy, and M. C. D. Kaluza, "Identifying Key Sectors in the Regional Economy: A Network Analysis Approach Using Input-Output Data," 2020, Archive: arXiv:2005.11285v1 [econ.GN]. [Online]. Available: arXiv.org.

[47] P. Nuss, H. Ohno, W.-Q. Chen, and T. E. Graedel, "Comparative analysis of metals use in the United States economy," en, *Resources, Conservation and Recycling*, vol. 145, pp. 448–456, Jun. 2019, ISSN: 0921-3449. DOI: 10.1016/j.resconrec.2019.02.025. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921344919300825.

[48] E. P. Harvey and D. R. J. O'Neale, "Using network science to quantify economic disruptions in regional input-output networks," 2019, Archive: arXiv:1910.12498v1 [physics.soc-ph]. [Online]. Available: arXiv.org.

[49] L. C. Freeman, "Centrality in social networks conceptual clarification," en, *Social Networks*, vol. 1, no. 3, pp. 215–239, Jan. 1978, ISSN: 0378-8733. DOI: 10.1016/0378-8733(78)90021-7. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0378873378900217.

[50] U. Brandes, "On variants of shortest-path betweenness centrality and their generic computation," *Social Networks*, vol. 30, no. 2, pp. 136–145, May 2008, ISSN: 0378-8733. DOI: 10.1016/j.socnet.2007.11.001. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378873307000731.

[51] P. Nuss, W.-Q. Chen, H. Ohno, and T. E. Graedel, "Structural Investigation of Aluminum in the U.S. Economy using Network Analysis," *Environmental Science & Technology*, vol. 50, no. 7, pp. 4091–4101, Apr. 2016, Publisher: American Chemical Society, ISSN: 0013-936X. DOI: 10.1021/acs.est.5b05094. [Online]. Available: https://doi.org/10.1021/acs.est.5b05094.

[52] Forinstance and Tara Eicher, *Python - networkx - meaning of weight in betwenness and current flow betweenness*, 2019. [Online]. Available: https://stackoverflow.com/questions/50497186/networkx-meaning-of-weight-in-betwenness-and-current-flow-betweenness.

[53] scikit-yb developers, *Elbow Method — Yellowbrick v1.3.post1 documentation.* [Online]. Available: https://www.scikit-yb.org/en/latest/api/cluster/elbow.html.

[54] Team Golden Kiwi, *Team Golden Kiwi: Economic Impact of COVID-19 by State*, en, 2020. [Online]. Available: https://app.mipasa.com/george.tolkachev/notebooks/view/Team-Golden-Kiwi-Economic-Impact-of-COVID-19-by-State?tab=Search+Results.

[55] M. G. Alatriste-Contreras, “The relationship between the key sectors in the european union economy and the intra-European Union trade,” en, *Journal of Economic Structures*, vol. 4, no. 1, p. 14, Aug. 2015, ISSN: 2193-2409. DOI: 10.1186/s40008-015-0024-5. [Online]. Available: https://doi.org/10.1186/s40008-015-0024-5.

[56] Has QUIT–Anony-Mousse (https://stats.stackexchange.com/users/7828/has-quit-anony-mousse), *How to understand the drawbacks of K-means*, 2015. [Online]. Available: https://stats.stackexchange.com/questions/133656/how-to-understand-the-drawbacks-of-k-means.

[57] “A Nitrogen Physical Input-Output Table (PIOT) model for Illinois,” vol. 360, pp. 194–203, Sep. 2017, ISSN: 0304-3800. DOI: 10.1016/j.ecolmodel.2017.06.015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0304380017302168.

[58] L. Wachs and S. Singh, “A modular bottom-up approach for constructing physical input–output tables (PIOTs) based on process engineering models,” *Journal of Economic Structures*, vol. 7, no. 1, p. 26, Oct. 2018, ISSN: 2193-2409. DOI: 10.1186/s40008-018-0123-1. [Online]. Available: https://doi.org/10.1186/s40008-018-0123-1.

[59] H. Weisz and F. Duchin, “Physical and monetary input–output analysis: What makes the difference?” *Ecological Economics*, vol. 57, no. 3, pp. 534–541, May 2006, ISSN: 0921-8009. DOI: 10.1016/j.ecolecon.2005.05.011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S092180090500248X.

A. NAICS TO BEA CODE MAPPING

Table A.1. Mapping of reported NAICS codes in 2012 Cobalt EPA TRI to equivalent 2012 BEA modified NAICS codes.

	TRI code	BEA code		TRI code	BEA code		TRI code	BEA code
1	115210	115000	**54**	331210	331200	**107**	333514	333514
2	212112	212100	**55**	331221	331200	**108**	333515	33351B
3	212221	2122A0	**56**	331222	331200	**109**	333516	333517
4	212234	212230	**57**	331312	331313	**110**	333611	333611
5	212299	2122A0	**58**	331314	331313	**111**	333613	333613
6	213113	21311A	**59**	331315	33131B	**112**	333618	333618
7	221112	221100	**60**	331411	331410	**113**	333911	33391A
8	221121	221100	**61**	331419	331410	**114**	333922	333920
9	221122	221100	**62**	331421	331420	**115**	333924	333920
10	311119	311119	**63**	331423	331420	**116**	333991	333991
11	311221	311221	**64**	331491	331490	**117**	333992	33399A
12	314110	314110	**65**	331492	331490	**118**	333993	333993
13	321219	321200	**66**	331511	331510	**119**	333995	33399B
14	321911	321910	**67**	331512	331510	**120**	333996	33399B
15	322110	322110	**68**	331513	331510	**121**	333999	33399A
16	322121	322120	**69**	331525	331520	**122**	334413	334413
17	322130	322130	**70**	331528	331520	**123**	334514	334514
18	324110	324110	**71**	332111	33211A	**124**	335221	335221
19	325110	325110	**72**	332112	33211A	**125**	335228	335228
20	325131	325130	**73**	332116	33211A	**126**	335311	335311
21	325188	325180	**74**	332117	33211A	**127**	335911	335911
22	325192	325190	**75**	332213	332200	**128**	336120	336120
23	325193	325190	**76**	332311	332310	**129**	336211	336211
24	325199	325190	**77**	332321	332320	**130**	336212	336212
25	325211	325211	**78**	332323	332320	**131**	336311	336310
26	325212	3252A0	**79**	332420	332420	**132**	336312	336310
27	325311	325310	**80**	332510	332500	**133**	336330	3363A0
28	325312	325310	**81**	332618	332600	**134**	336360	336360
29	325314	325310	**82**	332710	332710	**135**	336370	336370
30	325320	325320	**83**	332721	332720	**136**	336399	336390

continued on next page

Table A.1. *continued*

	TRI code	**BEA code**		**TRI code**	**BEA code**		**TRI code**	**BEA code**
31	325510	325510	**84**	332722	332720	**137**	336412	336412
32	325613	325610	**85**	332811	332800	**138**	336413	336413
33	325910	325910	**86**	332812	332800	**139**	336611	336611
34	325991	3259A0	**87**	332813	332800	**140**	336999	336999
35	325998	3259A0	**88**	332912	33291A	**141**	337127	337127
36	326121	326120	**89**	332919	33291A	**142**	337215	337215
37	326122	326120	**90**	332994	33299A	**143**	339112	339112
38	326140	326140	**91**	332996	332996	**144**	339113	339113
39	326199	326190	**92**	332998	332999	**145**	339114	339114
40	326211	326210	**93**	332999	332999	**146**	339920	339920
41	326299	326290	**94**	333111	333111	**147**	339991	339990
42	327112	327100	**95**	333112	333112	**148**	339995	339990
43	327113	327100	**96**	333120	333120	**149**	339999	339990
44	327211	327200	**97**	333131	333130	**150**	423520	423A00
45	327213	327200	**98**	333132	333130	**151**	423930	423A00
46	327215	327200	**99**	333210	333242	**152**	424690	424A00
47	327310	327310	**100**	333291	33329A	**153**	424710	424700
48	327390	327390	**101**	333294	33329A	**154**	532412	532400
49	327910	327910	**102**	333319	333318	**155**	541712	541700
50	327993	327993	**103**	333412	333413	**156**	562211	562000
51	327999	327999	**104**	333415	333415	**157**	562920	562000
52	331111	331110	**105**	333511	333511	**158**	811310	811300
53	331112	331110	**106**	333512	333511	**159**	928110	S00500

B. CORRELATION BETWEEN NETWORK METRICS

Spearman correlation coefficient for each network metric pair

Table B.1.
orig_spearman_rho

	in_deg	out_deg	deg	weight_in_deg	weight_out_deg	weight_deg	close	between	EC	PR	hub	auth	BL	FL	diffusion
in_deg	1	-0.18	0.18	0.78	-0.10	0.29	1.00	0.22	1.00	0.39	0.22	0.60	0.78	-0.10	-0.11
out_deg	-0.18	1	0.86	-0.09	0.88	0.64	-0.19	0.71	-0.18	-0.89	0.71	0.21	-0.09	0.87	0.90
deg	0.18	0.86	1	0.21	0.77	0.64	0.18	0.84	0.18	-0.70	0.70	0.42	0.21	0.76	0.80
weight_in_deg	0.78	-0.09	0.21	1	0.08	0.50	0.78	0.18	0.78	0.24	0.42	0.84	1.00	0.08	0.05
weight_out_deg	-0.10	0.88	0.77	0.08	1	0.83	-0.10	0.63	-0.09	-0.92	0.87	0.39	0.08	1.00	0.99
weight_deg	0.29	0.64	0.64	0.50	0.83	1	0.29	0.49	0.30	-0.61	0.96	0.73	0.51	0.83	0.81
close	1.00	-0.19	0.18	0.78	-0.10	0.29	1	0.21	1.00	0.39	0.21	0.60	0.78	-0.10	-0.11
between	0.22	0.71	0.84	0.18	0.63	0.49	0.21	1	0.22	-0.55	0.53	0.30	0.18	0.63	0.64
EC	1.00	-0.18	0.18	0.78	-0.09	0.30	1.00	0.22	1	0.38	0.22	0.60	0.78	-0.09	-0.10
PR	0.39	-0.89	-0.70	0.24	-0.92	-0.61	0.39	-0.55	0.38	1	-0.70	-0.14	0.24	-0.91	-0.94
hub	0.22	0.71	0.70	0.42	0.87	0.96	0.21	0.53	0.22	-0.70	1	0.73	0.42	0.87	0.86
auth	0.60	0.21	0.42	0.84	0.39	0.73	0.60	0.30	0.60	-0.14	0.73	1	0.84	0.39	0.38
BL	0.78	-0.09	0.21	1.00	0.08	0.51	0.78	0.18	0.78	0.24	0.42	0.84	1	0.08	0.05
FL	-0.10	0.87	0.76	0.08	1.00	0.83	-0.10	0.63	-0.09	-0.91	0.87	0.39	0.08	1	0.99
diffusion	-0.11	0.90	0.80	0.05	0.99	0.81	-0.11	0.64	-0.10	-0.94	0.86	0.38	0.05	0.99	1

Table B.2.
national-disag_spearman_rho

	in_deg	out_deg	deg	weight_in_deg	weight_out_deg	weight_deg	close	between	EC	PR	hub	auth	BL	FL	diffusion
in_deg	1	-0.17	0.17	0.79	-0.10	0.32	1.00	0.21	1.00	0.38	0.24	0.62	0.79	-0.10	-0.11
out_deg	-0.17	1	0.87	-0.09	0.89	0.63	-0.18	0.73	-0.17	-0.89	0.70	0.18	-0.09	0.89	0.92
deg	0.17	0.87	1	0.19	0.79	0.64	0.17	0.86	0.18	-0.73	0.70	0.39	0.19	0.79	0.81
weight_in_deg	0.79	-0.09	0.19	1	0.06	0.52	0.79	0.18	0.79	0.24	0.43	0.84	1.00	0.07	0.03
weight_out_deg	-0.10	0.89	0.79	0.06	1	0.80	-0.10	0.67	-0.09	-0.92	0.84	0.35	0.06	1.00	0.99
weight_deg	0.32	0.63	0.64	0.52	0.80	1	0.32	0.50	0.32	-0.59	0.96	0.73	0.52	0.80	0.78
close	1.00	-0.18	0.17	0.79	-0.10	0.32	1	0.20	1.00	0.38	0.23	0.62	0.79	-0.10	-0.11
between	0.21	0.73	0.86	0.18	0.67	0.50	0.20	1	0.21	-0.58	0.54	0.29	0.18	0.67	0.68
EC	1.00	-0.17	0.18	0.79	-0.09	0.32	1.00	0.21	1	0.38	0.24	0.62	0.79	-0.09	-0.10
PR	0.38	-0.89	-0.73	0.24	-0.92	-0.59	0.38	-0.58	0.38	1	-0.68	-0.11	0.24	-0.92	-0.94
hub	0.24	0.70	0.70	0.43	0.84	0.96	0.23	0.54	0.24	-0.68	1	0.72	0.43	0.84	0.83
auth	0.62	0.18	0.39	0.84	0.35	0.73	0.62	0.29	0.62	-0.11	0.72	1	0.84	0.35	0.34
BL	0.79	-0.09	0.19	1.00	0.06	0.52	0.79	0.18	0.79	0.24	0.43	0.84	1	0.07	0.03
FL	-0.10	0.89	0.79	0.07	1.00	0.80	-0.10	0.67	-0.09	-0.92	0.84	0.35	0.07	1	0.99
diffusion	-0.11	0.92	0.81	0.03	0.99	0.78	-0.11	0.68	-0.10	-0.94	0.83	0.34	0.03	0.99	1

Table B.3.
mrio_spearman_rho

	Total industry output	In-degree	Out-degree	Degree	Weighted in-degree	Weighted out-degree	Weighted degree	Closeness	Betweenness	Eigencentrality	PageRank	Hub score	Authority score	Back linkage	Forward linkage	Diffusion
Total industry output	1	0.05	-0.04	0.15	-0.18	-0.18	-0.18	0.27	0.52	0.15	-0.47	0.40	-0.37	-0.24	0.71	0.71
In-degree	0.05	1	-0.25	0.00	-0.02	-0.02	-0.02	0.03	0.01	0.00	-0.02	0.02	-0.03	-0.04	0.04	0.04
Out-degree	-0.04	-0.25	1	-0.01	0.00	0.00	0.00	-0.03	0.00	-0.02	0.01	-0.03	0.00	0.01	-0.03	-0.03
Degree	0.15	0.00	-0.01	1	0.65	0.65	0.65	0.44	0.42	0.29	-0.14	0.34	0.48	0.62	0.30	0.29
Weighted in-degree	-0.18	-0.02	0.00	0.65	1	1	1	0.23	0.18	0.46	0.44	-0.17	0.40	0.96	-0.22	-0.22
Weighted out-degree	-0.18	-0.02	0.00	0.65	1	1	1	0.23	0.18	0.46	0.44	-0.17	0.40	0.96	-0.22	-0.22
Weighted degree	-0.18	-0.02	0.00	0.65	1	1	1	0.23	0.18	0.46	0.44	-0.17	0.40	0.96	-0.22	-0.22
Closeness	0.27	0.03	-0.03	0.44	0.23	0.23	0.23	1	0.26	0.11	-0.26	0.51	0.35	0.13	0.43	0.43
Betweenness	0.52	0.01	0.00	0.42	0.18	0.18	0.18	0.26	1	0.17	-0.38	0.35	-0.14	0.13	0.67	0.66
Eigencentrality	0.15	0.00	-0.02	0.29	0.46	0.46	0.46	0.11	0.17	1	0.30	-0.11	0.15	0.46	-0.03	-0.03
PageRank	-0.47	-0.02	0.01	-0.14	0.44	0.44	0.44	-0.26	-0.38	0.30	1	-0.69	0.09	0.51	-0.74	-0.74
Hub score	0.40	0.02	-0.03	0.34	-0.17	-0.17	-0.17	0.51	0.35	-0.11	-0.69	1	0.23	-0.21	0.73	0.73
Authority score	-0.37	-0.03	0.00	0.48	0.40	0.40	0.40	0.35	-0.14	0.15	0.09	0.23	1	0.40	-0.18	-0.18
Back linkage	-0.24	-0.04	0.01	0.62	0.96	0.96	0.96	0.13	0.13	0.46	0.51	-0.21	0.40	1	-0.27	-0.28
Forward linkage	0.71	0.04	-0.03	0.30	-0.22	-0.22	-0.22	0.43	0.67	-0.03	-0.74	0.73	-0.18	-0.27	1	1
Diffusion	0.71	0.04	-0.03	0.29	-0.22	-0.22	-0.22	0.43	0.66	-0.03	-0.74	0.73	-0.18	-0.28	1	1

Table B.4.
Spearman correlation p-value, original national IO

	In-degree	Out-degree	Degree	Weighted in-degree	Weighted out-degree	Weighted degree	Closeness	Betweenness	Eigencentrality	PageRank	Hub score	Authority score	Back linkage	Forward linkage	Diffusion	Diffusion
In-degree	0.00	2.29×10^{-4}	1.97×10^{-4}	8.43×10^{-84}	5.11×10^{-2}	1.72×10^{-9}	6.67×10^{-74}	6.40×10^{-3}	4.19×10^{-84}	7.00×10^{-16}	1.10×10^{-5}	1.11×10^{-40}	1.49×10^{-83}	5.11×10^{-2}	3.09×10^{-2}	0.0
Out-degree	2.29×10^{-4}	0.00	3.91×10^{-120}	6.52×10^{-2}	4.34×10^{-130}	2.83×10^{-48}	1.20×10^{-8}	1.72×10^{-32}	8.36×10^{-4}	3.54×10^{-137}	2.40×10^{-62}	2.41×10^{-5}	6.57×10^{-2}	5.57×10^{-129}	3.94×10^{-151}	3.0×10^{-6}
Degree	1.97×10^{-4}	3.91×10^{-120}	0.00	1.99×10^{-5}	1.04×10^{-79}	5.66×10^{-49}	8.37×10^{-1}	1.23×10^{-32}	2.92×10^{-3}	1.52×10^{-61}	9.83×10^{-62}	3.74×10^{-19}	2.04×10^{-5}	7.96×10^{-79}	9.55×10^{-90}	8.2×10^{-4}
Weighted in-degree	8.43×10^{-84}	6.52×10^{-2}	1.99×10^{-5}	0.00	1.01×10^{-1}	1.39×10^{-27}	1.03×10^{-129}	1.90×10^{-6}	4.54×10^{-259}	1.40×10^{-6}	6.53×10^{-19}	1.65×10^{-107}	0.00	9.93×10^{-2}	3.37×10^{-1}	0.0
Weighted out-degree	5.11×10^{-2}	4.34×10^{-130}	1.04×10^{-79}	1.01×10^{-1}	0.00	8.97×10^{-106}	1.48×10^{-2}	1.08×10^{-54}	7.35×10^{-1}	9.72×10^{-162}	5.42×10^{-124}	2.32×10^{-16}	1.00×10^{-1}	0.00	0.00	1.4×10^{-187}
Weighted degree	1.72×10^{-9}	2.83×10^{-48}	5.66×10^{-49}	1.39×10^{-27}	8.97×10^{-106}	0.00	1.82×10^{-9}	9.56×10^{-46}	1.09×10^{-20}	6.75×10^{-43}	7.95×10^{-234}	4.68×10^{-69}	1.32×10^{-27}	7.47×10^{-106}	1.12×10^{-95}	1.4×10^{-187}
Closeness	6.67×10^{-74}	1.20×10^{-8}	8.37×10^{-1}	1.03×10^{-129}	1.48×10^{-2}	1.82×10^{-9}	0.00	1.25×10^{-2}	1.83×10^{-147}	7.05×10^{-19}	5.48×10^{-5}	6.94×10^{-48}	1.10×10^{-129}	1.51×10^{-2}	2.02×10^{-3}	1.4×10^{-187}
Betweenness	6.40×10^{-3}	1.72×10^{-32}	1.23×10^{-32}	1.90×10^{-6}	1.08×10^{-54}	9.56×10^{-46}	1.25×10^{-2}	0.00	2.05×10^{-4}	2.60×10^{-28}	2.56×10^{-41}	1.06×10^{-15}	1.87×10^{-6}	8.83×10^{-55}	4.32×10^{-52}	0.0
Eigencentrality	4.19×10^{-84}	8.36×10^{-4}	2.92×10^{-3}	4.54×10^{-259}	7.35×10^{-1}	1.09×10^{-20}	1.83×10^{-147}	2.05×10^{-4}	0.00	8.23×10^{-10}	7.19×10^{-14}	6.56×10^{-90}	9.22×10^{-259}	7.23×10^{-1}	7.17×10^{-1}	0.0
PageRank	7.00×10^{-16}	3.54×10^{-137}	1.52×10^{-61}	1.40×10^{-6}	9.72×10^{-162}	6.75×10^{-43}	7.05×10^{-19}	2.60×10^{-28}	8.23×10^{-10}	0.00	3.01×10^{-61}	4.71×10^{-3}	1.44×10^{-6}	6.85×10^{-161}	4.28×10^{-184}	2.9×10^{-4}
Hub score	1.10×10^{-5}	2.40×10^{-62}	9.83×10^{-62}	6.53×10^{-19}	5.42×10^{-124}	7.95×10^{-234}	5.48×10^{-5}	2.56×10^{-41}	7.19×10^{-14}	3.01×10^{-61}	0.00	7.20×10^{-70}	6.30×10^{-19}	9.47×10^{-124}	3.42×10^{-119}	0.0
Authority score	1.11×10^{-40}	2.41×10^{-5}	3.74×10^{-19}	1.65×10^{-107}	2.32×10^{-16}	4.68×10^{-69}	6.94×10^{-48}	1.06×10^{-15}	6.56×10^{-90}	4.71×10^{-3}	7.20×10^{-70}	0.00	1.65×10^{-107}	2.40×10^{-16}	3.96×10^{-15}	0.0
Back linkage	1.49×10^{-83}	6.57×10^{-2}	2.04×10^{-5}	0.00	1.00×10^{-1}	1.32×10^{-27}	1.10×10^{-129}	1.87×10^{-6}	9.22×10^{-259}	1.44×10^{-6}	6.30×10^{-19}	1.65×10^{-107}	0.00	9.82×10^{-2}	3.35×10^{-1}	1.2×10^{-123}
Forward linkage	5.11×10^{-2}	5.57×10^{-129}	7.96×10^{-79}	9.93×10^{-2}	0.00	7.47×10^{-106}	1.51×10^{-2}	8.83×10^{-55}	7.23×10^{-1}	6.85×10^{-161}	9.47×10^{-124}	2.40×10^{-16}	9.82×10^{-2}	0.00	0.00	2.6×10^{-293}
Diffusion	3.09×10^{-2}	3.94×10^{-151}	9.55×10^{-90}	3.37×10^{-1}	0.00	1.12×10^{-95}	2.02×10^{-3}	4.32×10^{-52}	7.17×10^{-1}	4.28×10^{-184}	3.42×10^{-119}	3.96×10^{-15}	3.35×10^{-1}	0.00	0.00	0.0
Diffusion	0.0	3.0×10^{-6}	8.2×10^{-4}	0.0	1.4×10^{-187}	1.4×10^{-187}	1.4×10^{-187}	0.0	0.0	2.9×10^{-4}	0.0	0.0	1.2×10^{-123}	2.6×10^{-293}	0.0	0.0

Table B.5.
Spearman correlation p-value, disaggregated national IO

	In-degree	Out-degree	Degree	Weighted in-degree	Weighted out-degree	Weighted degree	Closeness	Betweenness	Eigencentrality	PageRank	Hub score	Authority score	Back linkage	Forward linkage	Diffusion	Diffusion
In-degree	0.0	3.5×10^{-4}	3.7×10^{-4}	2.0×10^{-91}	4.8×10^{-2}	1.8×10^{-11}	2.0×10^{-77}	8.8×10^{-3}	1.9×10^{-91}	1.1×10^{-15}	1.1×10^{-6}	9.8×10^{-46}	3.6×10^{-91}	5.0×10^{-2}	3.1×10^{-2}	0.0
Out-degree	3.5×10^{-4}	0.0	1.6×10^{-131}	6.0×10^{-2}	4.6×10^{-143}	1.7×10^{-46}	2.1×10^{-9}	2.0×10^{-37}	7.7×10^{-4}	7.1×10^{-146}	7.4×10^{-62}	1.8×10^{-4}	6.0×10^{-2}	4.8×10^{-142}	1.4×10^{-165}	3.0×10^{-6}
Degree	3.7×10^{-4}	1.6×10^{-131}	0.0	7.0×10^{-5}	1.8×10^{-89}	2.4×10^{-48}	7.6×10^{-1}	2.0×10^{-37}	6.8×10^{-3}	3.7×10^{-69}	3.6×10^{-62}	1.0×10^{-16}	7.2×10^{-5}	9.9×10^{-89}	4.4×10^{-100}	8.2×10^{-4}
Weighted in-degree	2.0×10^{-91}	6.0×10^{-2}	7.0×10^{-5}	0.0	1.9×10^{-1}	8.8×10^{-30}	3.5×10^{-132}	8.3×10^{-6}	3.9×10^{-269}	6.0×10^{-7}	1.1×10^{-19}	2.6×10^{-113}	0.0	1.8×10^{-1}	4.9×10^{-1}	0.0
Weighted out-degree	4.8×10^{-2}	4.6×10^{-143}	1.8×10^{-89}	1.9×10^{-1}	0.0	4.9×10^{-93}	3.2×10^{-3}	1.6×10^{-60}	9.8×10^{-1}	4.6×10^{-171}	5.1×10^{-110}	2.6×10^{-13}	1.9×10^{-1}	0.0	0.0	1.4×10^{-187}
Weighted degree	1.8×10^{-11}	1.7×10^{-46}	2.4×10^{-48}	8.8×10^{-30}	4.9×10^{-93}	0.0	4.9×10^{-10}	2.3×10^{-44}	1.6×10^{-22}	1.0×10^{-39}	1.4×10^{-231}	2.8×10^{-69}	8.3×10^{-30}	1.8×10^{-93}	9.4×10^{-86}	1.4×10^{-187}
Closeness	2.0×10^{-77}	2.1×10^{-9}	7.6×10^{-1}	3.5×10^{-132}	3.2×10^{-3}	4.9×10^{-10}	0.0	6.1×10^{-2}	2.3×10^{-151}	2.6×10^{-20}	4.9×10^{-5}	1.5×10^{-51}	3.5×10^{-132}	3.4×10^{-3}	3.8×10^{-4}	1.4×10^{-187}
Betweenness	8.8×10^{-3}	2.0×10^{-37}	2.0×10^{-37}	8.3×10^{-6}	1.6×10^{-60}	2.3×10^{-44}	6.1×10^{-2}	0.0	5.9×10^{-4}	1.8×10^{-32}	1.4×10^{-40}	9.3×10^{-14}	8.2×10^{-6}	1.2×10^{-60}	1.8×10^{-57}	0.0
Eigencentrality	1.9×10^{-91}	7.7×10^{-4}	6.8×10^{-3}	3.9×10^{-269}	9.8×10^{-1}	1.6×10^{-22}	2.3×10^{-151}	5.9×10^{-4}	0.0	3.3×10^{-10}	1.5×10^{-14}	5.4×10^{-96}	5.9×10^{-269}	9.5×10^{-1}	5.4×10^{-1}	0.0
PageRank	1.1×10^{-15}	7.1×10^{-146}	3.7×10^{-69}	6.0×10^{-7}	4.6×10^{-171}	1.0×10^{-39}	2.6×10^{-20}	1.8×10^{-32}	3.3×10^{-10}	0.0	2.2×10^{-58}	2.6×10^{-2}	6.2×10^{-7}	2.9×10^{-170}	1.6×10^{-192}	2.9×10^{-4}
Hub score	1.1×10^{-6}	7.4×10^{-62}	3.6×10^{-62}	1.1×10^{-19}	5.1×10^{-110}	1.4×10^{-231}	4.9×10^{-5}	1.4×10^{-40}	1.5×10^{-14}	2.2×10^{-58}	0.0	1.4×10^{-68}	1.0×10^{-19}	2.9×10^{-110}	1.0×10^{-107}	0.0
Authority score	9.8×10^{-46}	1.8×10^{-4}	1.0×10^{-16}	2.6×10^{-113}	2.6×10^{-13}	2.8×10^{-69}	1.5×10^{-51}	9.3×10^{-14}	5.4×10^{-96}	2.6×10^{-2}	1.4×10^{-68}	0.0	2.7×10^{-113}	2.2×10^{-13}	2.2×10^{-12}	0.0
Back linkage	3.6×10^{-91}	6.0×10^{-2}	7.2×10^{-5}	0.0	1.9×10^{-1}	8.3×10^{-30}	3.5×10^{-132}	8.2×10^{-6}	5.9×10^{-269}	6.2×10^{-7}	1.0×10^{-19}	2.7×10^{-113}	0.0	1.8×10^{-1}	4.8×10^{-1}	1.2×10^{-123}
Forward linkage	5.0×10^{-2}	4.8×10^{-142}	9.9×10^{-89}	1.8×10^{-1}	0.0	1.8×10^{-93}	3.4×10^{-3}	1.2×10^{-60}	9.5×10^{-1}	2.9×10^{-170}	2.9×10^{-110}	2.2×10^{-13}	1.8×10^{-1}	0.0	0.0	2.6×10^{-293}
Diffusion	3.1×10^{-2}	1.4×10^{-165}	4.4×10^{-100}	4.9×10^{-1}	0.0	9.4×10^{-86}	3.8×10^{-4}	1.8×10^{-57}	5.4×10^{-1}	1.6×10^{-192}	1.0×10^{-107}	2.2×10^{-12}	4.8×10^{-1}	0.0	0.0	0.0
Diffusion	0.0	3.0×10^{-6}	8.2×10^{-4}	0.0	1.4×10^{-187}	1.4×10^{-187}	1.4×10^{-187}	0.0	0.0	2.9×10^{-4}	0.0	0.0	1.2×10^{-123}	2.6×10^{-293}	0.0	0.0

Table B.6.
Spearman correlation p-value, MRIO

	Total industry output	In-degree	Out-degree	Degree	Weighted in-degree	Weighted out-degree	Weighted degree	Closeness	Betweenness	Eigencentrality	PageRank	Hub score	Authority score	Backward linkage	Forward linkage	Diffusion
Total industry output	0.0	2.7×10^{-9}	1.1×10^{-7}	1.4×10^{-85}	5.8×10^{-120}	5.8×10^{-120}	5.8×10^{-120}	5.0×10^{-269}	0.0	1.2×10^{-79}	0.0	0.0	0.0	5.0×10^{-224}	0.0	0.0
In-degree	2.7×10^{-9}	0.0	9.2×10^{-237}	6.2×10^{-1}	1.2×10^{-3}	1.2×10^{-3}	1.2×10^{-3}	5.0×10^{-4}	1.8×10^{-1}	7.7×10^{-1}	5.8×10^{-3}	6.3×10^{-3}	1.2×10^{-5}	5.2×10^{-7}	3.7×10^{-6}	3.0×10^{-6}
Out-degree	1.1×10^{-7}	9.2×10^{-237}	0.0	1.5×10^{-1}	6.6×10^{-1}	6.6×10^{-1}	6.6×10^{-1}	1.6×10^{-5}	7.6×10^{-1}	4.7×10^{-2}	8.3×10^{-2}	2.5×10^{-4}	5.3×10^{-1}	1.2×10^{-1}	8.5×10^{-4}	8.2×10^{-4}
Degree	1.4×10^{-85}	6.2×10^{-1}	1.5×10^{-1}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.8×10^{-77}	0.0	0.0	0.0	0.0	0.0
Weighted in-degree	5.8×10^{-120}	1.2×10^{-3}	6.6×10^{-1}	0.0	0.0	0.0	0.0	5.2×10^{-207}	6.3×10^{-120}	0.0	0.0	6.4×10^{-110}	0.0	0.0	3.0×10^{-180}	1.4×10^{-187}
Weighted out-degree	5.8×10^{-120}	1.2×10^{-3}	6.6×10^{-1}	0.0	0.0	0.0	0.0	5.2×10^{-207}	6.3×10^{-120}	0.0	0.0	6.4×10^{-110}	0.0	0.0	3.0×10^{-180}	1.4×10^{-187}
Weighted degree	5.8×10^{-120}	1.2×10^{-3}	6.6×10^{-1}	0.0	0.0	0.0	0.0	5.2×10^{-207}	6.3×10^{-120}	0.0	0.0	6.4×10^{-110}	0.0	0.0	3.0×10^{-180}	1.4×10^{-187}
Closeness	5.0×10^{-269}	5.0×10^{-4}	1.6×10^{-5}	0.0	5.2×10^{-207}	5.2×10^{-207}	5.2×10^{-207}	0.0	6.9×10^{-254}	9.0×10^{-48}	3.7×10^{-247}	0.0	0.0	7.3×10^{-66}	0.0	0.0
Betweenness	0.0	1.8×10^{-1}	7.6×10^{-1}	0.0	6.3×10^{-120}	6.3×10^{-120}	6.3×10^{-120}	6.9×10^{-254}	0.0	2.4×10^{-105}	0.0	0.0	2.7×10^{-73}	1.3×10^{-67}	0.0	0.0
Eigencentrality	1.2×10^{-79}	7.7×10^{-1}	4.7×10^{-2}	0.0	0.0	0.0	0.0	9.0×10^{-48}	2.4×10^{-105}	0.0	0.0	5.8×10^{-49}	3.9×10^{-82}	0.0	8.4×10^{-4}	2.9×10^{-4}
PageRank	0.0	5.8×10^{-3}	8.3×10^{-2}	7.8×10^{-77}	0.0	0.0	0.0	3.7×10^{-247}	0.0	0.0	0.0	0.0	2.3×10^{-30}	0.0	0.0	0.0
Hub score	0.0	6.3×10^{-3}	2.5×10^{-4}	0.0	6.4×10^{-110}	6.4×10^{-110}	6.4×10^{-110}	0.0	0.0	5.8×10^{-49}	0.0	0.0	5.6×10^{-200}	5.2×10^{-174}	0.0	0.0
Authority score	0.0	1.2×10^{-5}	5.3×10^{-1}	0.0	0.0	0.0	0.0	0.0	2.7×10^{-73}	3.9×10^{-82}	2.3×10^{-30}	5.6×10^{-200}	0.0	0.0	8.3×10^{-122}	1.2×10^{-123}
Backward linkage	5.0×10^{-224}	5.2×10^{-7}	1.2×10^{-1}	0.0	0.0	0.0	0.0	7.3×10^{-66}	1.3×10^{-67}	0.0	0.0	5.2×10^{-174}	0.0	0.0	1.6×10^{-284}	2.6×10^{-293}
Forward linkage	0.0	3.7×10^{-6}	8.5×10^{-4}	0.0	3.0×10^{-180}	3.0×10^{-180}	3.0×10^{-180}	0.0	0.0	8.4×10^{-4}	0.0	0.0	8.3×10^{-122}	1.6×10^{-284}	0.0	0.0
Diffusion	0.0	3.0×10^{-6}	8.2×10^{-4}	0.0	1.4×10^{-187}	1.4×10^{-187}	1.4×10^{-187}	0.0	0.0	2.9×10^{-4}	0.0	0.0	1.2×10^{-123}	2.6×10^{-293}	0.0	0.0