DEVELOPMENT OF SCALABLE STAKEHOLDER-NEEDS METRICS APPLIED IN ECONOMIC INPUT-OUTPUT SOCIAL IMPACT ASSESSMENT MODELS

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

School of Environmental and Ecological Engineering

West Lafayette, Indiana

May 2019

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This work is dedicated to my family for their support and inspiration, my wife for her strength of conviction and faith, and my Savior for setting me free.

ACKNOWLEDGMENTS

Several individuals require my deepest gratitude. Beginning with my co-advisors, Dr. Larry Nies and Dr. John W. Sutherland, who have been instrumental in instilling the continuous questioning of status quo and posing the challenge of “so what? Why is it important?” I am forever grateful for their mentorship, guidance, and support during the course of this work. Additionally, my committee members, Dr. Shweta Singh and Dr. Fu Zhao, have offered a welcome sounding board for ideas, offered challenging reciprocation of ideas, and added useful paths for deeper exploration. I am always encouraged by their thoughtful perspectives.

The care and love for each ESE student shown by Dr. Linda Lee, Christal Musser, and Dierdre Carmicheal have made this journey a path supported by family. I am truly grateful for their sincerity, compassion, and patience.

Several faculty members and researchers have provided guidance and opportunities along the way: Dr. Carol Handwerker (Purdue, MSEE) for welcoming me to the IGERT and providing countless other blessings passed my way; Dr. Nina Robinson (Purdue, EEE) for taking a chance and opening the door to EEE; Dr. Margot Hutchins (Sandia) for the influential dissertation work and willingness to ‘talk shop’; Dr. Angel Aguiar (Purdue, GTAP) for insightful critique and always being interested in a discussion; Dr. Geoffrey Hewings (UIUC) for connecting me to a larger network beyond my limited vision; and Dr. Randall Jackson (WVU) for granting access to the IOSnap modeled data. The data informing deeper exploration of social impacts was made available through the generosity of all U.S. taxpayers, for which this work could not have progressed.

I am grateful for the support and friendship of past and present fellow graduate students and postdocs, especially Dr. Gladys Andino, Dr. Raymond ‘Studie’ Red Corn, Dr. Bill Bernstein, Dr. Ruchit Mehta, Dr. Ayan Sinha, Dr. Gamini Mendis, Dr. Junkai Wang, José Ferney Rivera, and Matt Triebe. My love and appreciation go also to our friends Lee, Mary, and Anna Hargitt, and our care group at Kossuth Street Baptist Church.

My studies at Purdue and this research were generously supported by the Fehsenfeld Family Endowment through the Environmental and Ecological Engineering department, the NSF IGERT on Sustainable Electronics (DGE 1144843), and the Brian Lamb School of Communication.

In closing, I wish to express love and appreciation for my family in Colombia and Chicagoland for consistently providing encouragement, patience, support, and inspiration during this journey. I am eternally grateful for my wife, Helena Avila Arias, who has provided for me much more than anyone could ask of another person, yet seems to have an endless reserve of love and support available. My stars aligned when she decided to come to Purdue.

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LIST OF ABBREVIATIONS

AM	Advanced Manufacturing
BEA	Bureau of Economic Analysis (U.S.)
BLS	Bureau of Labor Statistics (U.S.)
bn	billion
COB	Cost of (Employee) Benefits
COI	Cost of Injuries
COT	Cost of Turnover
DAFWr	Days Away From Work
ECEC	Employer Cost for Employee Compensation
ELW	Employees below a Living Wage
EIO	Economic Input-Output
EMP	Total number of Employees
FW	Far West
GL	Great Lakes
GPIs	Goods Producing Industrial Sectors
GSP	Gross State Product
IA	Impact Assessment
IIF	Injuries, Illnesses, & Fatalities
INS	Insurance Benefits
IO	Input-Output
JOLTS	Job Openings and Labor Turnover Survey
LCA	Life Cycle Assessment
LD	Layoffs and Discharges
LEG	Legally Required Benefits
LPC	Labor Productivity and Costs
ME	Mideast
MMIs	Measures, Metrics, and Indicators
NAICS	North American Industrial Classification System
NCS	National Compensation Survey

NE	New England
OES	Occupational Employment Statistics
OP	Other Separations
PL	Paid Leave
PLN	Plains
PROD	Output per employee
QT	Quits
RET	Retirement and Savings
RM	Rocky Mountain
SE	Southeast
SI	Social Impact
SIA	Social Impact Assessment
SLCIA or	
S-LCIA	Social Life Cycle Impact Assessment
SPIs	Service Providing Industrial Sectors
SUP	Supplemental Pay
SW	Southwest
S&W	Salary & Wages
Tcomp	Total Compensation
TEN	Tenure Time per Employee
THW	Total Hours Worked
TS	Total Separations
TTY	Total Tenure Years
VA	Industry Value Added
X	Total Commodity Output
YAFW	Total Work Years Away From Work
1A	1 Adult household
2A	2 Adults household
2A1W1C	2 Adults with 1 Working adult and 1 Child household

ABSTRACT

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Degree Received: May 2019
Title: Development of Scalable Stakeholder-Needs Metrics Applied in Economic Input-Output Social Impact Assessment Models
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In the last half century, much research effort has gone into identifying the causes and effects of societal burdens. Industrial activity may arguably be the most widely responsible cause, but the effects, or social impacts (SIs), resulting from industrial activity are typically considered externalities and not evaluated alongside economic performance of industries. It is clear however that people are fundamental to the progress and development of economies. Understanding how people are affected by economies, and in particular industrial economic activity, starts with recognizing that impacts on people can no longer be considered externalities. The coordinating lack of understanding of social performance, i.e., how stakeholder needs are impacted by industrial production, limits the capacity of decision makers to make fully informed choices. A multidisciplinary perspective is needed to address this gap in understanding. The new approach, economic input-output social impact assessment, integrates economic production with social impacts and is further demonstrated to provide a measurable path forward to evaluate the social performance of industries. It is shown that changes in industrial activity, e.g., growth, in the U.S. will have a directly related and predictable change in social impact.

CHAPTER 1. THE NEED TO QUANTIFY SOCIAL IMPACTS

1.1 Introduction

The last several decades have seen the emergence of sustainability as a key benchmark of industrial function. In fact, one of the pillars of sustainability, economic performance, has been used for centuries to judge industrial efficiency. Over the last thirty years, a second dimension of sustainability, environment, has increasingly become a consideration for industrial decision makers. Recently, the third dimension of sustainability has begun to be considered: society. Such importance is placed on the social dimension that 8 of the 17 United Nations Sustainable Development Goals [United Nations, 2015] can be directly attributed to social issues and an additional 4 can be linked to social accessibility challenges.

The social dimension of sustainability is suggested to incorporate all aspects of society, culture, and human interaction. The relatively abstract nature of social sustainability requires a comprehensive multidisciplinary approach to address the underlying complexity. From the social sciences, researchers have used stakeholder theory [Crane & Ruebottom, 2011; Dewey, 1927; Mitchell et al., 1997] to identify a diverse set of stakeholder groups for companies [Hutchins et al., 2013; UNEP-SETAC, 2009]. From the psychological sciences, the theories of human and societal needs [Maslow, 1958; Maslow et al., 1970] have been used to identify levels of requirements for the aforementioned stakeholders [Esteves & Vanclay, 2009; Max-Neef et al., 1992]. The intersection of these two theories provides a framework in which needs can be defined for each stakeholder group (Figure 1.1). These theories have helped guide a partial understanding of societal systems but lack the measurable component needed for effective management.

		Stakeholder Group					
		Society/ Public	**Local Community**	**Value Chain/ Suppliers**	**Owners/ Shareholders**	**Consumers/ Customers**	**Workers/ Employees**
Needs Level	**Actualization**						
	Esteem						
	Affiliation						
	Safety/Security						
	Basic						

Figure 1.1 - Framework for the intersection of stakeholder and human needs theories. Adapted from Hutchins et al. [2010].

Developed in parallel with both the stakeholder and needs theories, but typically not used in conjunction, impact assessment (IA) arose in the 1970s out of a political imperative to acknowledge and predict the impact that a project may have on the surrounding areas and communities [Freudenburg, 1986]. The social aspects of IA were slow developing behind environmental considerations until the late 1980s, but have recently been adapted for use with life cycle assessment (LCA) methodologies [Chhipi-Shrestha et al., 2015; Feschet et al., 2013; Hsu et al., 2013; Parent et al., 2010; Reitinger et al., 2011; Wang et al., 2016; Wu et al., 2015]. Social IA, or SIA, and LCA have been combined to quantify and predict social impacts within an analytical measurement framework, often referred to as social life cycle impact assessment (SLCIA or S-LCIA). These tools have helped guide a partial quantification of societal impacts but lack causal linkages between activity and impact, sufficient and publicly available data, suitable and applicable metrics, and consensus on what should be measured and how to do so [Chhipi-Shrestha et al., 2015; Ebrahim & Rangan, 2014; Morrison-Saunders et al., 2014; Rasmussen et al., 2017; Sutherland et al., 2016].

The challenge of measurability goes back centuries. Galileo Galilei was attributed with living by the motto, "count what is countable, measure what is measurable, and what is not measurable make measurable" [Aumala, 1999]. As societies continue to become more complex, the measurability of societal attributes will become increasingly more important and significantly more complicated. The difficulty in understanding how a complex system, such as a society, functions can be further compounded by the uncertain connection between what is measured, what the measures mean, and the impact attributable to those measures [Rossi, 2007]. For example, can wages paid to local employees be linked to a high quality-of-life for those employees? What if those wages are not enough for the employee to meet the basic needs of their household? In this line of reasoning, the public domain houses a veritable treasure trove of measured and estimated values without clear and defined utility. Connecting those measures to an instance of relatable and useful impact, i.e., data that tells a truthful and compelling story of humanity, can be quite challenging.

Attempts at describing the human story through measures and data have expanded over the last century, from portrayal of the entire economy with flows of goods and services [Leontief, 1936] to assessment of the corruption of modern nations [Xiao et al., 2017]. Specifically in the last half century, much research effort has gone into identifying the causes and effects of societal burdens [Andrews & Withey, 1976; Atkinson, 2002; Azar et al., 1996; Bauer, 1966; Boulanger, 2008; Diener & Suh, 1997; Hutchins et al., 2010; UNEP-SETAC, 2009]. There is an abundance (and continually growing volume) of measures, metrics, or indicators (MMIs) in the research literature that attempt to quantify social impacts [Rasmussen et al., 2017]. The challenge remains in the inconsistency of applicability and suitability of such social MMIs across a myriad situations [Sutherland et al., 2016].

While both economic and environmental performance MMIs are well documented [Sutherland et al., 2016], understanding of social performance MMIs is still lacking consensus. Much of the recent work on social MMIs is based on the foundational indicator development effort of UNEP-SETAC [2009] and Benôit-Norris et al. [2013]. In the research literature, the majority of studies focus on social factors such as employment, working hours, labor conditions, or occupational health [Benoît-Norris et al., 2012; Chhipi-Shrestha et al., 2015; De Luca et al., 2015; Di Cesare et al., 2018; Dreyer et al., 2010; Ebrahim & Rangan, 2014; Hardadi & Pizzol, 2017; Hosseinijou et al., 2014; Husgafvel et al., 2013; Iribarren & Vázquez-Rowe, 2013; Kühnen & Hahn, 2017; Macombe et al., 2013; Murphy, 2012; Papong et al., 2016; Petti et al., 2018; Popovic et al., 2018; Rugani et al., 2012; Saidani et al., 2019; Santochi & Failli, 2013; Searcy et al., 2016; Silva et al., 2019; Simas et al., 2014; Singh & Gupta, 2017; Traverso et al., 2012; Zamani et al., 2018; Zhang & Haapala, 2014]. Hardadi & Pizzol [2017] suggest that measures such as working hours, salaries, and unemployment rate can be used to evaluate overall human well-being and productivity.

Neugebauer et al. [2017] consider a similar link between wages and worker well-being but suggest that fairness in wages should include an evaluation of working time. Working hours were used to identify areas of concern, or hotspots, in the Swedish clothing supply chain [Zamani et al., 2018] utilizing the Social Hotspots Database (SHDB), spun out of the UNEP-SETAC [2009] efforts. Also using the SHDB, Xiao et al. [2017] included corruption perception indices with employment measures to suggest sources, flows, and destinations of corruption throughout the global economy. In summary, there is little consensus on what social impacts to measure and how to measure them.

Over the last decade specifically, the research literature has made great strides in identifying, evaluating, and quantifying aspects of social performance [Husgafvel et al., 2014; Popovic et al., 2018; Rajak & Vinodh, 2015; Sutherland et al., 2016]. However, the majority of metrics proposed to quantify social performance lack tangible supporting datasets that are publicly available. Further, in the absence of a baseline value, or simple starting point, for any social impact (SI), understanding of what is relatively good or bad, positive or negative, becomes a challenge to discern. Without product-, industry-, or supplier/consumer-related data, it is also difficult to estimate current, or predict future SIs. Fortunately, lessons can be gleaned from methods used to create and evaluate both economic and environmental performance. Combining economic performance, environmental impacts, with the progress made in social sciences on human needs creates a robust perspective on how the socio-enviro-industrial system functions. What typically existed in exclusive silos of research is brought together through the work that follows. Collectively, this work pioneers the quantitative description of how people are affected by industrial activity and enhances the discussion of industrial social performance.

The following section will identify the need for a comprehensive and scalable model to evaluate social performance of U.S. industrial sectors.

1.2 Literature Review and Gap Analysis

To capture social performance, a perspective using the tools from a diverse set of disciplines is required. The multidisciplinary method established in this work integrates social impact assessment (SIA) with an input-output (IO) economic model. This method evaluates social performance using the IO analysis framework and closely mirrors the procedural developments established in economic input-output environmental LCA, or EIO-LCA [Hendrickson et al., 1998; Joshi, 1999; Lave et al., 1995; Matthews & Small, 2000]. IO models characterize the monetary flows in an economy where it is understood that materials, goods, services, and embedded labor move opposite to the monetary flows. This system is depicted in Figure 1.2, where sector 1 is both a producer of goods, labor, and services flowing to itself and sector 3, and a consumer of goods, labor, and services from sector 2. For a typical economy, there are many industrial sectors, both producers and consumers, where flows of goods, labor, services, and money are in both directions. A large economy may have hundreds of industrial sectors depending on one another, creating a vast network of interconnected industries. IO models may be used to capture the economic portion of the complexity inherent in modern global economies. Utilizing national IO data with the IO models linked to publicly available social data can highlight industrial influence, interconnectedness, and areas of social impact challenges. The combination of SIA with IO analysis further generates insight into how integral an industry or group of industries is to the success of the economy.

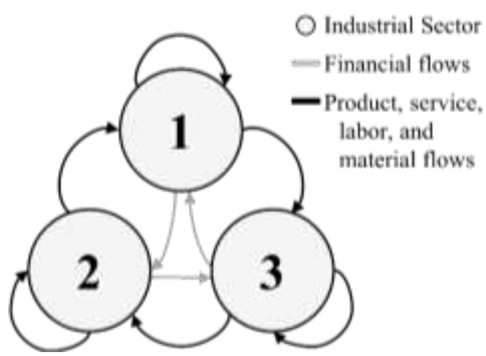

Figure 1.2 - Simplified model of inflows and outflows of capital, goods, services, and labor among industrial sectors. Producing sectors initiate each arrow which flow to the consuming sectors at the end of the arrow.

The input-output analysis (IOA) framework has increasingly been used to address social impacts in what the research literature terms “social life cycle assessment” (S-LCA). However, connecting social issues with the input–output databases using economic allocation is insufficient. The challenge evident in the literature is that societal impacts are quite often considered independent of the industrial system that was created by the society it serves. Industries are responsible for much of the impacts experienced by society and the life within it. Consider the philosophical existence of industry. In the U.S., if the Industrial Revolution never happened, could society claim a relatively better or worse state of quality? The point to realize is that without one, industry or society, the other may not exist and societal impacts would be drastically different than they are today. There is a clear need to tie industrial activity to societal impacts. However, many social indicators that attempt to measure social impacts are created independent of industrial production.

There also seems to be confusion throughout the literature regarding MMIs for social impacts. Many researchers claim a social indicator is significant when the values observed or tested are simply measures. An indicator lacking context of purpose or usefulness giving no dependency or relation with some other variable is only a measure, a state-of-being. When a measure is compared to something understood, e.g., another measure from a prior year, a relative position of comparison is created: a metric. A metric identifies context and purpose of what to measure and how, but makes no statement of condition, e.g., good, bad, or good enough. Metrics can be evaluated together to establish a baseline for which all following metrics or measures are compared. Where there exists an understanding of a baseline value, an indicator can be created. An indicator will identify the condition and relative nature of something measured. The gap in knowledge identified here is where much of the following work concentrates. In addition, special case studies regarding highly important U.S. industries present the proposed metrics in a tangible and accessible way.

The case studies included in the work focus on select industrial sectors within U.S. manufacturing. Both economic and social importance to a nation is explored for a special cluster of industries [Porter, 2000] in the U.S.: the Advanced Manufacturing (AM) industrial cluster [Muro et al., 2015]. The AM cluster is a group of industrial sectors within the North American Industrial Classification System (NAICS) with recognized capacity for innovation and technological advancement [NAMRI/SME, 2014; Proceedings of the National Academy of Sciences, 2017]. The AM cluster of sectors is highly integrated into all other sectors of the national economy and provides valuable performance enhancing products to all tiers of customers, e.g., metal alloys, computer servers, robotics, and energy storage [Muro et al., 2015]. AM sectors in the U.S. are likely to be the portion of manufacturing economy that will grow in the coming years [Jin et al., 2017; Muro et al., 2016; Tassey, 2014]. Consistently, the AM sectors offer some of the highest paying jobs within the manufacturing sectors due to the required skill level of labor, while in comparison, other manufacturing sectors compete against low-wage countries for market share [Miles, 2018]. Given the importance of AM, it is appropriate to understand how SIs will change as a result of growth in this key sector of the U.S. economy.

1.3 Objectives

A need exists to describe, in a measurable and quantifiable way, how people are affected by industrial activity. This thesis endeavors to address this problem through the following objectives.

1.3.1 Economic Input-Output Social Impact Assessment

Objective: Identify and describe a method to quantify social impacts utilizing economic input-output (EIO) analysis and publicly available datasets.

- In this thesis, a method to establish an economic input-output social impact analysis (EIO-SIA) will be developed. This method will build upon and expands the basic EIO procedure by incorporating industry cluster expansion and integrating social impact metrics.
- The EIO-SIA method will then be demonstrated using U.S. Bureau of Economic Analysis (US BEA) economic data from year 2012 with two proposed SI metrics: i) cost of injuries, COI, and ii) employees below the living wage, ELW. COI and ELW are metrics based on work that identified the best social indicators for each stakeholder-needs category (Figure 1.1) from Hutchins et al. [2019]. Suggested metrics address two fundamental employee needs, i.e., safety/security and basic, from the perspective of the organization or industry.
- The specific metrics selected were chosen to demonstrate the utility of the EIO-SIA methodology using publicly available U.S. data. The analysis will show how the AM industry cluster economic contributions affect social performance at a national level.

1.3.2 Stakeholder-Needs Metrics

Objective: Identify and create quantifiable metrics to describe social impacts for the stakeholder group workers/employees, using data from public sources.

- Use stakeholder-needs framework (Figure 1.1) to build a suite of social impact metrics for stakeholder worker/employee.

- Identify a clear dependent relationship between industrial economic output, e.g., gross state product, total value added, or total commodity output, and created social impact metric.
- Discuss national social performance for industrial sectors in response to worker/employee needs.

1.3.3 Regional Social Competitiveness

Objective: Identify and analyze region-level application of methods presented above utilizing the SI metrics presented above to describe regional industrial social impacts.

- Validate scalability for metrics created at National level by applying EIO-SIA model to regional level economic data.
- Assess regional social impacts within the U.S. in total for all sectors.
- Analyze the social performance of AM-Advanced Manufacturing compared to sector 31R-Rest of Manufacturing, using the employee-need metrics described above.

1.4 Synopsis

Work relating to the objectives from section 1.3 is presented in Chapter 2, 3, and 4, respectively. To develop a quantitative description of industrial social performance, Chapters 2, 3, and 4 are structured such that each is a standalone contribution to scientific literature. As a result each chapter is presented with independent literature review, exclusive method and subsequent results, followed by discussion, summary, and conclusions, where applicable. Finally, in Chapter 5, general conclusions and further research directions are presented.

CHAPTER 2. A METHOD FOR ECONOMIC INPUT-OUTPUT SOCIAL IMPACT ANALYSIS WITH APPLICATION TO U.S. ADVANCED MANUFACTURING

This chapter was published: Richter, J. S., Mendis, G. P., Nies, L., and Sutherland, J. W. (2019) A method for economic input-output social impact analysis with application to U.S. advanced manufacturing. *Journal of Cleaner Production*, 212, 302-312. doi:10.1016/j.jclepro.2018.12.032

Keywords: Social impact metricsInput-output methodIndustrial social performanceEconomic allocationAdvanced manufacturing

2.1 Abstract

Manufacturing, and in particular Advanced Manufacturing, shows high levels of economic activity, enables technological growth and innovation in all other industrial sectors, and employs a large portion of skilled labor. While Advanced Manufacturing is integral to the economy, the effects of production activity on society are still largely unknown. The lack of understanding of social performance, i.e., how stakeholder needs are impacted by industrial production, limits the capacity of decision makers to make fully informed choices. Fortunately, large quantities of economic and social data exist in the public domain, enabling the creation of metrics that can describe how industry directly affects society. However, methods have not been developed to evaluate these data for social impacts. A multidisciplinary modeling approach, economic input-output social impact assessment, is employed to integrate economic production with two social impact metrics based on employee safety/security and basic needs: Cost Of Injuries and Employees below a Living Wage. Applying the economic input-output social impact assessment model to Advanced Manufacturing industrial sectors, 10.5% and 5.6% of the total national social impacts were found to be attributable to Advanced Manufacturing for the Cost Of Injuries and Employees below a Living Wage metrics, respectively. In comparison, the Advanced Manufacturing cluster is responsible for 7.8% of the total national economy. The economic input-output social impact assessment method is demonstrated to provide a measurable path forward to evaluate the social performance of industries.

2.2 Introduction

The last several decades have seen the emergence of sustainability as a key benchmark of industrial function. In fact, one of the pillars of sustainability, economic performance, has been used for centuries to judge industrial efficiency. Over the last thirty years, a second dimension of sustainability, environment, has increasingly become a consideration for industrial decision makers. Recently, the third dimension of sustainability has begun to be considered: society. Such importance is placed on the social dimension that 8 of the 17 United Nations Sustainable Development Goals [United Nations, 2015] can be directly attributed to social issues and an additional 4 can be linked to social accessibility challenges.

The social dimension of sustainability is suggested to incorporate all aspects of society, culture, and human interaction. The relatively abstract nature of social sustainability requires a comprehensive multidisciplinary approach to address the underlying complexity. From the social sciences, researchers have used stakeholder theory [Crane & Ruebottom, 2011; Dewey, 1927; Mitchell et al., 1997] to identify a diverse set of stakeholder groups for companies [Hutchins et al., 2013; UNEP-SETAC, 2009]. From the psychological sciences, the theories of human and societal needs [Maslow, 1958; Maslow et al., 1970] have been used to identify levels of requirements for the aforementioned stakeholders [Esteves & Vanclay, 2009; Max-Neef et al., 1992]. The intersection of these two theories provides a framework in which needs can be defined for each stakeholder group (Figure 2.1). These theories have helped guide a partial understanding of societal systems but lack the measurable component needed for effective management.

		Stakeholder Group					
		Society/ Public	**Local Community**	**Value Chain/ Suppliers**	**Owners/ Shareholders**	**Consumers/ Customers**	**Workers/ Employees**
Needs Level	**Actualization**						
	Esteem						
	Affiliation						
	Safety/Security						
	Basic						

Figure 2.1 - Framework for the intersection of stakeholder and human needs theories. Adapted from Hutchins et al. [2010].

Developed in parallel with both the stakeholder and needs theories, but typically not used in conjunction, impact assessment (IA) arose in the 1970s out of a political imperative to acknowledge and predict the impact that a project may have on the surrounding areas and communities [Freudenburg, 1986]. The social aspects of IA were slow developing behind environmental considerations until the late 1980s, but have recently been adapted for use with life cycle assessment (LCA) methodologies [Chhipi-Shrestha et al., 2015; Feschet et al., 2013; Hsu et al., 2013; Parent et al., 2010; Reitinger et al., 2011; Wang et al., 2016; Wu et al., 2015]. Social IA, or SIA, and LCA have been combined to quantify and predict social impacts within an analytical measurement framework, often referred to as social life cycle impact assessment (SLCIA or S-LCIA). These tools have helped guide a partial quantification of societal impacts but lack causal linkages between activity and impact, sufficient and publicly available data, suitable and applicable metrics, and consensus on what should be measured and how to do so [Chhipi-Shrestha et al., 2015; Ebrahim & Rangan, 2014; Morrison-Saunders et al., 2014; Rasmussen et al., 2017; Sutherland et al., 2016].

While both economic and environmental performance metrics are well documented, social performance metrics are gaining consensus based on the foundational indicator development effort of UNEP-SETAC [2009] and Benôit-Norris et al. [2013]. Over the last decade, the research literature has attempted to identify, evaluate, and quantify aspects of social performance [Husgafvel et al., 2014; Popovic et al., 2018; Rajak & Vinodh, 2015; Sutherland et al., 2016]. Much of the current work has focused on frameworks and indicator identification for social impacts [Arce-Gomez et al., 2015; dos Santos & Brandi, 2015; Gómez-Paredes et al., 2015; Hutchins et al., 2010; Hutchins et al., 2019; Kühnen & Hahn, 2017; Popovic et al., 2018; Shin et al., 2015], but applicability is not always universal.

In a recent review of social LCA frameworks and indicators, Sureau et al. [2017] suggested that a clear line could not be drawn between frameworks and indicators that assess processes or performance and those that assess impacts. Further, Sureau et al. [2017] recommend assessment criteria that is suitable for the specific situation, i.e., “legitimate and meaningful for stakeholders,” potentially leaving much up to the discretion of the user. While suitability of frameworks and indicators may be judgment-based, the data supporting them may not be readily accessible or even adaptable across a variety of situations. In contrast, public datasets abound with social impact (SI) data, but lack the framework with which to contextualize the impact with an action. Further, the absence of a baseline value, or simple starting point, for any SI described in either the framework/indicator or public datasets perspectives above makes understanding of what is relatively good or bad, positive or negative, a challenge to discern. Without publicly available product-, industry-, or supplier/consumer-related data, it is also difficult to estimate current, or predict future SIs. Fortunately, lessons can be gleaned from methods used to create and evaluate both economic and environmental performance.

The multidisciplinary method pursued in this paper integrates social impact assessment (SIA) with an input-output (IO) economic model. This method evaluates social performance using the IO analysis framework and closely mirrors the procedural developments established in economic input-output environmental LCA, or EIO-LCA [Hendrickson et al., 1998; Joshi, 1999; Lave et al., 1995; Matthews & Small, 2000]. IO models characterize the monetary flows in an economy where it is understood that materials, goods, services, and embedded labor move opposite to the monetary flows as depicted in Figure 2.2, where sector 1 is both a producer of goods, labor, and services flowing to itself and sector 3, and a consumer of goods, labor, and services from sector 2. For a typical economy, there are many industrial sectors, both producers and consumers, where flows of goods, labor, services, and money are in both directions. A large economy may have hundreds of industrial sectors depending on one another, creating a vast network of interconnected industries. IO models may be used to capture the economic portion of the complexity inherent in modern global economies. Utilizing national IO data with the IO models linked to publicly available social data can highlight industrial influence, interconnectedness, and areas of social impact challenges. The combination of SIA with IO analysis further generates insight into how integral an industry or group of industries is to the success of the economy.

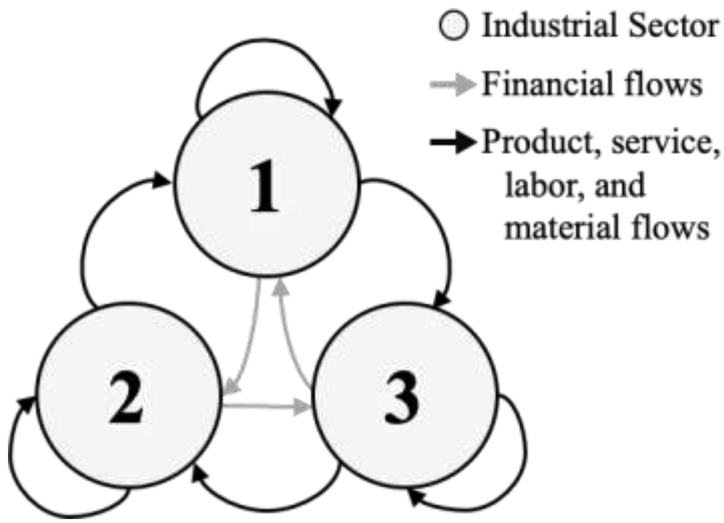

Figure 2.2 - Simplified model of inflows and outflows of capital, goods, services, and labor within and among industrial sectors. Producing sectors initiate each arrow which flow to the consuming sectors at the end of the arrow.

Both economic and social importance to a nation is explored for a special cluster of industries [Porter, 2000] in the U.S.: the Advanced Manufacturing (AM) cluster [Muro et al., 2015]. The AM cluster (also referred to as AM industrial sectors, or simply AM) is a group of six industrial subsectors within the North American Industrial Classification System (NAICS) that are a part of the aggregated Manufacturing (31G) industrial sector (See Table A.3 for a list of NAICS industrial sector classifications). AM is broadly recognized for a leading capacity to create innovative technological advancements [NAMRI/SME, 2014; Proceedings of the National Academy of Sciences, 2017]. The AM cluster of sectors is highly integrated into all other sectors of the national economy and provides valuable performance enhancing products to all tiers of customers, e.g., metal alloys, computer servers, robotics, and energy storage [Muro et al., 2015].

AM sectors are likely to continue to be the portion of manufacturing economy that will grow in the U.S. in the coming years [Jin et al., 2017; Muro et al., 2016; Tassey, 2014], outpacing growth in the remaining 15 manufacturing subsectors by 24% from 2005 to 2015. In 2015, the six subsectors comprising the AM cluster were responsible for over 43% of the total manufacturing output and 8% of the total national output [United States Bureau of Labor Statistics, 2015], and employed over 48% of the manufacturing workforce in the U.S. [BLS, 2015]. Consistently, the AM sectors offer some of the highest paying jobs within the manufacturing sectors. The annual mean wage for the AM cluster was nearly 28% higher that the remaining manufacturing sectors, which may be due in part to the advanced skill level of labor required by AM sectors. In comparison, other manufacturing sectors compete against low-wage countries for market share [Miles, 2018]. Given the importance of AM, it is appropriate to understand how SIs will change as a result of growth in this key sector of the U.S. economy.

The objective of this paper is to develop a method that builds upon and expands the basic EIO procedure by incorporating industry cluster expansion and integrating social impact metrics to establish an economic input-output social impact analysis (EIO-SIA) method. The EIO-SIA method is then demonstrated using U.S. Bureau of Economic Analysis [U.S. BEA, 2012] economic data with two proposed SI metrics: i) cost of injuries, COI, and ii) employees below the living wage, ELW. COI and ELW are metrics based on work that identified the best social indicators for each stakeholder-needs category (Figure 2.1) from Hutchins et al. [2019]. The suggested metrics address two fundamental employee needs, i.e., safety/security and basic needs, from the perspective of the organization or industry. These metrics are then used to demonstrate the capability of the EIO-SIA methodology. Utilizing only publicly available U.S. data from the year 2012 ensures consistency through the model and eliminates time as a potential variable in the estimates. In addition, the use of public data ensures the repeatability that is generally lacking, but necessary for model robustness, in application studies. The analysis shows how the AM industry cluster economic contributions affect social performance at a national level.

The subsequent section presents a description of the economic model utilized in the proposed EIO-SIA method, developed with further explanation of recent model extensions, data extensions, and model adaptation for use with public data. Section 2.4 describes the integration of SIs into the economic model, and suggests the calculation of the two metrics used to validate the EIO-SIA method. Section 5 discusses the results of the method applied to the AM cluster and Section 6 presents a summary followed by concluding remarks.

2.3 Economic Input-Output Analysis Extensions

Wassily Leontief [1936, 1970, 1986] is widely credited for pioneering the theory and methodologies associated with economic input-output (EIO) modeling. Section A.2 briefly reviews the EIO modeling approach. The sections that follow explain model adaptations that are needed for industry cluster derivation and transformations to the basic model that are required when using common public IO tables of data.

2.3.1 Economic Input-Output Model Extensions

Depending on the interest of the modeler, an IO model may be used to describe international trade among countries, national supply chains, industrial sectors in an economy, etc. IO modeling has evolved over the last fifty years, from evaluating the labor implications of industrial production [Hardadi & Pizzol, 2017; Rugani et al., 2012; Simas et al., 2014] to monetarily quantifying the environmental impacts of products, services, and international trade [Hendrickson et al., 1998; Leontief, 1970; Matthews, 2007; Minx et al., 2009; Peters et al., 2011; Wiedmann, 2009]. Recent adaptations and extensions to the IO models include analysis of waste streams and waste generation [Lenzen & Reynolds, 2014; Liao et al., 2015; Nakamura & Kondo, 2002], water transport and consumption [Dilekli et al., 2018; Duarte et al., 2002], energy production and consumption [Chen & Chen, 2015; Lenzen, 1998; Noori et al., 2015], and the most recent SI-related extension exploring the import and export of international corruption [Xiao et al., 2017]. The scholarly work using IO models for environmental sustainability has served as a quick screening tool to help identify the need for deeper analysis, e.g., process- or unit-based evaluation, especially considering the growing global attention to the impacts of human activities on the environment. For future work to effectively capture social impacts, the available data requires extensive transformation.

2.3.2 Economic Input-Output Data Extensions

The basic EIO model has been applied through many modern adaptations that are focused on the entire economy. The EIO model can effectively address multiple levels of data aggregation but the navigation between major sector and disaggregated subsectors has received little attention and no research application. In addition, it must be noted that EIO models have only one data point that represents a flow from one sector to another. With such limited data, the assumption of a proportional linear relationship between input and output is required, e.g., a 25% increase in output mandates a 25% increase in the input. The following sections describe typical sources of public IO data in the U.S., a method for major sector disaggregation and industrial cluster creation, and the procedure to transform non-square IO matrices for EIO model calculation.

2.3.2.1 Input Output Data - Source and Aggregation

Sources for U.S. National public IO data are available for multiple levels of industrial activity. The most common IO tables are compiled annually by the U.S. BEA in 15 sector aggregated (1- and 2-digit NAICS) or 71 industry summary (3- and 4-digit NAICS) levels. Each of the 71 industries is a component of one of the 15 sectors, with similar industries aggregated into one of the 15 sector hierarchy. The IO tables describe the economic flows from industrial sectors into and out of one another. In this work, the two sets of tables used are the 2012 Make and Use of Commodities by Industries, After Redefinitions at Producer's Prices in both the 15 sector and 71 industry varieties. Make tables show the production of commodities by industries and use tables show the uses of commodities by intermediate and final users. When the desired IO table is constructed, a dimensionally-equal table of SIs can be integrated with the EIO model to offer insight into a more comprehensive social sustainability analysis of economic production.

2.3.2.2 Sector Expansion - Industrial Sector Cluster Derivation

Major industrial sectors, e.g., Agriculture, Manufacturing, and Information, are comprised of many hundreds of subsectors within the NAICS categorization. Often the higher levels of aggregation, i.e., 15 sector, can be used to describe national trends, but fail to capture the detail of a specific subsector with interesting performance attributes. On the contrary, the disaggregated sector, i.e., 71 sector, data may provide a wealth of information but fail to present any clear observable trends or relationships. Data from both the high order aggregated sectors and the disaggregated subsectors can be used in conjunction to extract interesting clusters of industrial productivity. Figure 2.3 captures the increasing complexity that results from cluster creation and includes the bidirectional relationships that may change when industrial clusters are extracted from the higher order industrial sectors. Both clusters 2a and 2b in Figure 2.3 result from a disaggregation, reorganization, and grouping of subsectors, as described in the example with AM and 31R above, within sector 2 from Figure 2.2.

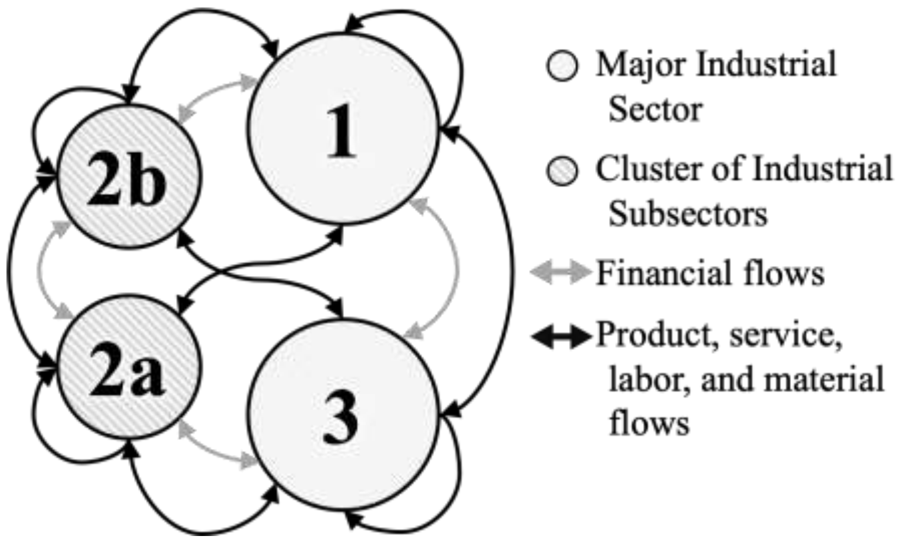

Figure 2.3 - An example expanded economy with sector 2 (Figure 2.2) disaggregated into sectors 2a and 2b. Flows are bidirectional suggesting that sectors are both suppliers and consumers of products, services, labor, material, and financial value.

To calculate the expansion of the 15 sectors and integrate detail for the AM cluster of industries, the 71 industry table entries for AM (NAICS 331-3364 - identification of the complete BEA 15- and 71-sector NAICS numbering and naming is found in Table A.3) must be re-organized according to the following:

$$O_{ij}^{target} = \sum_i \sum_j O_{ij}^{expansion} \tag{2.1}$$

where O is the entry at each intersection of sectors in the IO table, from sector i to sector j (See **Table 2.1** for a sample IO expansion table). The expansion entry is found in the 71-industry IO table and the target, in the case of this work, is the set of advanced manufacturing cluster of industries and will be used in the 15-sector aggregated IO model.

Table 2.1 - Input-output expansion of an economy use table with industry sector interactions.

		Industrial Sector (j) "to" or "consuming"				Intermediate Output (**O**)	Final Demand (**F**)	Total Commodity Output (**X**)
		1	2_a	2_b	3			
Industrial Commodity (i) "from" or "producing"	1	O_{11}	O_{12a}	O_{12b}	O_{13}	O_1	D_1	X_1
	2_a	O_{2a1}	O_{2a2a}	O_{2a2b}	O_{2a3}	O_{2a}	D_{2a}	X_{2a}
	2_b	O_{2b1}	O_{2b2a}	O_{2b2b}	O_{2b3}	O_{2b}	D_{2b}	X_{2b}
	3	O_{31}	O_{32a}	O_{32b}	O_{33}	O_3	D_3	X_3
	Intermediate Input (I)	I_1	I_{2a}	I_{2b}	I_3			
	Value Added (V)	V_1	V_{2a}	V_{2b}	V_3		GDP	
	Total Industry Output (X)	X_1	X_{2a}	X_{2b}	X_3			

To extract one subsector (or cluster of subsectors) from a major, or higher order, sector requires the subsector outputs be subtracted from the outputs of the higher order NAICS (1- and 2- digit). For example, the major sector of Manufacturing (31G) required $1.94 billion worth of commodities from industries in the 31G sector in 2012. Extracting AM from the 31G sector, it can be seen that AM provides over $967 million (of the $1.94bn) to all of 31G. Just over $857 million is utilized in AM (self-consumption) and the remaining $110 million is required by the rest of manufacturing (31R). In turn, 31R provides the balance of $973 million to 31G, where nearly $848 million is used in 31R (self-consumption) and the balance of about $125 million is used by AM. What previously was one entry in the table for 31G thus becomes four entries (two new rows and two new columns), a column and row for the AM cluster and a column and row for the rest of manufacturing (31R). The associated entries take the form

$$O_{ij}^{rest\ of\ main\ sector} = O_{ij}^{main\ sector} - O_{ij}^{target} \tag{2.2}$$

Each adjustment to a sector requires column and row additions to the IO tables. An example of this can be seen in Table 2.1 and Figure 2.3, where sector 2 (Figure 2.2) is disaggregated into 2a and 2b (both shaded). The sector and industry cluster expansion affects all other components of the table, i.e., Final Demand, Total Commodity Output, Value Added, and Total Industrial Output, where the grand totals of the entire economy, e.g., GDP, will remain unchanged.

The new IO tables with subsector expansion and ensuing industry cluster creation are now in a form where the Leontief inverse may be calculated. Quite often however, IO matrices from public data are not able to be inverted due to non-square dimensions. The transformation of non-square IO matrices requires additional steps described in the following section.

2.3.2.3 Non-square Make and Use Tables

Most IO models, and the research incorporating them, assume the direct requirements matrix, A (defined in Section A.2), to be square and invertible. This is typically not the case with publicly available data unless the user truncates the Use tables (Industry-by-Commodity, see Section 2.3.2.1) to exclude the commodity entries of Used - Scrap, used, and secondhand goods, and Other - Noncomparable imports and rest-of-the-world adjustments. While these are a minor fraction of the total economic output, the aforementioned commodities play a vital role as material resource inputs for the manufacturing sector and should not be neglected. A thorough description of how to accommodate a non-square use matrix for creation of the direct requirements matrix can be found in Miller & Blair [2009], and is summarized below.

For the model in this text, all commodities within the Use table are included and the resulting direct requirements matrix is rectangular in dimension. Incorporating the Make table, which is inversely rectangular to the Use table, is therefore necessary.

First, assume the rectangular direct requirements matrix is B, where

$$B_{ij} = O_{ij}/X_j \tag{2.3}$$

and X is the total commodity output for sector j. A coordinated analog using the Make table is required where

$$D_{ij} = V_{ij}/\mathrm{Q}_j \tag{2.4}$$

and D represents the market share of an industry for the commodity output, V is the value of the industry contribution to the commodity, and Q is the total commodity output, all with flows from i to j. The resulting Market Shares matrix (D) is combined with the direct requirements matrix (B) to create the requisite square matrix for Eq. (A.8), where

$$\mathbf{A} \cong \mathbf{BD} \tag{2.5}$$

Replacing all A in Eqs. (A.5-A.8) with BD, results in the following

$$[\mathbf{I} - \mathbf{BD}]^{-1}\mathrm{F} = \mathrm{X} \tag{2.6}$$

where $[\mathbf{I}\text{-}\mathbf{BD}]^{-1}$, the Leontief inverse (Section A.2), is a Commodity-by-Commodity total requirements matrix. A total requirements matrix identifies the total economic activity required to create 1 unit (or $1) of commodity output, and is often larger than the $1 of commodity output.

Additional versions of the total requirements tables can be created, e.g., Industry-by-Industry and Industry-by-Commodity, based on final reporting needs. For this paper, the analysis will focus on the Industry-by-Commodity total requirements tables (a rectangular matrix). A further calculation is needed, where

$$\mathrm{D}[\mathbf{I} - \mathbf{BD}]^{-1}\mathrm{F} = \mathrm{X} \tag{2.7}$$

adjusts the Leontief inverse by the market shares matrix resulting in the Industry-by-Commodity total requirements matrix. The following section expands the use of EIO to include the calculation and evaluation of social impacts from economic activity.

2.4 Extending the EIO Model to Social Impacts

Combining an SI matrix with the EIO model allows for the calculation of industry-related impacts once appropriate metrics for SIs are selected. However, it is to be noted that care must be exercised in identifying suitable and measurable social metrics. An ideal social metric for an IO application would demonstrate a connection to economic activity as shown in Figure 2.4 (a negatively sloped, or decreasing, relationship is also possible). The trend can identify growth of a social benefit, e.g., charitable giving for local schools, or the reduction of a social cost, such as decreasing unskilled labor by workforce development and training.

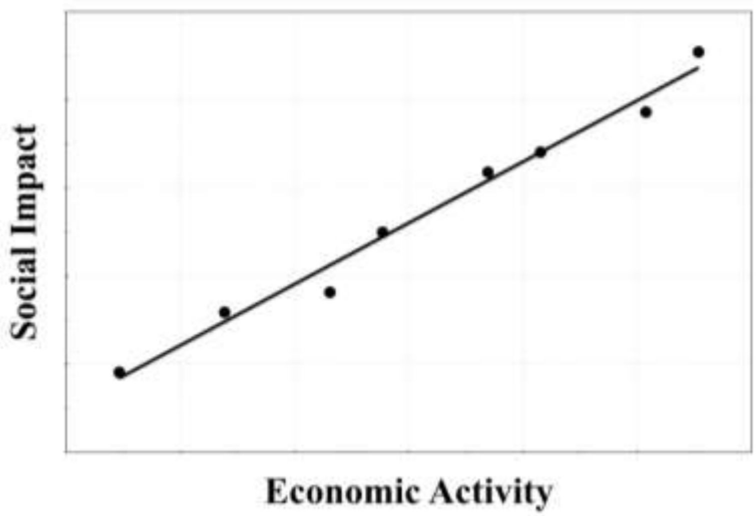

Figure 2.4 - A possible relationship between economic activity and social impact.

Commonly assumed in EIO models however, a single data point for social impact measures is expected to describe a linear relationship between a social outcome and economic production. The assumed linear relationship is incorrect for a vast majority of the suggested “indicators” throughout the literature, where a typical indicator relationship to economic production is anything but linear. While the literature presents such measures as wages, jobs, working hours, and injuries as capable “indicators” [Hardadi & Pizzol, 2017; Husgafvel et al., 2014; Kühnen & Hahn, 2017; McBain & Alsamawi, 2014; Papong et al., 2016; Popovic et al., 2018; Searcy et al., 2016; Zhang & Haapala, 2014] of industrial performance, these measures assume an observable relationship with industrial economic production, but are not validated as such. A trend in relationship with economic production is necessary because any expected growth or reduction in an industrial sector output will be associated with a corresponding change in associated social impacts. At best, measures suggested throughout the literature can identify the total impact created by an industrial sector but are unable to provide a mathematically justified prediction with variable industrial sector output.

Consider the example of wages paid to employees in a high-tech device industry. If that industry sees a growth in demand due to a recent market disrupting innovation, is it fair to predict that employee wages or jobs will increase accordingly? Will working hours per employee also increase? Should the industry expect a drastic increase in injuries as well? Although the answer to these question may be affirmative, there is no present method to validate each answer in the current state of misunderstanding for measures, metrics, and indicators (MMIs). The research literature is rife with the interchangeable use of the terms measure, metric, and indicator to represent the quantifiable measurement of social impacts. For this work, the definitions of MMIs were adopted from Sutherland et al. [2016], where a measure is a value, count, or identity of something; a metric places the measure in context, and offers a comparison to a known value; and an indicator can then compare a measure or metric to an understood baseline of behavior. The social impact measures found in the public domain require transformation before becoming social impact metrics. The following sections describe the data and transformations for the two proposed social impact metrics in this work. An additional challenge is evident when using data that represents social impacts: applicability. Many proposed social impacts are currently unrelated to economic output and cannot therefore be attributable to the economic activity of industry. The underlying factors causing some other social impacts are likely outside of direct economic influence, which does not imply that they lack importance, validity, or worthiness of investigation. Connecting unrelated social impacts to IO models may provide little benefit, and unnecessarily complicate any prediction of future social impacts with changes in economic activity.

Modeling SIs as a function of economic flows ties production activity to the people both responsible for and affected by production activity. Examining the mathematical details of the EIO model and its connections to the SIs reveal insights that provide for a deeper understanding of the interactions at work in the system.

With total, i.e., both direct and indirect, requirements (BD) and total economic output (X) for each sector known, a vector of SI factors for each sector can be calculated. Utilizing again the Leontief inverse yields Eq. (2.8),

$$\mathrm{S} = \mathbf{R}\mathrm{X} = \mathbf{RD}[\mathbf{I} - \mathbf{BD}]^{-1}\mathrm{F} \tag{2.8}$$

where S is the vector of social impacts (e.g., cost of injuries or employees below the living wage), and **R** is a diagonal matrix of sector-related SI per dollar of economic output. The intermediate multiplication of $\mathbf{RD}[\mathbf{I}\text{-}\mathbf{BD}]^{-1}$ creates a matrix of SI allocation and is utilized to identify industrial sectors of significant influence. This calculation method follows EIO-LCA for environmental impacts very closely and quantifies the social burden (or potential social benefit) produced from any change in industrial economic production.

2.4.1 Calculation of Selected Social Metrics

Quantifiable social metrics linked to industrial economic activity, i.e., SI per dollar output, enable the construction of an SI matrix, i.e., Eq. (2.8). In this paper, two metrics designed to be related to economic activity, Cost of Injuries (COI) and Employees Below the Living Wage (ELW), were created. These metrics address the worker/employee stakeholder basic and safety/security needs from the stakeholder-needs categorization framework presented in Figure 2.1, and are used to validate the EIO-SIA method.

2.4.1.1 Cost of Injuries

Injuries happen at work, and it is expected that some work sites (industries) would be more prone to accidents and injuries than others. There are a number of ways to characterize injuries, e.g., quantity, type, and severity of injuries. Injuries severe enough to require time away from work cause loss of productivity and create a negative impact, or cost, to both the employer and the employee. In this paper, the selected injury metric, COI (cost of injuries), is based on a combination of industrial productivity, injury severity, and length of time away from work. The COI metric accumulates total days away from work using statistics publicly available through the U.S. Bureau of Labor Statistics (BLS): Injuries, Illnesses, and Fatalities datasets. The accumulated days away from work (DAFW) are then combined with the industry sector productivity per employee to create the COI metric:

$$COI_i = \left(\frac{X_i}{EMP_i}\right) * \sum_i \frac{DAFW_i * DAFWr_{LB}}{50*5} \tag{2.9}$$

where X and EMP are total commodity output (see Section 2.3.2.2 and Table 2.1) and employees in sector i, respectively. DAFW represents the count of days away from work, while DAFWr is the range and LB is the lower bound of the range for the “time away from work” range. Additionally, the constants in the denominator establish the working weeks in a year and working days in a week, which are assumed to be equivalent across all sectors. The constant for working weeks and days per year is a simplifying assumption incorporated for model utility.

2.4.1.2 Employees Below the Living Wage

The compensation that employees receive for work helps to address their basic needs. The compensation can come in the form of benefits, training, stocks, and/or wages. Wages vary among and within industrial sectors, and therefore provide a valuable measure of industrial sector wage competitiveness. Wage variations in conjunction with regional living wage (LW) levels, i.e., cost-of-living expenses, means that there are differences in the degree to which compensation meets the basic needs of employees within each industrial sector. The selected wage metric ELW, Employees below the Living Wage, is based on a combination of annual wage levels, number of employees, and cost-of-living expenses. The ELW metric calculates the fraction of employees below a LW level [Glasmeier, 2014; Ryan, 1906], e.g., for a household with 2 Adults (one of whom is working) and one Child, in each industrial sector using statistics publicly available from the BLS Occupational Employment Statistics (OES) datasets. The fraction is combined with total employment per industrial sector to calculate national values for the ELW metric as described by

$$ELW_j = \sum_r pnorm_j * EMP_j \tag{2.10}$$

where pnorm is the employment fraction below the LW threshold and EMP is the number of employees in industrial sector j. Values are summed across region r (in this case, each state). ELW can be compared across cities, counties, states, regions, and industrial sectors. The household considered in the ELW metric does not reflect or consider the household that consumes final products from the IO tables. An extension that considers household consumption is beyond the scope of this work.

2.4.2 Social Impact Metrics Related to Economic Production

The two metrics, COI and ELW, were chosen because both show an observable trend when compared to varying levels of economic output. Considering economic expansion of an industrial sector, the IO model assumes a mathematically scalar expansion for all coordinated sectors via the direct requirements matrix B (refer to Section 2.3.3). The linear economic relationship observed using the IO model provides a strong indication of how integrated an economy may be. In previous literature, this linear relationship has not been described for social impacts. A single measure is commonly used but is insufficient in describing a meaningful relationship to economic expansion. In other words, the rate at which a social impact changes with economic production is integral to predicting the social impacts resulting from additional industrial activity. In addition, the SI metrics are comprised of data that is not immediately connected to economic output and created independent of the IO tables.

2.5 Results and Discussion

At the National level, IO tables can be used to describe how money, labor, goods, and services flow between all U.S. industrial sectors. Unlike the flow of goods and services however, in EIO-SIA, SIs are allocated to input sectors based on economic contributions from sector to sector. The resulting SIs from industrial production can be evaluated for stakeholders at various needs levels. The two metrics assessed in this work detail the primary needs levels, i.e., basic needs and safety & security needs [Maslow et al., 1970], for the stakeholder group employees. The results from this analysis are discussed below.

The first major data step requires evaluating the total SIs for individual sectors. The resulting values were then compared to the total commodity output for each respective sector. In essence, each individual sector creates a total amount of social impact, when compared to every dollar of output for that same sector, an SI multiplier is created. The AM SIs per dollar of output, or SI multipliers, are summarized in Table 2.2, where the values shown are used as the diagonal entries for each SI in matrix **R** from Eq. (2.8). It may appear straightforward to multiply any change in industrial sector economic output by the multipliers of Table 2.2, but this would be misleading. Table 2.2 cannot directly be used to calculate the effect of economic expansion on social impacts. To use the values in Table 2.2, they must be combined with the economic flows, i.e., IO tables, to obtain the expected sectoral level social impacts across the economy. The AM multipliers show that for every million dollar of output, the cost of injury multiplier is $572.76 and the employees below the living wage multiplier is 1.339. The COI multiplier for AM lies between the PROF - Professional and business services ($171.03, min) and 48TW - Transportation and warehousing ($1,368.63, max) sector multipliers. The ELW multiplier for AM lies between the 22 - Utilities (0.272, min) and 7 - Arts, entertainment, accommodation, and food services (11.420, max) sector multipliers. While AM is within the low-high range and near the median for both SIs in Table 2.2, it will become clear that these multipliers are an intermediate output, and they must be combined with the economic flows to identify the true allocated SIs in the economy.

Table 2.2 - Social impact multipliers extracted from the diagonal R matrix for all sectors in the U.S., 2012. Both COI, cost of injuries, and ELW, employees below the living wage, are evaluated per US$ million output.

NAICS ID	Sector Name	Social impact multiplier	
		COI (US$)	**ELW (Employees)**
11	Agriculture, forestry, fishing, and hunting	708.06	0.834
21	Mining	584.82	0.609
22	Utilities	501.85	0.272
23	Construction	753.01	2.727
31R	Other manufacturing	492.63	1.216
AM	**Advanced Manufacturing**	**572.76**	**1.339**
42	Wholesale trade	581.38	2.275
44RT	Retail trade	413.20	10.582
48TW	Transportation and warehousing	1368.63	3.053
51	Information	386.50	0.999
FIRE	Finance, insurance, real estate, rental, and leasing	273.16	0.835
PROF	Professional and business services	171.03	2.874
6	Educational services, health care, and social assistance	458.42	7.391
7	Arts, entertainment, recreation, accommodation, and food services	317.13	11.420
81	Other services, except government	336.41	4.149
G	Government	1329.78	1.708
Median for total economy		497.24	1.99

Consider an expansion, or growth in final demand, F_{AM}, of \$1bn in the AM sectors, which produces economy-wide consequences. The effects that this AM sector expansion has on the COI and ELW SIs for every other sector of the economy are shown in Table 2.3. The COI for AM is slightly greater than 70% (\$919,146) of the total COI impact, whereas the ELW for AM is slightly less than 58% (2,148) of total economy-wide ELW impact, both resulting from the \$1bn increased demand. The large values for each SI are due to the AM sector requiring a high fraction of total inputs from itself, also known as sector self-consumption (recall Figure 2.2). This AM self-consumption may be driven by a variety of reasons, e.g., technological importance, legal requirement, or foundational component of other value added products. After removal of self-allocation, all other sectors combined realize SIs of \$390,703 for COI and 1,559 for ELW. While it may then appear that some sectors are of lower essential value to AM, all sectors are very interconnected within the economy through the IO model. Economic expansion affects all sectors.

The proposed \$1bn AM sector expansion would bring significant monetary value to the entire economy and also create an influx of nearly 7,000 new employees. The AM sector investment would incur a total of $1.3m in injury costs (COI) and further, of those nearly 7,000 new employees, over 3,700 employees would be unable to meet the basic needs of their household (ELW). The AM investment example highlights how a change in one sector can have economy-wide effects and sector self-consumption can be a large component of the total impacts observed.

Table 2.3 - An expansion of US$1bn to the Advanced Manufacturing sectors and the effects allocated from other sectors in the economy.

NAICS Sector	**Sector Name**	**Final Demand**	**Social Impact (SI) COI‡**		**ELW°**	
		US$bn	US$	%	Employees	%
11	Agriculture, forestry, fishing, and hunting		14,008	1.07	17	0.45
21	Mining		32,991	2.52	34	0.93
22	Utilities		6,773	0.52	4	0.10
23	Construction		5,138	0.39	19	0.50
31R	Other manufacturing		95,750	7.31	236	6.38
AM	Advanced Manufacturing	1	919,146	70.17	2,148	57.95
42	Wholesale and trade		62,881	4.80	246	6.64
44RT	Retail trade		1,899	0.14	49	1.31
48TW	Transportation and warehousing		72,951	5.57	163	4.39
51	Information		11,045	0.84	29	0.77
FIRE	Finance, insurance, real estate, rental, and leasing		18,543	1.42	57	1.53
PROF	Professional and business services		28,610	2.18	481	12.97
6	Educational services, health care, & social assistance		200	0.02	3	0.09
7	Arts, entertainment, recreation, accommodation, & food services		3,901	0.30	141	3.79
81	Other services, except government		3,237	0.25	40	1.08
G	Government		32,773	2.50	42	1.14
All other sectors without self-consumption			390,703	29.83	1,559	42.05
Total		1	1,309,849	100	3,707	100

‡ COI - Cost of Injuries; ° ELW - Employees below the Living Wage; (See 2.4.1 and Eq. (16))

The previous illustration of an AM sector expansion shows that AM directly affects other sectors in the economy, but also has a significant impact on itself. Due to the fact that each sector can require a large portion of commodity inputs from itself, the discussion that follows will focus on a broader analysis of the entire U.S. economy without sector self-consumption. After running the EIO-SIA model, each sector total SIs can be allocated to input sectors. The fractional share of inputs can therefore explain the intensity of social impact that any one sector is assigned by another. As a result, each consuming sector can have a drastically different SI composition. Shown in Figure 2.5 is the amount of SI that each sector has allocated to AM. Also shown in Figure 2.5 is the AM value compared to the largest amount of SI that is allocated to any sector of the economy. For the COI metric, it can be observed that AM is allocated the largest share of the total SI from sectors Mining (21), Construction (23), Information (51), and Other services, except government (81). For the ELW metric, it can also be observed that AM is appropriated a notable share of the total SI from sectors 23, 31R, 51, and 81, although far less than the largest for each sector. Some of these effects can be explained by the sector productivity in the case of COI, or number of employees for ELW, but also suggest the tie to economic output is also strong.

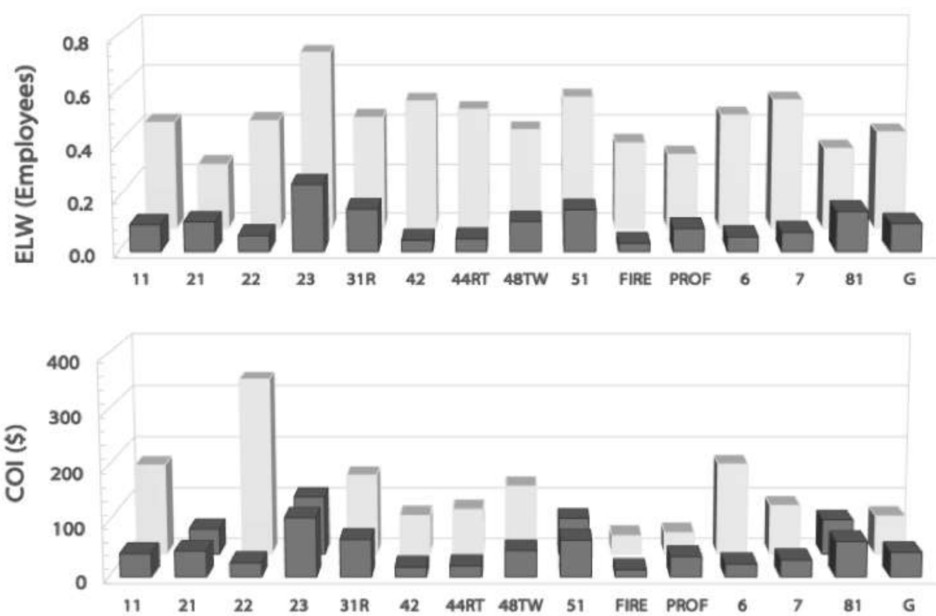

Figure 2.5 - Total social impacts allocated to Advanced Manufacturing (AM, darker bar) from each industrial sector. Also shown are the allocated SIs for the sector with the highest value (lighter bar). Where the SI for AM is highest, both front and back bars are darker. Both Cost of Injuries (COI) and Employees below the Living Wage (ELW) units are displayed per US$ million of output.

The AM cluster is a major industrial (economic) contributor to each sector of the U.S. economy which means AM is also assigned a significant portion of the total SIs for every sector. Consider the NAICS sectors again 21, 23, 51, and 81, where AM is a supplier of technology and innovation. Seen in Table 2.4, the AM sectors contribute 19%, 22%, 18%, and 18% of economic inputs and simultaneously are allocated, for COI, 22%, 24%, 22%, and 23%, and for ELW, 13%, 13%, 10%, and 13%, of total SIs to sectors 21, 23, 51, and 81, respectively. Where the assigned COI fraction of the AM sectors is greater than the economic contribution, the assigned ELW for the AM sectors is a smaller fraction than the economic contribution. This distinction is important because as one industrial sector can be a superior performer for one SI, it may fall short in another social performance metric. Further, consider the service providing industries of Professional and business services (PROF) and Government (G) where each acquires 12% of economic inputs from the AM sectors. Both sectors allocate nearly 15% of COI, and 9% and 8% of ELW respectively to the AM cluster. The trend of AM being assigned a COI fraction greater and an ELW fraction smaller than the economic contribution fraction is consistent in all but COI for the Utilities (22) sector. The anomaly could be due to large economic contributions from other sectors, due to greater social factor allocation, or both.

The breakdown of AM economic contribution to and social impact allocation fractions from all other sectors is presented in Table 2.4. The results suggest that AM is highly impactful to the social performance of the national economy. The SI multipliers allocated to AM from all other sectors in the economy are also summarized in Table 2.4. As seen with the expansion of AM by $1bn described previously, the SI multipliers are the scalar AM-assigned impacts that can be expected if any particular sector of interest experiences an increase in demand. For example, consider a $1bn expansion of the Arts, entertainment, recreation, accommodation, & food services (7) sector by way of creation of a new professional sporting venue. The sector 7 growth would allocate $31,574 in COI and nearly 74 employees in ELW to the AM sectors. The aforementioned values of COI and ELW are simply the portion of the total for sector 7 SI that would be allocated to AM after the expansion. Similar exercises can be done for other sectors with increases in demand to assess the comparative AM assigned SIs. The data for Table 2.4 is enabled by integrating the social impact metrics into the IO tables. The SI metrics are defined independently to have different units, COI in $US and ELW in Number of Employees, while both compared to economic activity (See Section 2.4.1). The capacity of the IO model to calculate diverse SI metrics agnostic of unit, and associated with economic activity, supports the robustness of the method.

Table 2.4 - Summarized Advanced Manufacturing (AM) economic contribution and social impact (SI) allocation fractions (%) with SI multipliers to other industrial sectors.

NAICS Sector	Sector Name	Economic Contribution %	COI*‡		ELW*°	
			$US	%	Employees	%
11	Agriculture, forestry, fishing, and hunting	8.1%	43.25	9%	0.101	6%
21	Mining	19.4%	48.23	22%	0.113	13%
22	Utilities	5.8%	26.14	4%	0.061	4%
23	Construction	21.9%	109.47	24%	0.256	13%
31R	Other manufacturing	12.2%	69.42	12%	0.162	10%
42	Wholesale and trade	5.9%	18.40	7%	0.043	4%
44RT	Retail trade	5.7%	20.53	7%	0.048	4%
48TW	Transportation and warehousing	9.4%	48.83	11%	0.114	7%
51	Information	18.1%	68.23	22%	0.159	10%
FIRE	Finance, insurance, real estate, rental, and leasing	6.9%	13.37	8%	0.031	3%
PROF	Professional and business services	12.9%	37.58	15%	0.088	9%
6	Educational services, health care, & social assistance	5.1%	24.00	5%	0.056	4%
7	Arts, entertainment, recreation, accommodation, & food services	6.7%	31.57	8%	0.074	5%
81	Other services, except government	18.1%	65.60	23%	0.153	13%
G	Government	12.0%	45.32	15%	0.106	8%

* Impact per million $US; ‡ COI - Cost of Injuries; ° ELW - Employees below the Living Wage; (See 2.4.1)

There are however, assumptions that require attention when utilizing the methods presented here. IO models necessitate the assumption that impacts are calculated by a scalar multiplier suggesting a causal relationship from expanding economic production. For example, with every million dollars of output, AM is allocated on average greater than 1.5 employee paid below a living wage that would be required for a 3-person (2 adult, 1 working, with 1 child) household. This quantity may seem trivial, but in 2012, none of the 2-digit NAICS industrial sector total commodity output was less than US$400 billion, and the economy-wide average sector output was nearly US$1.8 trillion [U.S. BEA, 2012]. Across the economy, the total of industrial activity is directly associated with, at minimum, several hundreds of thousands of employees below the living wage threshold.

The approach described here could underestimate the number of employees below the living wage. The living wage data was selected to assume that American household are homogeneous with two adults, one working, with a single child. This is a simplifying assumption for model validation based on the 2012 reported average household size of 2.64 people [Vespa et al., 2013]. Using this household size and associated living wage threshold, this paper has calculated and reported on the employees below the living wage (ELW). These employees are wage earning members of households, whether single or part of a family. Since families constitute about 66% of the households in the U.S., and the average American family has 3.34 people, the ELW metric could underestimate the employees living below their basic need levels. Again, caution must be exercised because the assumption is for single-wage earning households, where a dual-income household facilitates a decrease in the LW threshold and fewer employees below the living wage. Under the current assumption, as soon as another person is added to a household, the LW threshold is raised. Therefore, a demographic analysis of the labor force and households, while beyond the scope of this paper, will be required to optimize the accuracy of the ELW metric.

In addition to the assumptions in the IO model and the ELW metric, the COI metric requires a assumption that all employees are equally productive in a given sector. This simplifying assumption may not capture the cost of time away from work assignable to highly productive employees. Also, a constant for total days of work in a year is assumed for all sectors. It is clear that sectors have varying requirements for work hours, days off, and seasonality, but analysis of this complexity is suggested as continuing work. As a product of these assumptions, the injuries requiring time away from work may be underestimated in sectors with part-time or undocumented workers. Through this effort, it is apparent that large costs of injuries can be assigned to supply chain partners, i.e., another stakeholder in the stakeholder-needs framework of Figure 2.1. Therefore, it would benefit consuming sectors to consider the working conditions, safety protocols, and health and wellness of producing sector workers. An additional challenge for accurately calculating the COI metric is the lack of transparency for supply chains and industry partnerships. Consequently, it is possible that the COI metric is undervalued for total impact.

While the two SIs, COI and ELW, communicate a great deal about the social performance of the AM cluster of sectors and the economy as a whole, complete understanding of social performance requires additional complementary SI metrics to be developed. The framework suggested by Hutchins et. al [2010] in Figure 2.1 presents the opportunity for thirty potential social impact metrics, each representing a different combination of stakeholder and needs level. A comprehensive and quantifiable suite of SI metrics using this framework would enhance the cumulative understanding of industrial social performance. Starting with COI and ELW, work will continue to explore further development of metrics to capture the true social impact of industrial activity.

2.6 Summary and Conclusions

In the search for sustainable solutions, solely focusing on decreasing resource consumption, improving efficiency, and reducing environmental damage is insufficient. Social impacts associated with industrial activity require increasing consideration but remain difficult to measure. The three pillars of sustainability (economy, environment, and society) together require a common platform for evaluation and a method that has clear operational and functional applicability. Previous work attempting to connect economy, society, and environment in a measurable way has been limited mostly to the economy-environment relationship. The quantifiable method linking economy to society described through this work enables a larger overall assessment of the anthropocentric effects of industrial production activity and the resulting societal effects.

The suggested method, integrated economic input-output social impact analysis, EIO-SIA, can be used to estimate SIs across several spatial scales, within industrial sectors, or throughout industrial sector relationships. While this work is explicitly attentive to the U.S. economy, the expanded EIO-SIA method is also capable of describing SIs for important industrial subsectors in any country with developed economic input-output accounts, e.g., OECD countries. Some adjustments may be required for industrial sector coordination from NAICS to the International Standard Industrial Classification (ISIC) revision 3 system or any country specific industry coding system. Identification of high performance clusters in other classification systems may not be a 1-to-1 fit, but similar industrial sectors are present in most IO datasets, e.g., ISICrev3 maps sector codes 27-34 to the NAICS codes for AM. Parallel to economic accounts that may require coordination, the SI data may also require transformation.

Labor-related SI data in other countries may require transformation similar to that proposed in this work. The BLS statistics and measures used to create the COI and ELW metrics are mostly comparable to those provided by the International Labour Organization (ILO). For example, the COI metric utilizes BLS data for time away from work. The ILO analog would access values from the dataset for "Days lost due to cases of occupational injury with temporary incapacity for work by economic activity." Similarly, the ELW metric requires spatially specific wage-related and cost-of-living data. Additional work would be required to access and transform similar international data. The ILO offers the "Mean nominal monthly earnings of employees by sex and economic activity (Local currency)," but is not available at scale smaller than the country level as used in the ELW metric. Also, while the spatially specific cost-of-living data, i.e., Living Wage data, is needed for the ELW metric, adaptation to other countries may require a concerted effort to access country-by-country cost-of-living statistics. As is evident, standardization of data and reporting is an opportunity, but only when a general consensus on MMIs is achieved.

Developing appropriate MMIs will be a continuous challenge going forward. Appropriate social MMIs, and more specifically, SI metrics, to quantify and clarify social impacts will enable progress toward true sustainable performance. Decision makers seeking to reduce their negative social impacts or enhance their social performance can use the EIO-SIA method as a quick assessment tool before deeper analysis is required. Managers and policy makers can use the EIO-SIA method with appropriate SI metrics to identify industrial sectors with significant social impacts or those that have exceptional social performance. The knowledge of what industries have high social performance can guide policy toward effective SI management. Utilizing the EIO-SIA method, managers can highlight suppliers and supply chain partners that may require additional attention to social performance. The cost of failing on social performance is still unknown, but through this work, social impacts have been intimately tied to economic output. It is clear however that considering the two dimensions of sustainability - social and economic - separately is at the dertiment to understanding total sustainability performance.

Future work will address social performance with the exploration of additional social metrics for other stakeholder groups and add to the research informing the development of EIO-SIA. Work in this area has potential implications for national security and international competitiveness with specific attention to the social aspects of the UN Sustainable Development Goals.

CHAPTER 3. STAKEHOLDER-NEEDS METRICS TO EVALUATE SOCIAL PERFORMANCE OF U.S. INDUSTRIES

The following chapter is currently in preparation for journal submission.

Keywords: Social Impact Metrics; Social Performance; Stakeholder-Needs; Sustainability; Measures, Metrics, Indicators

3.1 Abstract

People are fundamental to the progress and development of economies. Understanding how people are affected by economies, and in particular industrial economic activity, starts with recognizing that impacts on people can no longer be considered externalities. Evaluating such social impacts is enabled by the large amounts of social data in the public space. However, social data are limited in current utility, and must be transformed from measure to an adaptable, repeatable, and scalable metric. The metric, in turn, informs baseline development for indicators that can effectively portray the true nature of industrial social performance. This work develops the crucial step from measure to meaning by proposing five quantitative social impact metrics that capture how industrial activity affects the needs of arguably the most intimately connected stakeholder - the employee. It is shown that changes in industrial activity, e.g., growth, in the U.S. will have a directly related and predictable change in social impact.

3.2 Introduction

Measurability is a core value in scientific exploration. Within the realm of sustainability, the extraction of meaning from measures has consistently relied upon the creation of performance indicators [Hammond et al., 1995; Husgafvel et al., 2014; Joung et al., 2013; Labuschagne et al., 2005; Popovic et al., 2018; Searcy et al., 2016]. Indicators are commonly used to state the condition of something relative to a standard or baseline of performance [Sutherland et al., 2016]. In the case of sustainability-related research literature, Rasmussen et al. [2017] identified that not only are the number of publications addressing sustainability increasing, the quantity of indicators representing all three pillars of sustainability (economic, environment, and society) are also expected to continue expanding. Further, while agreement on suitable indicators is inconsistent in general, economic and environmental indicators are shown to have greater overall consensus than social indicators, commonly due to lack of applicability, repeatability, and scalability. Therefore, the challenge to create reproducible, adaptable, and scalable social indicators presents a clear opportunity to further the discussion on measurability of social performance.

Steps to quantify industrial social performance require a concerted effort to locate and transform suitable data into a meaningful metric. From that metric, the priority becomes creation of a baseline understanding for acceptable behavior, i.e., good, bad, or good enough performance. A performance baseline can then be used to compare subsequent measures or metrics, thus strengthening validity of the related performance indicator. The pathway that transforms a measure (data) to metric to indicator can be visualized in Figure 3.1, and incorporates the definitions of measures, metrics, and indicators (MMIs) suggested by Sutherland et al. [2016]. The definition enables creation of more broadly applicable, repeatable, and adaptable social performance indicators. A challenge arises when indicators lack the support of a requisite metric tied to a transformed measure. Without underlying metrics, indicators may not support true understanding of social performance and will subsequently fail to identify any real baseline of social performance.

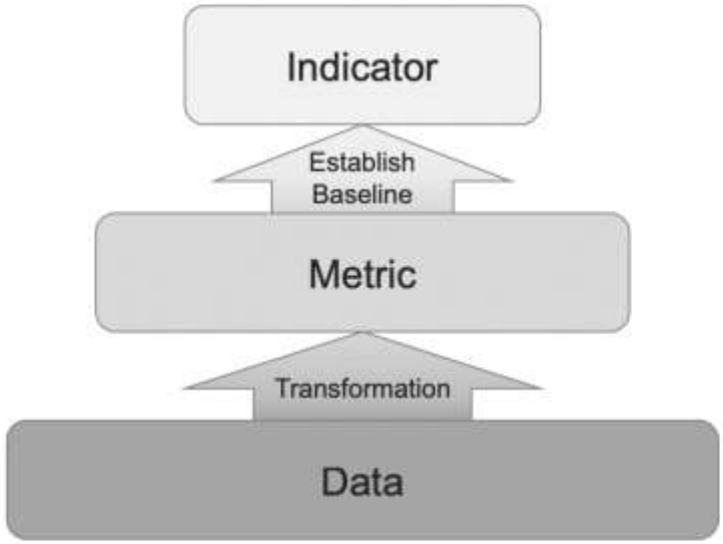

Figure 3.1 - Pathway to create an indicator from raw data. Data (measures) require transformation into a metric that then is used to establish a baseline of performance, for which an indicator needs to create relative comparisons.

As sustainability performance becomes a growing concern for industrial activity, the social performance component will require greater clarity and transparency in quantification. Therefore, measurable, traceable, and repeatable metrics become the linchpin that connects measures to meaning. As suggested by Richter et al. [2019], an ideal social metric shows a clear connection between social performance and industrial economic activity, where any growth or reduction of industrial activity would result in a corresponding change in respective social impact (SI). However, it is often difficult to identify a metric that is both appropriate and relatable to economic production.

When economic performance is linked to social performance, two pillars of sustainability are connected, and a richer understanding of sustainability performance can be evaluated. The value of connecting industrial economic activity and SIs suggests a reflection on society and existence. In the literature, societal impacts are often indirectly suggested to be independent of the industrial system that was created by the society it serves. Historically considered externalities, much of the impacts experienced by society result from industrial activity. Reflecting on the philosophical existence of industry for a moment, in the U.S., if the Industrial Revolution never happened, could society claim a relatively better or worse state of quality? The point to realize is that without one, industry or society, the other may not exist and societal impacts would be drastically different than they are today. There is a clear need to tie modern industrial activity to societal impacts.

The objective of this work is to enable the connection that is currently missing from measure to meaning, i.e., reputable, publicly available data transformed into SI metrics designed to inform social performance indicators. By describing how industrial activity affects the needs [Maslow, 1943; Maslow et al., 1970], i.e., basic, safety/security, affiliation, esteem, and self-actualization, of the stakeholder [Freeman, 2010; Mitchell et al., 1997] group workers/employees [Hutchins & Sutherland, 2008], the developed metrics contribute to the measurability of social performance. Inspired by the best ranked employee-needs indicators suggested by Hutchins et al. [2019], the work that follows enables the connection from measure to meaning that is not well established throughout the industrial social performance literature.

The subsequent section presents a description of data, methods, and calculations used to develop each employee-needs metric. Section 3.4 describes the results of the transformed data and presents outcomes from the created metrics. Section 3.5 presents the results and discusses the Top 4 contributing industrial sectors for the developed national stakeholder-needs metrics. Finally, Section 3.6 presents a summary, suggestions for future work, and concluding remarks.

3.3 Metric creation

The focus of this work is on the systematic creation of metrics that are capable of measuring the impact an industry may have on the needs for the stakeholder group worker/employee. This section lays out the motivation, framework, and assumptions guiding creation of the employee-need metrics to follow.

3.3.1 Motivation

Economic impact of industries is often considered the most important perspective to evaluate industrial value. Nevertheless, the people who comprise the labor within an industrial sector are at present, fundamental to creating that industrial value. While there is still a fractured understanding of how industries affect worker/employees, progress is made when industrial economic activity is linked to measurable SIs.

Social data, and specifically SI data, can be located through many government supported organizations and bureaus. Studies concerning the employee group have the benefit of large quantities of data available in the public domain, typically through the U.S. Bureau of Labor Statistics (BLS) and the U.S. Census. While data are plentiful and tied to sectors and industries in the North American Industrial Classification System (NAICS, see Appendix Table S.3 of Richter et al. [2019] for sector and industry mapping), the utility of the data is limited to the measures they represent. For example, total employee wages, e.g., all wages paid to all employees in an industrial sector, are often cited to represent a capable indicator of industrial activity [Searcy et al., 2016]. High industrial sector wages do not, in fact, indicate high levels of industrial production (or productivity for that matter), but merely that the goods or services produced in that sector could be of high value to the consuming market. More context is required to enable the measure of employee wages to truly capture a SI created by industrial activity. A similar challenge is present for most social data, thus motivating the opportunity to create suitable and applicable metrics guided by a structured framework. Going forward, the SI metrics developed in this work utilize an established framework of stakeholder identified human needs [Hutchins et al., 2010].

3.3.2 Framework

Across all need levels of the employee stakeholder group, additional data transformations and an operational context are required to create metrics that link industrial social performance with industrial activity. The metrics described herein are inspired by work that identified a statistically ‘best’ indicator for each combination of stakeholder and needs [Hutchins et al., 2019]. The subset of stakeholder-needs indicators for the employee/worker stakeholder group, presented in Figure 3.2, inform the development of metrics for the same respective categories. Where indicators are created to identify social performance, the data informing each indicator necessitated further exploration. As such, the metrics presented in this work create the fundamental link between raw data and indicator. The metrics are therefore used to establish the baseline understanding of social performance that can then identify how an industry performs for each social performance indicator.

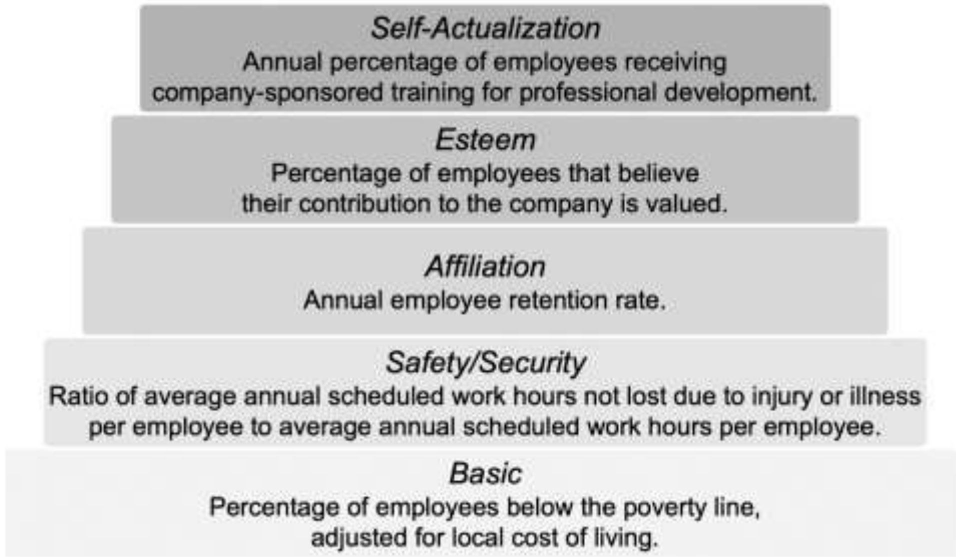

Figure 3.2 - Employee-needs (italicized) and respective indicators, adapted from Hutchins et al. [2019].

3.3.3 Simplifying Assumptions

An exploration of the entire economy and the associated SIs is impractical so a summarized selection of industrial sectors will be presented in this work, with additional content available in Supplementary Information. Some metrics will be explained using a selection of Goods Producing, Service Providing, Manufacturing, or a combination/selection of All Sectors or Industries. In addition, showing the metrics at multiple scales of industrial activity allows for potential future adaptation with data from other developed economies or at a variety of spatial scales. Further, the purpose of presenting the selected data is to highlight the development of the metrics based on a robust logical framework of stakeholders and needs level combinations, where data for all available industries and sectors were used in calculation of the metrics.

The following sections describe the origin, data sources, calculations, transformations, limitations, and adaptations for the SI metrics presented in this work.

3.3.4 Employee Needs Metrics

The year 2012 was chosen as a reference year due to the availability of public SI data. Metrics are proposed to address each need level for the stakeholder group employees. The need levels are basic, safety/security, affiliation, esteem, and self-actualization needs and are captured by the metrics Employees below the Living Wage (ELW), Cost of Injuries (COI), Cost of Turnover (COT), Total Tenure Years (TTY), and Cost of Benefits (COB), respectively (Figure 3.3).

Figure 3.3 - Proposed metrics to assess the impact an industry may have on the needs (italic) for the stakeholder group worker/employee.

3.3.4.1 Basic Needs - Employees below the Living Wage (ELW) Metric

The basic needs of employees are much the same as the basic needs of every human being, e.g., food, water, clean air, clothing, and shelter, that can be met when compensation is given in exchange for the labor service provided. Compensation, or wage, is often suggested to be a proxy for the well-being of the stakeholder group employee [Alsamawi et al., 2014; Jørgensen et al., 2009; Neugebauer et al., 2017; Papong et al., 2016; Traverso et al., 2012], and can be reported in a number of ways, e.g., wage per employee or total wages paid in an industrial sector. To describe the living standards of industrial sector employees working in a particular area, a link between a regionally specific living wage [Glasmeier, 2014; Glickman, 1997; Ryan, 1906] and industrial activity or economic output is required. The argument follows that higher wages lead to a higher quality of life, but this measure does not account for regional cost of living. In this regard, an annual wage of $45,000 in the Midwest states of the U.S. would allow a worker, their partner, and 1 child to meet basic needs [Glasmeier, 2015]. However, considering this same wage in California or New York, a worker in the same family situation would find it very difficult to support the household.

To capture the variations of wages in each industrial sector across the U.S. and evaluate how employees can meet their basic needs, the metric "employees below the living wage" (ELW) was created. ELW is the quantified metric to be used in establishing the highest ranked indicator identified by Hutchins et al. [2019] for the employee-basic needs category seen in Figure 3.2. The ELW metric utilizes wage level and occupation data gathered from BLS research estimates through the Occupational Employment Statistics (OES) program [United States Bureau of Labor Statistics, 2012]. The estimates provide a quantile breakdown of wages for all occupations per industrial sector in every state. Wage quantiles in each state and across all industrial sectors for all employment job codes were compared to the living wage [Glasmeier, 2015; Nadeau, 2017] for 1 Adult (1A), 2 Adults (2A), and 2 Adults with 1 Working adult and 1 Child (2A1W1C) households (Figure 3.4). These household compositions are broadly representative of several living circumstances across the United States [Vespa et al., 2013] and suggest that the employee is the wage-earning individual in that household.

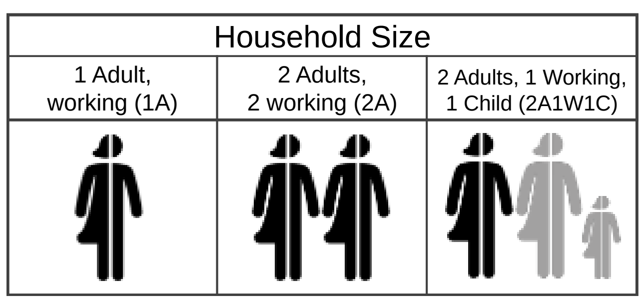

Figure 3.4 - Selected household sizes representing the workforce of the U.S. in 2012. Non-working individuals are colored gray. Image: Gender Neutral by Matt Brooks c/o The Noun Project.

For the lower wage quantiles (e.g., 10th, 25th) in an industrial sector, it is expected that an employee could not meet the basic needs of their household based on that wage alone (Table 3.1).

Since some regions have a higher cost of living it also may be possible that the higher wage quantiles (e.g., > median) still do not provide enough for an employee to meet basic needs of their household. A sample of the OES wage quantiles are presented in Table 3.1, comparing sectors 31G-Manufacturing to 00-All industrial sectors. Mean wage and up to the 75th wage quantile for 31G is higher than the total economy, but at the higher quantiles, the difference becomes less significant. It can be stated that in general, manufacturing industry wages are higher than wages in the total economy, but the trend is highly variable across all sectors in all 50 states.

Table 3.1 - Sample of data for wage quantiles and employment from OES research estimates used in the ELW metric.

Region	NAICS	Name	Occupation	Employees	Mean Wage (US$)	Wage Quantiles (US$)				
						10th	25th	Median	75th	90th
US	00	All industry	All Occupations	130,287,700	45,790	18,090	22,480	34,750	56,200	86,810
US	31G	Manufacturing	All Occupations	11,866,540	47,240	20,790	26,980	37,400	56,290	86,620

For the 50 U.S. states, Washington, D.C., and across 123 2-, 3-, and 4-digit NAICS sectors and industries (see Appendix Table S.3 of Richter et al. [2019] for sector/industry associations), the wage quantiles were lognormally regressed using the R software package *rriskDistributions* [Belgorodski et al., 2017]. Each distribution is compared to three Living Wage thresholds, 1A, 2A, and 2A1W1C (Figure 3.4), obtained from the Living Wage Calculator [Glasmeier, 2015; Nadeau, 2017]. The intersection of the LW threshold with the regressed sectoral wages identifies the employment fraction below the living wage, as conceptually illustrated in Figure 3.5. The number of employees below the living wage (ELW) can then be estimated and further compared with economic output, e.g., gross state product (GSP) [United States Bureau of Labor Statistics, 2017] or industrial sector total commodity output, depending on the needs of the decision-maker.

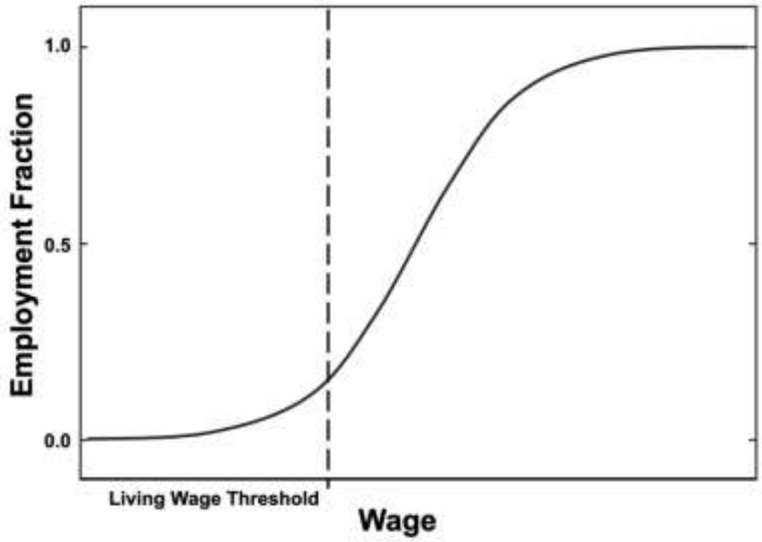

Figure 3.5 - The industrial sector wage quantile curve identifies the quantity of employees below a specific wage. The intersection of the living wage threshold and the wage quantile curve coincides with the fraction of employees in a region who cannot meet their basic needs.

From the combined state level data, a national statistic for each industrial sector ELW can then be calculated. The employment fraction (*pnorm*) below the LW threshold can be found according to Eq. (3.1),

$$Employees\ below\ the\ Living\ Wage\ = Employment\ fraction * \#\ of\ Employees$$

$$ELW_j = \sum_r pnorm_j * EMP_j \tag{3.1}$$

where all values in sector or industry *j* are summed across each area *r* to aggregate a National value of ELW for each industrial sector. The wage data limitations require some values to be estimated before calculation of ELW. Often, industry wage and employment statistics are suppressed to protect against identification of individual companies [National Academies of Sciences, 2017]. In addition, reporting of wage or employment statistics is inconsistent across all sectors. For example, sector 11-Agriculture, and more specifically industries 111-Crop production and 112-Animal production and aquaculture were not required by the BLS to report employment or wage information for 2012 (this was partially completed by the USDA). The 11-Agriculture sector employment and wage data were created as a supplement in 2011. Despite the data limitations, ELW still provides a robust quantification of the SI representing employee-basic needs.

ELW is a flexible metric in that it can be adapted similarly across cities, counties, states, regions, and industrial sectors (as data availability allows). In the absence of micro-level (e.g., company, organization) wage data, the ELW metric will still provide useful insight from the macro-level data, e.g., number of employees in a sector or industry. Across industrial sectors, ELW establishes a comparative baseline for whether the wage offered within a certain sector can provide for the basic needs of an employee and their household. The next highest order need to be met is safety/security, which is captured by the Cost of Injuries metric.

3.3.4.2 Safety and Security Needs - Cost of Injuries (COI) Metric

Employees in all industries encounter situations where accidents and injuries can occur. Some industries are more susceptible to accidents and injuries than others, which is often cited as indicative of the working conditions established in that particular industry [Breslin et al., 2007; Dembe et al., 2005; Smith et al., 2005]. While injuries can be characterized in many ways, e.g., type, severity, and quantity, those requiring time away from work directly affect the productivity of industries. The time away from work creates a clear negative impact, i.e., cost, on the employee as well as the industry [Leigh et al., 2004]. While one injury requiring time away from work is likely to have a negligible overall effect, an industry such as air transportation (NAICS 481) with over 58% of all injuries requiring time away from work (16,030 of 27,500 total injuries in 2012), had to internalize the substantial effects of the collective lost employee productivity. Although the type of injury is not explored here, it can be hypothesized that some industries may require more strenuous physical working conditions, may operate in more difficult environments, or any combination of increased risk factors, and therefore may have a higher fraction of injuries requiring time away from work. The length of time away from work is a useful proxy for severity of injuries which can vary widely across industries.

To capture the cost of lost production occurring from injuries requiring time away from work, the injury-related metric, cost of injuries (COI) was created. The COI metric represents the direct SI due to working conditions and characterizes a safety and security need [Maslow, 1958; Maslow et al., 1970] that all employees encounter on the job. From an enterprise perspective, COI identifies the economic losses from missing productivity and may better indicate the state of industrial working conditions. The COI metric aligns with the highest ranked indicator from Hutchins et al. [2019] for the employee-safety/security needs category seen in Figure 3.2. The COI metric utilizes data regarding injury severity to identify the total time required away from work due to injury. The data for the COI metric were extracted from the Injuries, Illnesses, & Fatalities (IIF) datasets [United States Bureau of Labor Statistics (BLS), 2012] for the year 2012. The IIF data provide national counts of injuries as well as the time away from work that injuries require for each industrial sector.

Consider a comparison case for two goods producing sectors in the U.S. economy. In 2012, for industry 3361-Motor vehicle manufacturing, the median days away from work caused by injuries was 27 days, while industry 211-Oil and gas extraction, had median days away from work caused by injury of 15 (Table 3.2). Both industries, 3361 and 211, have similar employment numbers of 169,020 and 181,580 employees respectively. However, the associated severity of injuries, measured by the fraction of injuries requiring time away from work, is drastically different. About 20% (2,400/12,000) of all injuries in sector 3361 require time away from work, but in sector 211, that fraction is over 45% (1,180/2,600). Although the severity is higher in sector 211, the total length of time away from work is far greater in sector 3361. Also seen in Table 3.2, the summary data for all occupations in both industries (3361 and 211) show that number of injuries requiring time away from work in industry 3361 is greater than double that of industry 211 for every length of time greater than 2 days. It can also be determined from Table 3.2 that the total injuries per total employees in industry 3361 is nearly 5 times that of industry 211. This example is not exclusive to goods producing industries in the U.S. but serves as a simple clarification that injury data vary across industrial sectors.

Table 3.2 - Summary data for injuries with days away from work (DAFW) used in the cost of injuries (COI) metric.

NAICS	**Name**	**Total Employees**	**Total Injuries**	**Cases involving days-away-from-work:**								**Median days away from work**
				Total	1 day	2 days	3-5 days	6-10 days	11-20 days	21-30 days	31+ days	
211	Oil and gas extraction	181,580	2,600	1,180	210	90	100	140	90	70	480	15
3361	Motor vehicle manufg.	169,020	12,000	2,400	190	110	310	300	190	190	1,100	27

The 2-, 3-, and 4-digit NAICS sector and industry data for cases involving days-away-from-work (DAFW) were used to calculate the total time (in days) away from work. The cumulative DAFW was calculated using the lower bound of the DAFW ranges, e.g., for cases involving 11-20 days away from work, 11 days was the multiplier. The cumulative DAFW was adjusted by hours worked in a year and then output per employee. Output per employee is used as a normalization factor for each industrial sector because it captures the economic value of average employee productivity. Any time lost to injury reduces potential economic activity. The resulting injury-related cost of lost productivity data were regressed using the R software package *ggplot2* [Wickham et al., 2018]. The lognormal fit intersected with the injury severity threshold, defined as the fraction of total injuries that require time away from work, identified the estimated COI for each industry (Figure 3.6).

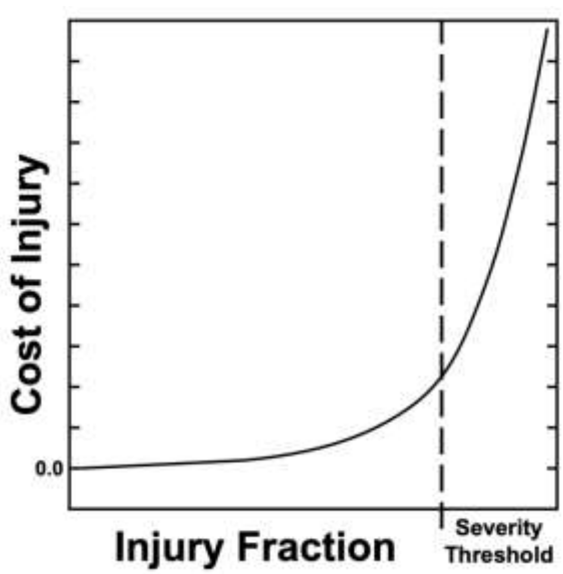

Figure 3.6 - Depiction of the cost of injuries requiring time away from work due to the severity of injury, or injury fraction, in an industrial sector. The severity threshold coincides with the lower bound of the cost of injuries.

The COI metric is evaluated in $US and is calculated according to Eq. (3.2),

$$Cost\ Of\ Injuries = \frac{Annual\ economic\ output}{employee} * Total\ work\ years\ away\ from\ work$$

$$COI_j = PROD_j * YAFW_j = \left(\frac{X_j}{EMP_j}\right) * \sum_j \frac{DAFW_j * DAFWr_{LB}}{\text{weeks} * \text{days}} \tag{3.2}$$

where *PROD* and *YAFW* are the output per employee and total work years away from work. In addition, *X* and *EMP* are total commodity output and employees, respectively. *DAFW* represents the instances, or count, of days away from work, while *DAFWr* is the range and *LB* is the lower bound for each time away from work range, e.g., 11 days from the 11-20 day range in Table 3.2. All variables are addressed for sector or industry *j*. Due to the shortcomings of the IIF data, a lower bound estimate is only available for the COI at the severity threshold. Lower bounds of the time away from work ranges set a baseline value for COI. The use of the lower bound of each DAFW range may underestimate the total economic impact of COI, however, an upper bound cannot be estimated from available data. Additionally, the constants in the denominator establish the working weeks in a year and working days in a week, assumed equivalent across all sectors, respectively. The COI does not assess seasonality of labor but can be adapted to adjust for seasonality and sector-specific work days per year in the future.

As with ELW, COI is a flexible metric that can be adapted similarly across states, regions, industrial sectors, and companies (as data availability allows). The COI metric establishes a comparative baseline for the severity of industrial sector injuries. In practice, COI can help to identify if a sector or industry requires a focused management strategy addressing employee safety/security needs with safety training, protocols, or guidelines. The next highest order need to be met is affiliation, which is captured in the Cost of Turnover metric in the next section.

3.3.4.3 Affiliation Needs - Cost of Turnover (COT) Metric

Most organizations seek to hire and maintain relationships with the most talented and capable employees. Unfortunately, an employment relationship may deteriorate for a variety of reasons resulting in employee turnover. Previously thought to be strongly related to job satisfaction [Schleicher et al., 2004], research on employee turnover has recently encompassed such reasons as access to resources, perceived organizational support, job fulfillment of initial employee expectation, demography, culture, and respect [Hom et al., 2017; O'Reilly III et al., 1989; Porter & Steers, 1973; Rhoades & Eisenberger, 2002; Rogers & Ashforth, 2017; Schleicher et al., 2004]. Turnover is viewed to result from a circumstance when an employee's affiliation need is not met by the employment relationship with a business or organization. The impact that turnover can have on an organization is significant and may have profound effects on the economic output of a business or industry. From the business or industry perspective, the loss of an employee could signify a production loss and further may result in opportunity costs for the organization [Abbasi & Hollman, 2000; O'Connell & Kung, 2007]. Continuing with the focus on SIs caused by industrial activity, the cost of employee losses is a result of business activity due to a severed relationship with an employee.

To capture the cost occurring from job separations and characterize the affiliation need [Maslow, 1958; Maslow et al., 1970] for an employee, the metric cost of turnover (COT) was created. COT is the quantified metric to be used in establishing the highest ranked indicator identified in Hutchins et al. [Hutchins et al., 2019] for the employee-affiliation need category seen in Figure 3.2. The COT metric utilizes data from the Job Openings and Labor Turnover Survey (JOLTS) [BLS, 2013], for employee separation, e.g., layoff and discharge, quit, retirement, disability, and transfer. A sample of the JOLTS dataset is shown in Table 3.3, where three industries of similar employment size experience varying levels of job separations. Table 3.3 shows that sector 44RT-Retail trade, and industries 61-Educational services and 62-Health care & social assistance depict a very different story of job separations. For example, sector 44RT has an 18% larger workforce than industry 61, but is challenged by a nearly three times greater number of separations. Sector 44RT has a 15% smaller workforce than industry 62, but also must function with a 38% greater number of separations. The comparison simply shows that industries with similar employment numbers may have drastically different separation results, and employment numbers and turnover data do not tell the complete story of impact caused by turnover. The JOLTS data require transformation to develop the job separation measures into the meaningful metric COT.

Table 3.3 - 2012 job separation data for similar sized industries. Data extracted from the Job Openings and Labor Turnover Survey (JOLTS) [BLS, 2013] were used to develop the COT metric.

NAICS	**Name**	**Total Employees**	**Separations ('000)**			
			Total	**Layoffs and discharges**	**Other**	**Quits**
			TS	LD	OS	QT
44RT	Retail trade	14,982,720	6,836	2,208	575	4,051
61*	Educational services	12,683,820	2,413	874	362	1,172
62†	Health care & social assistance	17,720,090	4,938	1,592	439	2,907

* Including private, state, and local government schools; † Including private, state, and local government hospitals.

The COT metric is developed by combining the JOLTS data with industrial sector output per employee. Output per employee is used to normalize the industrial sector data for sector employment size and total output. Output per employee captures the economic value of employee productivity and in the case of turnover, the loss of employee production. The COT metric represents the total cost of losing the labor productivity of an employee due to job separation, and is calculated according to Eq. (3.3),

$$Cost\ Of\ Turnover = Output\ per\ employee * Total\ separations$$

$$COT_j = PROD_j * TS_j = \left(\frac{X_j}{EMP_j}\right) * (LD_j + OS_j + QT_j) \tag{3.3}$$

where X is sector total commodity output, EMP is the number of employees, and TS represents the sum of total separations, i.e., layoffs and discharges (LD) + other separations (OS) + quits (QT), each for sector or industry j. Due to data limitations, the COT metric has included assumptions that require attention. First, all employees are assumed to have equal productivity in an industrial sector which simplifies the metric until future data become available for occupation-related productivity. Second, hires are excluded from the calculation. In the case of turnover, it is understood that hires replace job separations and may result in a zero sum change in number of jobs over the year. However, an argument could be made that the cost of recruitment, training, and benefits for a new hire [Abowd & Kramarz, 2003; Blatter et al., 2012; Blatter et al., 2016] could add to total cost of turnover and increase COT. It is argued further in this work that training and benefits address the higher order need of self-actualization. Therefore, limiting COT to include only job separations simplifies the metric to capture solely the cost associated with loss of an employee.

COT can be adapted across states, regions, industrial sectors, and companies (as data availability allows). The COT metric establishes a baseline for cost related to industrial sector turnover and addresses the employee need for affiliation. Analysis using the COT metric can help to identify if a business or industrial sector requires a focused management strategy addressing human resource activity, workplace culture, and employee job satisfaction. The next highest order need to be evaluated is esteem, which is captured in the following Employee Tenure Years metric of the next section.

3.3.4.4 Esteem Needs - Total Tenure Years (TTY) Metric

A successful and productive employee is worth keeping. If an employee feels esteem within a position, they are likely to stay within that position. Assuming that over time, an employee gains experience, knowledge, skill, and productivity, i.e., the human capital model, the employee may then provide increased value to the organization or industry [Becker, 2009; Blaug, 1976]. The increased value may be observed in many ways, e.g., production efficiency gains, enhanced supplier/customer relationships, technology and automation advancements, and waste reduction. Employees who spend longer periods of time in an industry have been associated with greater creativity and idea generation [Woods et al., 2018], greater organizational commitment [Cohen, 1993], and more stable levels of organizational self-esteem [Pierce & Gardner, 2004]. It follows then that employee esteem needs could be met by the time spent, or tenure, with an organization.

To capture industry-specific organizational tenure and characterize an esteem need [Maslow, 1958; Maslow et al., 1970] of the stakeholder group employee, the metric total tenure years (TTY) was created. TTY is the quantified metric to be used in supporting the highest ranked indicator from Hutchins et al. [2019] for the employee-esteem need category seen in Figure 3.2. The TTY metric utilizes data from the even-year Current Population Survey (CPS) regarding labor force status and employee tenure for the year 2012 [United States Bureau of Labor Statistics, 2016]. The data are reported in ranges of time working with current employer for 2- and 3-digit NAICS sectors and industries. The tenure data are then combined with the number of employees in each sector. Some sectors have significantly longer employee tenure than others [Auer & Cazes, 2000] that may point to happier, more satisfied, and loyal employees [Greenhaus et al., 1987]. Some sectors have orders-of-magnitude-larger employment numbers, which may identify a high demand for labor and could also suggest a relative short length of employment tenure. The TTY metric addresses a combination of employee dedication and industrial demand for skilled and educated labor.

Consider the tenure of the entire workforce in the United States, presented in Table 3.4. Across all sectors, greater than 20% of employees spend less than a year with their current company, and nearly 49% are with their current employer/industry fewer than 5 years. On the contrary, 29% of the workforce stays in the same industry for over ten years. In the case of the greatest range presented in the data, tenure times are considered as anything longer than 25 years with the same company in the same industry. Initially, it may seem quite rare to have employees remain in the same industry or with the same company for longer than 25 years, but the data show that 6% of the workforce, some 7.5 million employees, remain with their employer beyond 25 years. The long-term time commitment to an employer may imply that the employee feels valued by the company or industry. While this data represents a national statistic, individual industrial sector values may vary widely from the national average.

Table 3.4 - National summary for tenure time ranges and number of employees spent with current employer.

NAICS	**Name**	**Total employees ('000)**	**Tenure time with current employer**												
			6 months or less	7 to 12 months	13 to 23 months	2 years	3 years	4 years	5 years	6 years	7 to 9 years	10 to 14 years	15 to 19 years	20 to 24 years	≥25 years
			Number of employees ('000)												
0	Total	125,516	15,697	10,834	7,911	6,145	11,918	8,977	9,694	6,207	11,405	15,661	7,707	5,877	7,485

The TTY metric seeks to capture the value in experience that an industrial sector can claim for the employees that stay within that industry. The metric quantifies the total tenure years attributable to an industrial sector according to Eq. (3.4),

$$Total\ Tenure\ Years = Sum\ of\ \left(\frac{Tenure\ time}{Employee} * \#\ of\ employees\right)$$

$$TTY_j = \sum_t TEN_{t_{LB}} * EMP_t \qquad (3.4)$$

where *TTY* and *TEN* are the total tenure years and tenure time per employee respectively, in sector or industry *j* and tenure time range *t* at the lower bound *LB*. The TTY metric assumes the tenure time for employees below 1 year of service to be a fraction of a year for each industrial sector. For example, employees with 6 months or less of tenure would have a *TEN* value of 0.25 year. For tenure time within a range, e.g., 20 to 24 years, the lower value of the range is utilized for the *TEN* value. Notice in Table 3.3 that many of the tenure times cover a range, e.g., 7 to 12 months or 15 to 19 years. Similar to the COI metric calculation, the lower bound of the tenure time range is utilized. While this may underestimate total tenure years, it simplifies the calculation for TTY. When more detailed datasets, e.g., job code tenure, become available, the TTY metric can be enhanced accordingly.

Similar to the other metrics, TTY can be adapted across states, regions, industrial sectors, and companies (as data availability allows). TTY introduces the concept of value related to employee experience in an organization or industry. While units are in years, and not employees or dollars as prior metrics have been, the TTY metric could be enhanced to capture the monetary benefit of experienced employees within an industrial sector. Also notable is that if lower order needs are not met satisfactorily, the esteem needs metric presented here is of little consequence. The same can be stated for the final and highest order employee need to be evaluated, actualization, which is captured in the Cost of Benefits metric in the following section.

3.3.4.5 Self-Actualization Needs - Cost of (Employee) Benefits (COB) Metric

Enabling an employee to reach their highest potential may seem an abstract concept. After all, what can a company do to help an employee become everything that employee is capable of becoming? In the hierarchy of needs described by Maslow [1943], self-actualization results from an individual who is full-functioning with, “minimal presence of ill health, neurosis, psychosis, of loss or diminution of the basic human and personal capacities” [Maslow, 1962]. In other words, an employee can attain self-actualization if the lower order needs are met by the organization and conditions are created where that employee can not only succeed but thrive. An organization or industry would have had to provide additional benefits beyond a living wage, safe working environment, engaging workplace, and reasons for confidence in the organization to enable an employee to attain the self-actualization level in the needs hierarchy.

To capture the benefits compensation package and characterize a self-actualization need for employees, the cost of benefits (COB) metric was created. The COB metric represents the financial burden an industrial sector must bear in part, to enable employees to reach their full potential. COB is the quantified metric to be used in supporting the highest ranked indicator from Hutchins et al. [2019] for the employee-actualization need category seen in Figure 3.2. Instead of focus on training (where data are lacking), COB focuses on the package of services offered to an employee beyond wage that allow achievement of core self-actualization factors, e.g., preparation for future, time away from obligations, and pride in accomplishment [Sumerlin & Bundrick, 1996]. Components of this metric include,

- Paid leave - vacation, holiday, sick, and personal leave;
- Supplemental pay - overtime and premium, shift differentials, and nonproduction bonuses;
- Insurance benefits - life, health, short-term and long-term disability;
- Retirement and savings contributions - defined benefit and defined contribution; and
- Other legally required benefits - Social Security, Medicare, federal and state unemployment insurance, and workers' compensation [United States Bureau of Labor Statistics, 2018].

The COB metric utilizes data from the Employer Cost for Employee Compensation (ECEC) datasets extracted from the BLS National Compensation Survey (NCS) regarding the annual pay and benefits packages [United States Bureau of Labor Statistics, 2018]. The data are reported in $US per hour for an employer in 2- and a select few 3-digit NAICS sectors and industries [United States Bureau of Labor Statistics, 2012]. Sector 11-Agriculture, forestry, fishing, and hunting, and 21- Mining, oils and gas extraction, and support activities, were excluded from reporting any benefits compensation. Both sectors 11 and 21 were assumed to have at least the same compensation package as the aggregated goods-producing sectors summarized in Table 3.5. In addition to the goods-producing industries, Table 3.5 displays the summarized service-providing industries compensation package per hour worked, as well as the individual data components of the benefits packages that the COB metric utilizes. A further note must acknowledge that the Federal government was excluded from benefits compensation reporting, but data were accessible for the Federal government through the Congressional Budget Office [Falk, 2012].

Table 3.5 - Salary & Wages, and Benefits compensation pay per hour worked for employees in industrial sectors.

NAICS	**Name**	**Benefit Costs ($ per hour worked)**							
		Total compensation	Salaries & Wages	**Total benefits**	Paid leave	Supplemental pay	Insurance	Retirement savings	Legally required benefits
G00000	All workers, goods-producing industries	34.14	22.85	11.29	2.23	1.35	3.22	1.51	2.98
S00000	All workers, service-providing industries	27.83	19.81	8.02	1.93	0.71	2.19	0.94	2.25

There are two ways to arrive at the COB calculation. The first method is a top-down approach in which the total compensation package of an employee is reduced by the salary or wage earned, assuming the remaining compensation represents the total cost of a benefits package. This method is suggested as many organizations and businesses are required to report both total compensation and salary or wage packages for employees. The total COB for each industrial sector is obtained according to Eq. (3.5),

$$Cost\ of\ Benefits = Total\ hrs\ worked * [Total\ compensation - Salary\&Wages]$$

$$COB_j = THW_j * [TComp - S\&W]_j = THW_j * BEN_j \tag{3.5}$$

where *THW* represents total hours worked, *TComp* is Total Compensation, *S&W* are Salary & Wages, and *BEN* are total benefits compensation reported in dollar per hour worked averages, for each sector or industry j. The data for the total hours worked in a sector or industry were extracted from the Labor Productivity and Costs (LPC) datasets (also from the BLS) and was reported in millions of hours worked. Also utilizing the same THW data, a bottom-up approach is proposed when the data exist at the company level.

A complementary approach, and the one used herein, uses the same public data accessed above via the BLS. The compensation package is broken down to the component parts of hourly salary and wage and the total benefits package. The total benefits package is further disaggregated into the most common subcategories of benefits, and these subcategories are then utilized to capture the total cost of benefits according to Eq. (3.6),

$$Cost\ of\ Benefits = Total\ hrs\ worked * Total\ benefits\ compensation$$

$$COB_j = THW_j * BEN_j = THW_j * [PL + SUP + INS + RET + LEG]_j \tag{3.6}$$

where *PL*, *SUP*, *INS*, *RET*, and *LEG* represent paid leave, supplemental pay, insurance benefits, retirement and savings, and other legally required benefits in sector or industry j, respectively. Allowing COB to be addressed by either the top-down or bottom-up method enables flexibility in data accounting if either set of data is not readily available. It is quite possible that the total benefits compensation package may contain other subcategories of benefits, e.g., transportation allowance, discretionary expense account, or stock options [Blatter et al., 2012; Blatter et al., 2016; Herzberg, 1968], but additional benefit items are not tracked in public datasets. Self-reporting by industries and companies regarding additional benefits compensation could greatly enhance the accuracy of the COB metric.

Similar to the preceding lower order metrics, COB can be adapted across states, regions, industrial sectors, and companies (as data availability allows). COB introduces the concept of benefits which enable an employee to achieve their full potential in an organization or industry. Units are described in dollars (as prior metrics have been), to capture in part, the cost that an industry or company must absorb to support high achieving employees [Campion et al., 2018]. Also notable, as suggested by Maslow [1943], is that if lower order needs are not met, the self-actualization needs metric is of little consequence. Regardless of achieving the need levels in sequence, the important takeaway is that each need level can be measured in order to evaluate the impact of industrial activity on the stakeholder group employees.

3.3.5 Metric relationships with economic activity

As suggested earlier, attempts to measure SIs are commonly undertaken independent of industrial production, and a causal link between economic output and SI is not clearly understood. In response, each proposed SI metric was compared to various measures of economic output, i.e., total commodity output (X), gross state product (GSP), and industry value added (VA). In all cases, total commodity output, X, from the U.S. Input-Output tables [Horowitz & Planting, 2006] represented the most suitable form of economic output from industrial activity. An observable relationship between industrial activity and each SI metric can identify trends that may enable 1) prediction of SIs resulting from additional economic expansion/contraction and 2) identification of industrial sector outliers, i.e., potential hotspots. Similar trends were observable with other economic performance measures, but only the SI metric relationship with X is discussed in this text. The following section will summarize the output of each created metric and describe the relationship with economic activity.

3.4 Data Transformation and Metric Outcomes

Some datasets were more comprehensive for NAICS industry coverage than others and required additional transformation beyond the methods stated above. Where necessary, the transformation is elaborated within the section for each metric. The output from each employee-need metric was statistically regressed to highlight the requisite observable trend relative to economic activity in the U.S. and the results are described for each employee-need metric. The descriptions that follow will present specific cases of sectors and industries to provide a succinct depiction of both the data processing and transformation, and relationship to economic activity for each employee-needs metric; ELW, COI, COT, TTY, and COB.

3.4.1 ELW

The relationship of wages to economic production requires transformation before an observable trend becomes apparent. All 50 US states (including Washington, D.C.) were evaluated over 120 NAICS sectors and industries, summarized for All Occupation Codes data including total number of employees (EMP) and wages for annual mean, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile (see Table 3.1). Missing or suppressed data in the raw datasets were supplemented with national level estimates of wage quantile data for those respective industrial sectors.

The compiled dataset was fit to a regression model from the quantile wage data and output over 4,500 curves, e.g., the sampled regressions in Figure 3.7 for the U.S. Advanced Manufacturing

(AM) sectors [Proceedings of the National Academy of Sciences, 2017]. No weighting of quantile data was required for regression fit, however, tolerance sensitivity required adjustment for industrial sectors with quantile data showing drastic high (or low) percentile values. The wage regression curves were then compared against LW thresholds to identify the percentage (*pnorm*, see 3.3.4.1) of employees below the threshold wage. This work makes no statement as to household size of employees in an industrial sector, but acknowledges that more specific results can be obtained with understanding of employee household makeup for each industrial sector. However, what is clear from evaluation of the ELW metric is that as production increases, so do the number of employees not able to meet even the basic needs of supporting a household. While this result may be intuitive, the data require a significant amount of transformation to identify such trends.

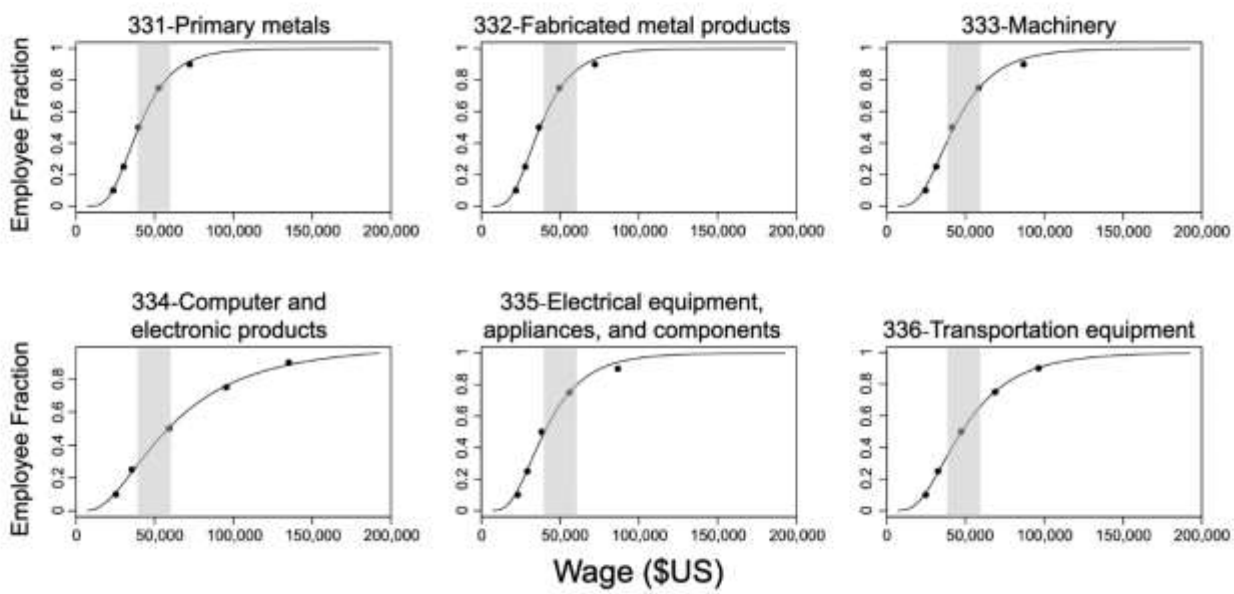

Figure 3.7 - Wage quantile curves for Advanced Manufacturing NAICS codes (L to R, 331-336). The gray bars represent the high and low living wage ranges for 2 Adult, 1 Working, 1 Child households in the 50 U.S. states and Washington D.C. The resulting employee fraction below the curve is used to estimate ELW.

Summarized at three different LW levels and compared across all 50 states including Washington, D.C., Figure 3.8 shows a strong correlation between total GSP and the total ELW across all industries and sectors in a state. GSP was displayed in this case because cost of living is region specific, and thus the living wage differs from state to state (it may also vary within a state, e.g., county or metro area). Therefore, ELW for the entire United States does not represent a logical or reasonable value. While the LW thresholds identify the number of employees earning wages below the respective regional standard of living, the assumption is that all households are of the same composition for the ELW metric. Future work in this area could explore a heterogeneous and potentially more representative household makeup for each region, and further utilize the demographic composition of employees within industrial sectors.

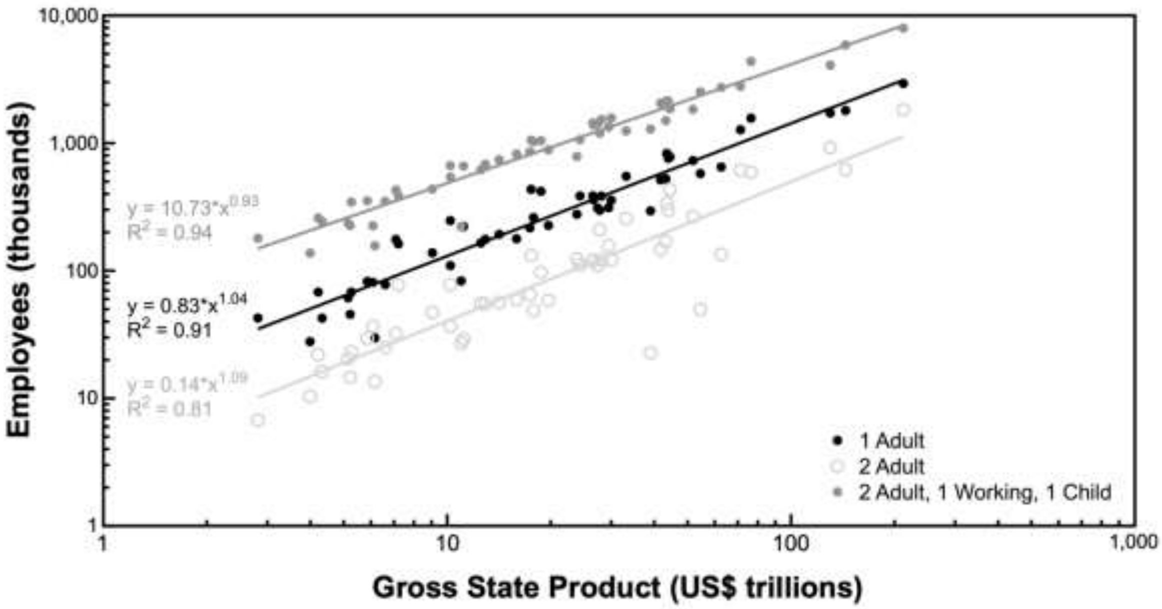

Figure 3.8 - A positively increasing relationship was created with the employees below the living wage (ELW) metric and economic output. The ELW for each U.S. state and Washington, D.C. at several household sizes (1 Adult, 2 Adult, 2 Adult, 1 Working with 1 Child) increases with increasing economic production (GSP), log-log scale.

The next stakeholder-needs metric to be evaluated is the COI, representing the safety/security needs of employees.

3.4.2 COI

The raw data used for calculation of the COI metric is found in a format similar to that in **Table 3.2** across 163 2-, 3-, and 4- digit NAICS sectors and industries (2-digit NAICS are aggregates of 3-digit NAICS, 3-digit NAICS are aggregates of 4-digit NAICS, etc.). The count of cases involving days away from work in each row sum to the total cases for that industrial sector. Each column is the number of instances that require time away from work within the time range displayed in the header of the column, e.g., the goods producing industrial sectors (GPIs) reported over 36% of injuries requiring time away from work lasting beyond 20 days. The GPIs and service providing industrial sectors (SPIs) presented in Table 3.2 are commonly reported in public datasets and are aggregations of individual sectors. The analysis done throughout this work used the disaggregated data that comprised each summary group, and this additional data can be found in the Supplementary Information.

The time away from work data were modeled with an exponential regression and output a curve for every industrial sector, as presented in Figure 3.9, again for the U.S. AM sectors. If the severity threshold is increased, i.e., shifted to the right in the plots in Figure 3.9, from the current LB baseline, a drastic cost of injuries can be observed. For example, due to employee productivity in sector 336-Transportation equipment, the COI metric identifies that over US$500 million was lost to injuries in 2012, where sector 334-Computer and electronics products lost just greater than US$50 million due to injuries. It is important to note that these outcomes are evaluated at the lower bound, but using more accurate data for time away from work would likely result in higher COI values.

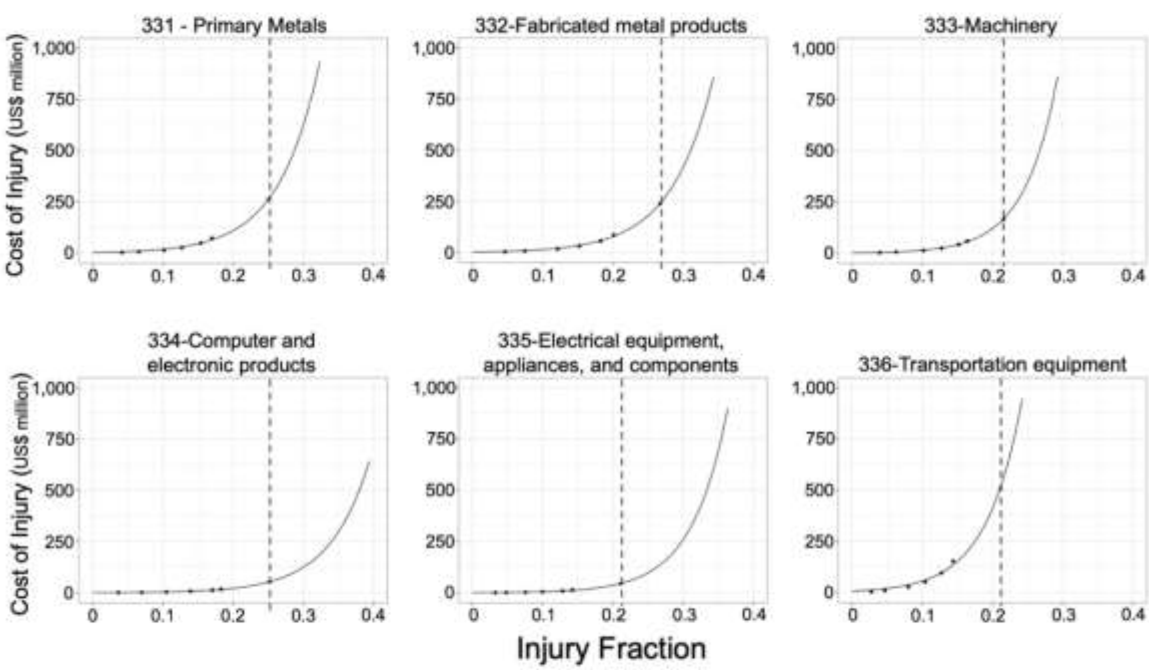

Figure 3.9 - Cost of injury (COI) quantile curves for Advanced Manufacturing NAICS codes (L to R, 331-336). The fraction of injuries requiring time away from work, or severity thresholds (dashed vertical lines), identify the COI estimates for each respective industry.

Workplace injuries serve as a useful proxy for working condition safety, but since this is not a function of production, it makes for a poor metric. From the basic sector specific injury data used in previous literature, a correlation is not clear, but with the adapted COI metric, an observable association is evident as seen in Figure 3.10. Further, as the GPIs and SPIs were evaluated relative to economic production, the relationship was positive such that as sector production increases, so does the COI. Several outlier service sectors were removed from analysis due to the low employment numbers and extreme low injury severity. Separating the total private industry group into GPIs and SPIs more strongly correlates the goods sectors to commodity output than the services sectors, but as a whole, the COI metric in the US for all sectors shows a strong positive correlation with total commodity output.

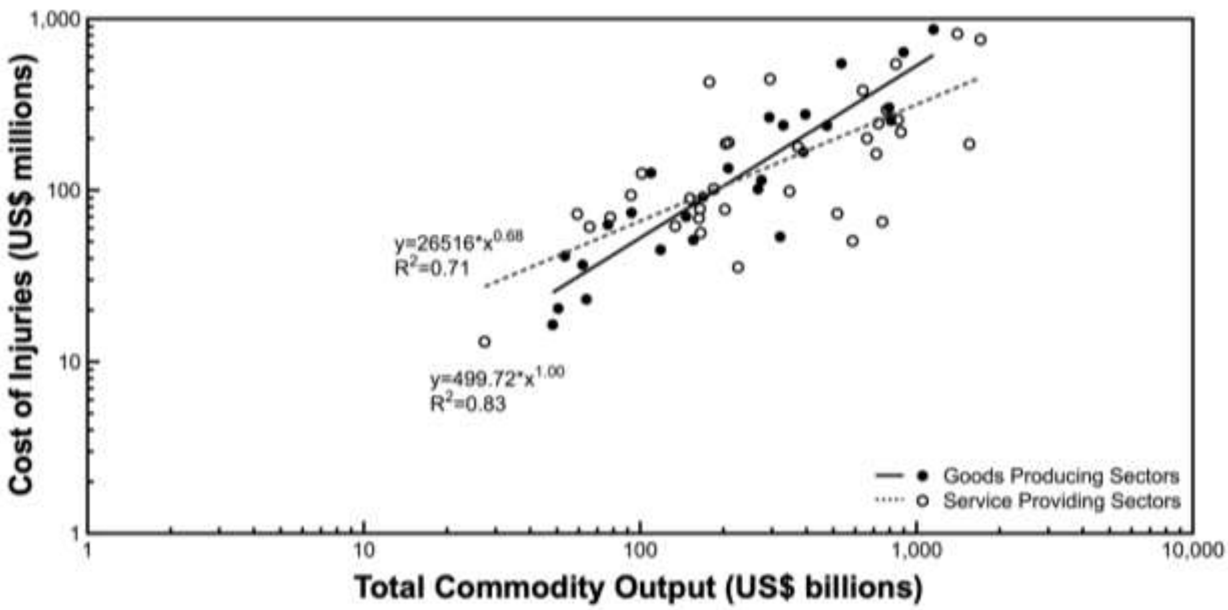

Figure 3.10 - A positively increasing relationship was created with the cost of injuries (COI) metric and economic output. COI for both Goods Producing and Service Providing sectors and industries in the U.S. are shown to increase with increasing total commodity output. Values normalized by individual sector productivity, log-log scale.

The next employee-needs metric to be evaluated is the COT, representing the affiliation needs of employees.

3.4.3 COT

Data for the COT metric come from the JOLTS datasets and are provided in annual counts of total separations for 28 industrial sectors. Several sectors and industries were combined in these datasets, e.g., 110099-Mining and logging, and 480099-Transportation, warehousing, and utilities, each requiring preliminary processing. Sector employment data were utilized for this intermediate processing calculation to allocate total separation data for each disaggregated sector per Eq. (3.7),

$$EMP_j = EMP_i + EMP_k$$

$$TS_k = \left(\frac{EMP_k}{EMP_i + EMP_k}\right) * TS_j = \left(\frac{EMP_k}{EMP_j}\right) * TS_j \tag{3.7}$$

where assuming sector k is the subsector of interest and sector i is an additional component subsector of j, the employment fraction (EMP_k/EMP_j) with respect to sector k is multiplied by the total separations, TS, of the aggregated sector j. In the 480099 (sector j) example preceding Eq. (3.7), sector i would be equivalent to 48TW-Transportation and warehousing and sector k would be 22-Utilities.

Total separations serve as a useful proxy for turnover, but alone are not enough to capture the impact that those separations may have. When combined with employee productivity, separations can begin to establish an understanding for the cost of the turnover resulting from job separations. In this way, COT is an effective metric for describing how losing an employee is a costly challenge and no industrial sector is immune. Comparing the COT metric to industrial sector total commodity output identifies the clear correlation visible in Figure 3.11. With an increase in sector output, one can expect with fair certainty that COT would also increase.

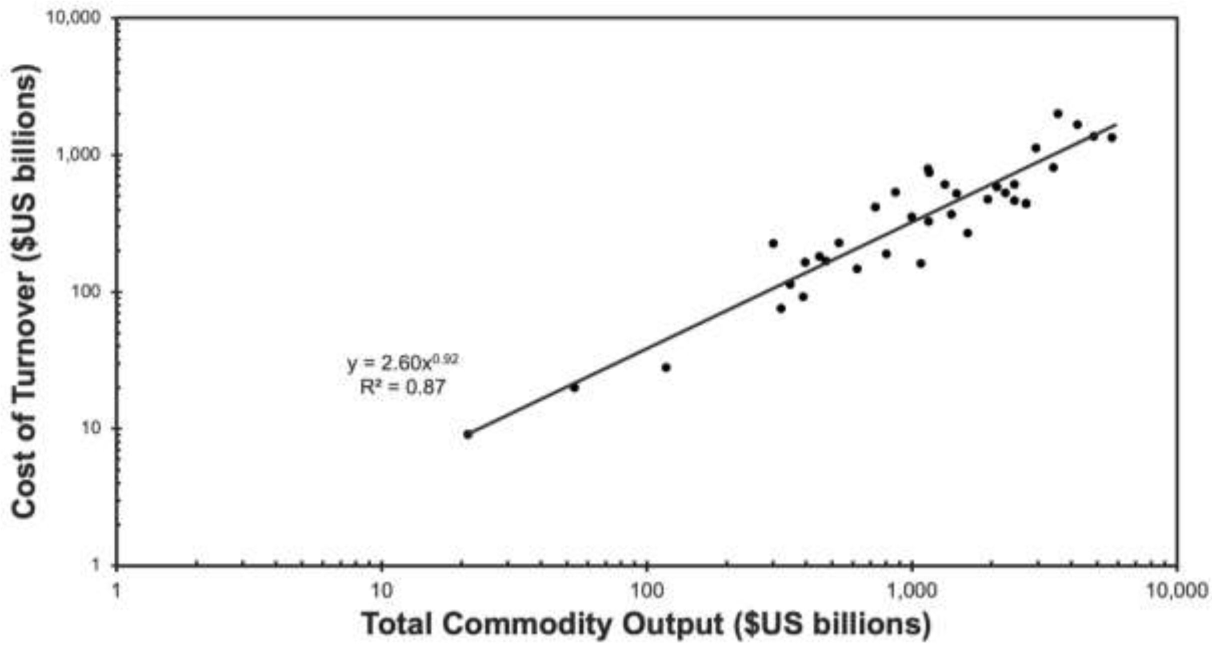

Figure 3.11 - A positively increasing relationship was created with the cost of turnover (COT) metric and economic output. COT for sectors and industries in the U.S. are shown to increase with increasing total commodity output. Values normalized by individual sector productivity, log-log scale.

While the COT metric assumes all employees work at the same level of productivity, the potential future expansion of COT to include occupation-level productivity could provide greater granularity in the COT metric. The next employee-needs metric to be evaluated is the TTY, representing the esteem needs of employees.

3.4.4 TTY

The TTY metric derives data from the unpublished (but publicly available) expansions of Table 3.5 from the BLS News Release - Employee Tenure Summary [United States Bureau of Labor Statistics, 2016]. Values are reported in "median years of tenure with current employer for employed wage and salary workers by industry," for the year 2012. Data were provided for sixty-nine 2- and 3-digit sectors and industries across thirteen time ranges for employee tenure. Both the median and mean years of tenure were included in the datasets. The median years of tenure (published and available online) were initially used to establish the TTY metric, but the disaggregated tenure time data provide a more complete count of tenured employees in each tenure time range. Both the median and mean years of tenure were compared against the accumulated total tenure years developed from Eq. (3.4). The median and mean total tenure years are shown as the ends of the low and high error bars in Figure 3.12, respectively. As the lower end of the range of tenure times was utilized for the TTY metric, the output still falls below the mean assessed TTY which could point to an underestimation of the total TTY for each sector or industry. The positive increasing relationship of the TTY to total commodity output, shown in Figure 3.12, allows the user to anticipate that with economic growth in a sector, a correlated increase in TTY can be expected.

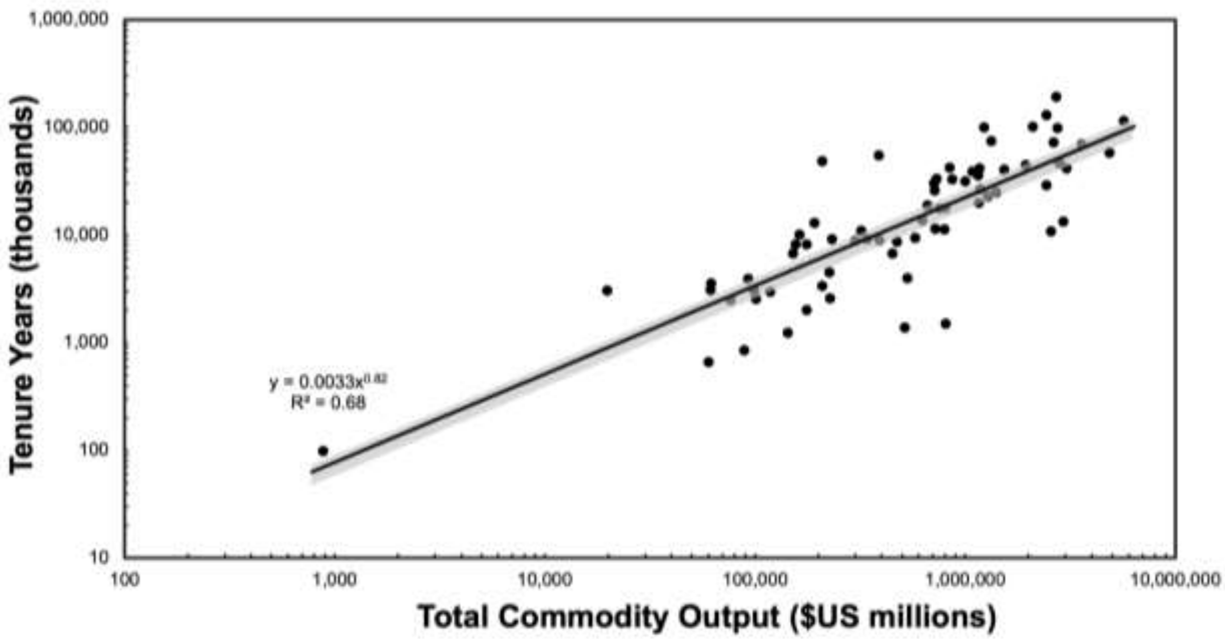

Figure 3.12 - A positively increasing relationship was created with the total tenure years (TTY) metric and economic output. TTY for sectors and industries in the U.S. are shown to increase with increasing total commodity output. Values are normalized by individual sector productivity, log-log scale. Gray range bar shows high and low TTY values using Mean and Median years of tenure per industrial sector, respectively.

The TTY metric is not monetized as prior metrics have been due to the broad range of perspectives offered for the economic value of employees over time [Fitz-Enz, 2000; Jacobs & Washington, 2003]. Throughout the literature, it is unclear where there may be the transition when an employee crosses from a negative value, or cost, to a company, over to a positive value thus creating a return on firm investment, visualized in Figure 3.13. There is general agreement on the concept, but little empirical evidence or supporting literature is offered to support the intuition. It is also expected that specific occupations may require a longer (or shorter) time to create positive value for a sector or industry. In addition, a variation of the range of occupations within sectors and industries is also expected, but supporting data are limited. With this understood, the unit of years for the TTY metric is presented to establish a starting point for future monetization of value from tenured employees.

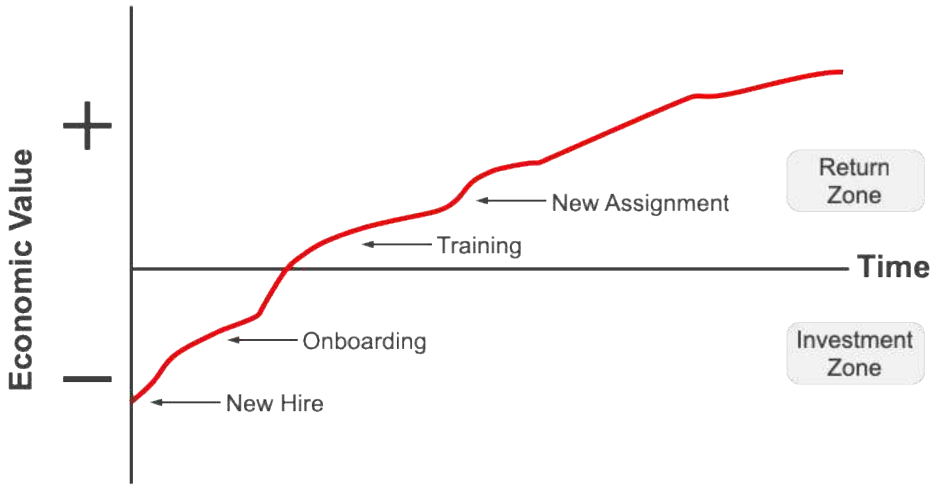

Figure 3.13 - The economic value of an employee to an organization showing positive return on company investment over time, adapted from [Bersin, 2013].

The future expansion of TTY to include occupation-level productivity over time could provide greater detail, and potential monetization, to the TTY metric. The next stakeholder-needs metric to be evaluated is the COB, representing the self-actualization needs of employees.

3.4.5 COB

The COB metric utilizes data from the ECEC and LPC datasets, i.e., total benefits compensation and total hours worked, for a select 28 sectors and industries. While the ECEC reports summary data for the sectors and industries, it is possible that certain occupations within the sectors or industries may have a larger fraction of the total compensation package dedicated to benefits. Consider the case of the Federal Government with 38% of the total cost of compensation attributed to benefits versus 61 - Educational services, having just over 26% of the total cost of compensation attributed to benefits. Both are service industries with the purpose to serve people, but the benefits packages vary widely in both costs per hour worked and the fraction of total compensation. This variation is even more drastic when considering all sectors and industries in the ECEC dataset.

Benefits compensation per hour worked serves as a useful comparable between industries, but alone is not enough to capture the total impact that benefits compensation may cost. In addition, the benefits compensation in each sector or industry has little relation to the economic output of the respective sector or industry. When combined with total hours worked, the total cost of benefits can then be assessed for each sector or industry. The COB metric, when compared to total commodity output of sectors and industries follows a positive increasing relationship as seen in Figure 3.14. With an increase in sector output, one can expect with fair certainty that COB would also increase.

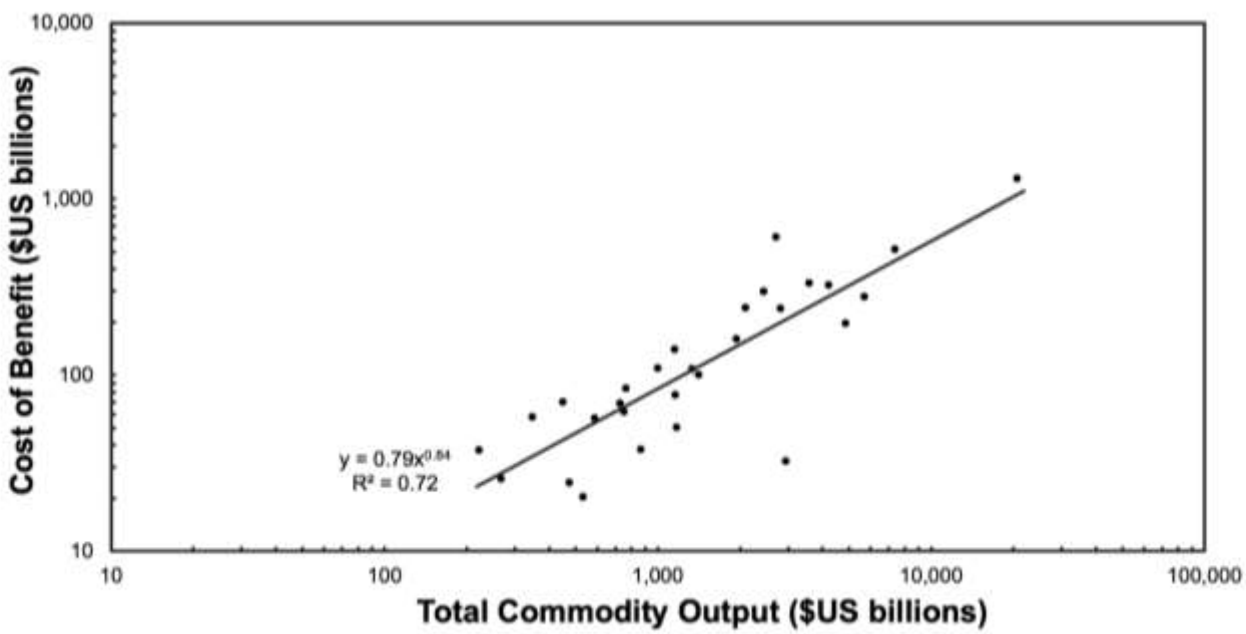

Figure 3.14 - A positively increasing relationship was created with the cost of benefits (COB) metric and economic output. COB for sectors and industries in the U.S. are shown to increase with increasing total commodity output, log-log scale. Both the linear and exponential regression curves are included for comparison.

The relationships between each metric and economic output identified through this section all show a positive increasing trend, but this may not be the case for all SI metrics. It is important to note that some metrics were supported with data that were more comprehensive for industry coverage, but at a minimum, all major NAICS sectors were accounted for in each metric. The following section will describe the values of each metric for the national whole, and the implications of such metrics for measuring the social performance of industries.

3.5 Results and Discussion

Some of the following discussion will include elaboration with the top 4 (of 15) individual sectors that contributed largely to the national totals for each proposed employee-needs metric. For a detailed industrial sector breakdown of all employee-needs metrics and contribution to national totals, see Table B.1. The overall discussion however, will explore the national totals for each employee-needs metric and how these will be used to develop the baseline of understanding for quantitative social impacts.

The quantitative total national outcome of each metric can be seen in Figure 3.15, where the four highest sector contributors (Top 4) are compared to the national totals for each needs metric. The Top 4 sectors in Figure 3.15 also can be seen to contribute well over 50% of the national total for each employee-needs metric. This may not be surprising since in several cases the Top 4 are also among the largest sectors in employment or total economic output. An interesting insight to identify however, is the mix of the Top 4 sectors varies for each employee-needs metric, i.e., 9 of the 15 total sectors are represented in at least one Top 4 ranking. It can be further noted that even though six sectors do not appear in the Top 4, a significant social impact is evident for all sectors.

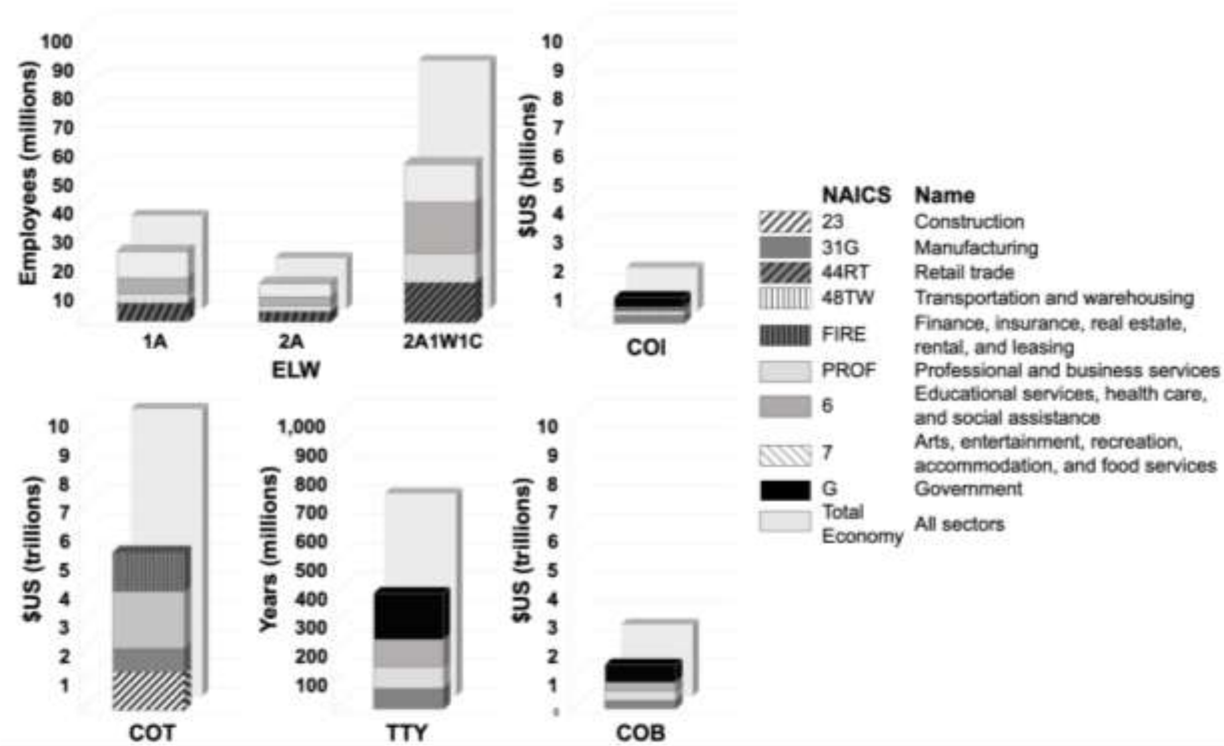

Figure 3.15 - The Top 4 NAICS industrial sectors compared to the national totals (light gray) for each employee-needs metric. In all cases, the top 4 contributors collectively exceed 50% of the national total social impact. For a description of each metric, see **Figure 3.3** and section 3.3.4.

Consider employee basic needs represented by the ELW metric in Figure 3.15. The ELW metric is split into three experimental households, 1A, 2A, and 2A1W1C (Figure 3.4). The household levels assume the entirety of the U.S. population is in that specific household size, e.g., for 1A all households are single individuals, where the employee is a wage earner in that household. Each ELW output identifies the quantity of employees within a sector that cannot meet basic needs by the wage they are paid. Figure 3.15 shows that sectors 44RT, PROF, 6, and 7 are the Top 4 and contribute the highest ELW to the national total for all three household sizes. While it is arguable that total numbers skew results in favor of larger sectors, the fraction of employees that are unable to meet their basic needs for each of the Top 4 is lower than sector 11-Agriculture (71%, 53%, and 95%), the smallest sector for employment and economic output in the U.S., in all but sector 7 (98%) for ELW2A1W1C, respectively (Table B.1). At the 2A1W1C household size, 66% of the working U.S. population earn wages below the regional cost of living. The national picture for the other household sizes, 1A and 2A, are slightly better however. If the U.S was comprised of only single people in the workforce, a full 25%, or over 32 million people, would still not earn enough in wages to satisfy their basic needs. For the dual income household (2A), i.e., assuming both members are wage earners, the fraction drops to 14%, or nearly 18 million employees, of the national working population. The ELW metric calculates basic employee-needs as number of employees, but units for the other metrics present additional valuable insight into national social performance.

The COI, COT, and COB metrics (Figure 3.3) each output values in millions of $US. Taken individually (Figure 3.15), COI is high for sectors with high relative employee productivity. The national total for COI was over US$15 billion, where two sectors, 31G-Manufacturing and G-Government, combined for 43%, and the Top 4 contributed 61% to the national total for COI. COT is also high for sectors with high employee productivity, but turnover of employees in a sector is a more damaging impact that lost work time. The national total cost of turnover calculated from the COT was nearly $10 trillion, where the Top 4 sectors, 23-Construction, 31G-Manufacturing, PROF-Professional and business services, and FIRE-Finance, insurance, real estate, rental, and leasing combined for over 55% of that total. The COB metric shows the high costs that a sector must pay to ensure that employees meet their potential. The national total for COB was nearly $2.5 trillion, where the Top 4 sectors, 31G, PROF, 6-Educational services, health care, and social assistance, and G, combined for 61% of that total. If the three cost metrics, COI, COT, and COB, are taken together, the national cost of employee-related SIs approached $12.5 trillion. The cost of these three metrics alone is equivalent to 43% of the total commodity output for the nation - not an insignificant financial impact from historically unlinked externalities of industrial activity.

For comparison, the total commodity output, i.e., total in $US demanded from each sector, and the total number of employees in the U.S. are included with the Top 4 in Figure 3.16. It is fair to discern that some sectors perform rather well compared to others for the total effect of SIs. While sectors with a large quantity of employees may seem to be disadvantaged for total SI, care must be given when comparing across sectors. The partial story that becomes readily apparent is sectors 31G, PROF, 6, and G each are in the top 4 for at least three SI metrics. These sectors are also in the top 5 for both total commodity output and number of employees. This suggests a logical correlation that with more employees, a higher value of SI can be expected, although this may not be always true. Consider that sector 23-Construction is a Top 10 sector for both economic output and employment but appears as a Top 4 sector for COT.

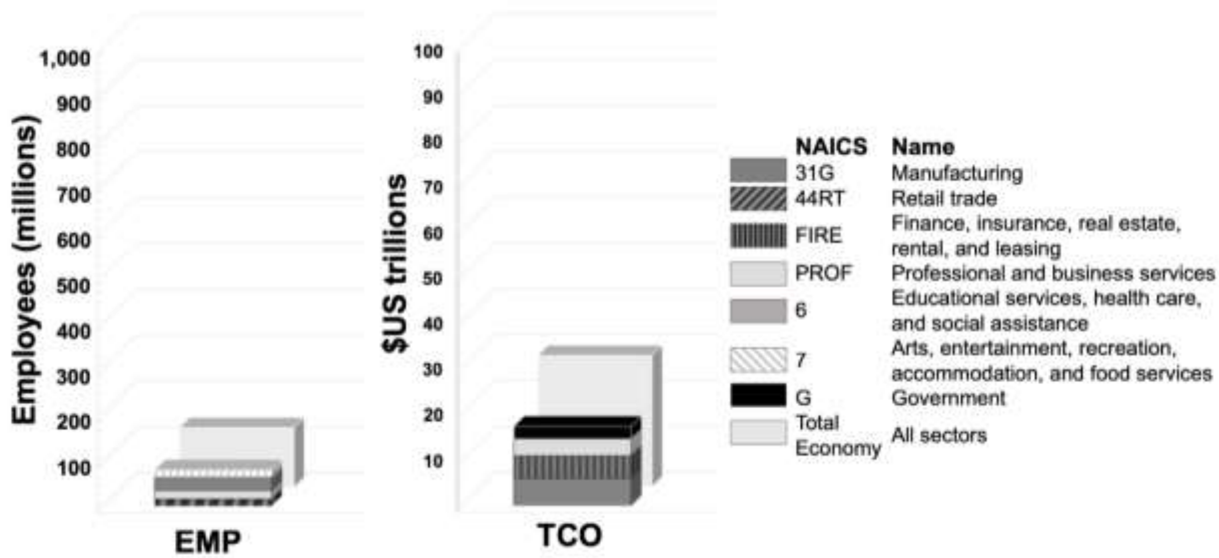

Figure 3.16 - U.S. employees and commodity output compared to the Top 4 sectors contribution to national totals. EMP - Employees; TCO - Total commodity output.

TTY is one of the two employee-needs metrics (ELW being the other) that are presented in units that do not capture an effective social cost of industrial activity. TTY is still nonetheless descriptive of the SIs borne out of industrial activity. While all of the suggested SI metrics have been designed to have a positive increasing relationship with industrial economic output (Figure 3.17), any economic growth can expect a resulting increase in respective SI values. The strength of the relationship between the proposed metrics and economic production validates the suitability of each metric as the starting point for evaluating the social performance of industries.

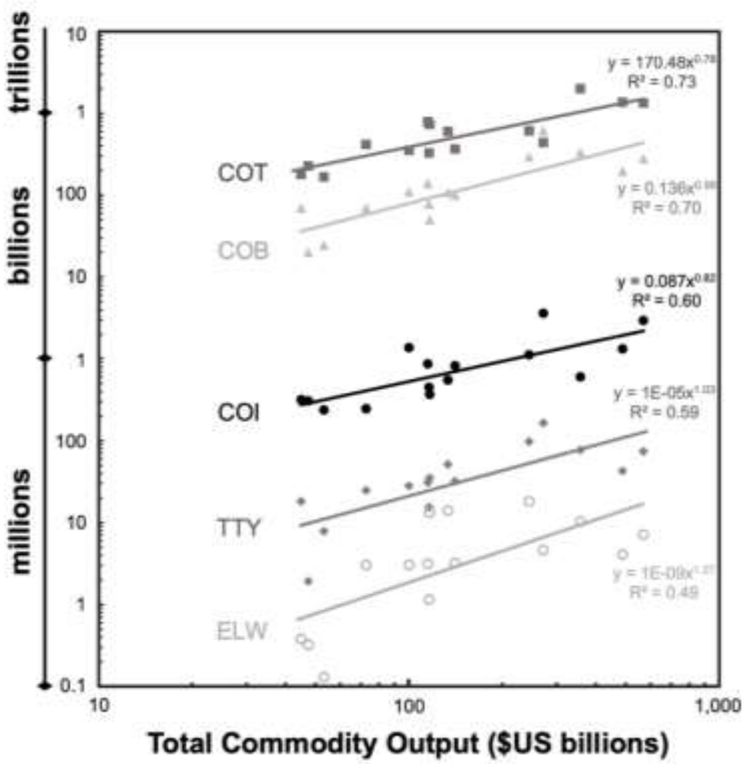

Figure 3.17 - Relationship of the 5 suggested social impact (SI) metrics to industrial economic activity (total commodity output, $US). ELW - Employees below the Living Wage (employees); COI - Cost of Injuries ($US); COT - Cost of Turnover ($US); TTY - Total Tenure Years (years); COB - Cost of Benefits ($US).

It must be reiterated here that evaluating social performance of industries by way of comparative indicators requires the development of suitable metrics. Metrics serve as the development step to establish a baseline for evaluating social performance. Without metrics supported by robust data measures, indicators will ultimately be limited in adaptability, scalability, and utility.

3.6 Summary and Conclusions

Industrial activity creates impacts on several stakeholders, in particular, the employees/workers. While challenging to quantify, SIs can be evaluated using readily available public data. The social data alone do not tell the story of employee-related SIs, but after considerable transformation, does begin to identify the effect that industrial activity has on the employee stakeholder group. Employees also have needs that can be met by the industry in which they work. Each need level presents a different challenge that may include data representativeness, industry coverage, and distribution across workers in a given sector. The SI metrics established in this work were created from the transformation of social data and represent each level of employee need. The employee-needs metrics begin to establish a baseline of understanding, that then informs the employee-needs indicators suggested by Hutchins et al. [2019]. The developmental path from measure transformed to metric and in turn, from metric creating a baseline for social performance indicator, further suggests that social performance of industrial activity can be measured, assessed, and adjusted.

The parameters of industrial social performance are evolving but must begin with an understanding of who are the impacted stakeholders. Since most industries have a set of stakeholders that extend beyond the employee/worker stakeholder group, it is worth noting the capability of the proposed SI metrics to address multiple stakeholder perspectives: ELW - owners, employees, local community; COI - owners, employees, regulators; COT - owners, employees, labor associations; TTY - owners, employees, local community, insurance; and COB - owners, supply chain partners, employees, local communities. Further, due to national (macro) level availability of many public datasets and subsequent suppression of disaggregated (micro) data, e.g., states, counties, or municipalities, building a macro scale metric may allow for micro scale simplification and assumptions to be made. When applied to a region (or individual state), sacrifices due to SI data availability may be required, but gaps can be filled with National level projections for industrial social performance.

The social performance of industries is in part described by the SI metrics developed through this work. The path described from measure to metric to indicator suggests a systematic approach to quantifying the true cost of social impacts from industrial activity. It has been shown that the impact of industrial activity on people is significant and should no longer be ignored. Potential future work could explore specific demographic data within each SI metric, including gender, race, and ethnicity, where available.

CHAPTER 4. ASSESSING THE SOCIAL COMPETITIVENESS OF U.S. MANUFACTURING SECTORS

The following chapter is currently in preparation for journal submission.

Keywords: Social Impact Metrics; Social Performance; Input-Output Economics; Social Sustainability; Regional Competitiveness

4.1 Abstract

In the last half century, much research effort has gone into identifying the causes and effects of societal burdens. Industrial activity may arguably be the most widely responsible cause, but the effects, or social impacts (SIs), resulting from industrial activity are typically considered externalities and not evaluated alongside economic performance of industries. In response to lacking social inclusion in performance models, this work applies quantified national SI metrics to an established economic input-output SI assessment (EIO-SIA) model. The output of the EIO-SIA model predicts SIs from industrial economic activity for eight regions and two divisions of manufacturing industries in the United States. Results are discussed in output per employee for each industry in each region, e.g., the total Cost of Turnover was over US$103,000 per employee in Advanced Manufacturing for the Great Lakes region. This work further proposes expanding the discussion on competitiveness to include social characteristics for industrial performance.

4.2 Introduction

Galileo is attributed with living by the motto, "count what is countable, measure what is measurable, and what is not measurable make measurable" [Aumala, 1999]. As societies continue to become more complex, the measurability of societal attributes will become increasingly more important and significantly more complicated. The difficulty in understanding how a complex system, such as a society, functions can be further compounded by the uncertain connection between what is measured, what the measures mean, and the impact reflected in those measures [Rossi, 2007]. In this way, researchers have expanded telling the human story through measures and data over the last century, from describing the entire economy with flows of goods and services [Leontief, 1936] to the corruption of modern nations [Xiao et al., 2017]. Specifically in the last half century, much research effort has gone into identifying the causes and effects of societal burdens [Andrews & Withey, 1976; Atkinson, 2002; Azar et al., 1996; Bauer, 1966; Boulanger, 2008; Diener & Suh, 1997; Hutchins et al., 2010; Sutherland et al., 2016; UNEP-SETAC, 2009]. It is suggested here, that industrial activity may be a leading contender for cause of societal, or social, impacts (SIs).

When SIs have a predictable relationship with industrial economic activity, one can then offer estimations to any further SIs that may arise from expanded (or reduced) economic activity. The relationship can also be further utilized at reduced spatial scales. Unfortunately, SIs caused by industrial activity are typically considered externalities and not evaluated with economic performance of industries. The following work considers intimately linking industrial economic activity with measurable SIs. The application of an economic model that describes national level industrial activity and related SIs was used to predict the resulting SIs at the regional level for the U. S. In turn, selected industries in the regions were then compared for social performance, against one another and then as contributors to the national total for each SI. In this way, it is suggested that industrial social competitiveness is a novel approach to include social impacts caused by industrial activity and expand research on industrial competitiveness [Bhawsar & Chattopadhyay, 2015, 2018; Dean & Sherwood, 1994; Neary, 2006; Oral & Reisman, 1988].

The subsequent section introduces the spatial, industrial, and social context of economic activity. Following in Section 4.4 is a description of the methods used to predict the regional SIs, starting with the model used, the economic data representing the regions, the quantified national SIs chosen, assumptions, and closing with limitations of the work. Section 4.6 presents the results of the model and discusses the regional outputs and industry competition for each of the selected SIs. Section 4.7 provides a summary and suggestions including future work.

4.3 Economic Regions, Industry Clusters, and Social Impacts

Before moving directly into the methods, data, and calculations, some explanation of the choices made to inform this work must be clarified. First, governmental organizations, e.g., U.S. Census, Federal Reserve, Agricultural Research Service, or U.S. Bureau of Economic Analysis (BEA), organize states into various regions according to several criteria, but most important is spatial proximity. For this work, the BEA regional groupings were used. Second, several classification systems, e.g., the North American Industrial Classification System (NAICS) or the International Standard Industrial Classification (ISIC) system, exist to categorize and group industries according to the goods produced or services provided. For this work, the NAICS system was used. Additionally, social impacts (SIs), and more specifically, the employee-needs SI metrics proposed by Richter et al. [Richter et al., Manuscript in preparation] were used to compare and evaluate regional, industrial social performance. Finally, the reference year for all data was 2012.

4.3.1 Bureau of Economic Analysis economic regions

The BEA defines regions as, “A set of geographic areas that are aggregations of the states.” Regional classifications date back to the mid-1950s [Kim, 1998] while additional grouping schemes have been suggested using more modern clustering techniques [Crone, 1998]. Other schemes were considered, but the simple criteria of proximity led to utilization of the BEA regional classification in this work. The BEA suggests that regional classifications are based in part on economic similarities of states, including labor force composition, as well as demographic, social, and cultural features [U.S. Bureau of Economic Analysis, 2019]. All 50 U.S. states including Washington D.C. were grouped according to the 2012 BEA region scheme seen in Figure 4.1. (For mapping of states to regions, see Table C.1).

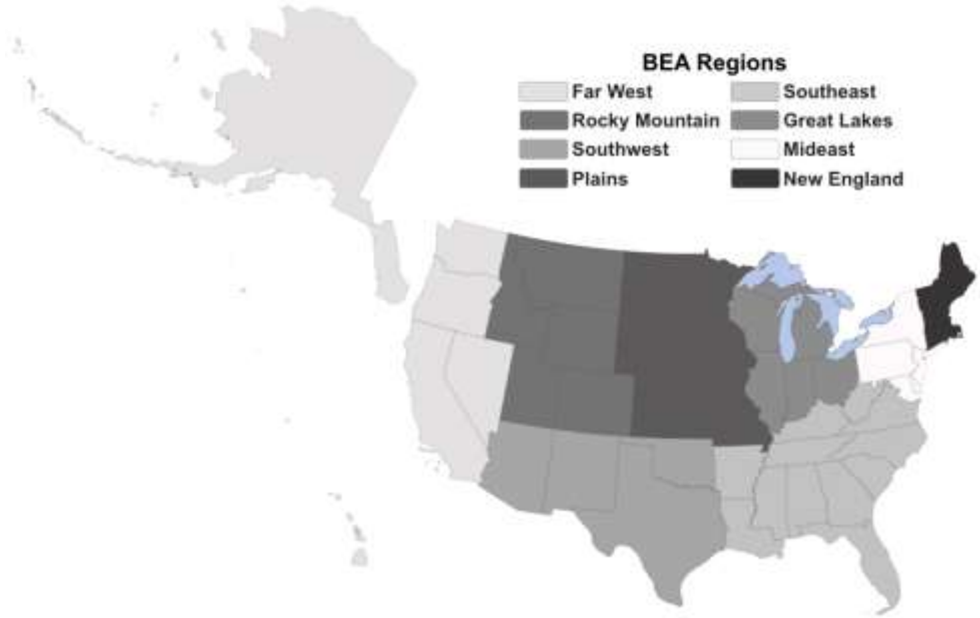

Figure 4.1 - Bureau of Economic Analysis regional clustering of all 50 United States including Washington D.C.

Similar to the regions defined above, industrial sectors also require selective grouping. A special classification case called industry clustering focuses on high performance industries and is described in the following section.

4.3.2 High performance industrial clusters

Industry clusters have been part of economic studies for at least the last two decades [Collard-Wexler & De Loecker, 2015; Delgado et al., 2014; Feser & Bergman, 2000; Porter, 2003; Porter, 1998; Rosenfeld, 1997; Slaper et al., 2018; Spencer et al., 2010]. Significant recent effort has focused on evaluating the performance of specific industry clusters known for innovation and technological change. The Advanced Manufacturing (AM) industry cluster is one of those innovative industry clusters and is of high interest to researchers, economists, policymakers, and development organizations [Bonvillian, 2013; Collard-Wexler & De Loecker, 2015; Muro et al., 2015; NAMRI/SME, 2014; Proceedings of the National Academy of Sciences, 2017; Waldman & Murray, 2013]. However, a consensus has not been reached on what industries to include in the AM cluster. For this work, seven industries within the 31G-Manufacturing sector were selected (See Table 4.1), consistent with the work from Richter et al. [Richter et al., 2019]. After extracting the AM industries from the main 31G sector, a new general manufacturing sector was created that will be referred to as 31R-Rest of Manufacturing going forward (Table C.2).

Table 4.1 - Industries and associated NAICS codes included in the Advanced Manufacturing industrial cluster.

NAICS	Name
AM	Advanced Manufacturing
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
3361MV	Motor vehicles, bodies and trailers, and parts
3364OT	Other transportation equipment

With the AM industry cluster defined, the next step is to select relevant, repeatable, and most essential, quantifiable social impacts.

4.3.3 National social impacts

A bounty of options are available in the research literature suggesting measurable impacts by way of social indicators, some dating back over a half century [Andrews & Withey, 1976; Atkinson, 2002; Bauer, 1966; Benoît-Norris et al., 2013; Hutchins et al., 2019; Joung et al., 2013; Richter et al., Manuscript in preparation; Sureau et al., 2017; UNEP-SETAC, 2009]. While most of the suggested indicators have strong foundations in logic and reasoning, the combined criteria of i) support with readily accessible datasets, ii) relation to industrial activity, and iii) stakeholder-relevant quantifiable impacts suggested use of something other than the available social indicators in the literature. As suggested by Sutherland et al. [Sutherland et al., 2016], social indicators are informed by the baselines of social performance established from capable social impact metrics. Metrics are the intermediary bridge between data and indicator, i.e., connecting a measure to meaning. As such, metrics for the stakeholder employee/worker, arguably the most impacted stakeholder were utilized. The metrics proposed by Richter et al. [Richter et al., Manuscript in preparation] were evaluated at a national level across a breadth of industries and sectors and present a strong empirical foundation to the quantifiable SIs that have eluded much of the social indicator literature.

Now that the regions are grouped, industries are clustered, and metrics are identified, application of established methods follows. The method, data sources, assumptions, and limitations are described in the subsequent section.

4.4 Application of Methods

Established calculation methods will be used to evaluate industry social performance for the regions identified in section 4.5.1 with the industry cluster suggested in 4.5.2 for the national metrics identified in section 4.5.3. The method for calculating total regional social impact will utilize the economic input output social impact assessment (EIO-SIA) method developed by Richter et al. [Richter et al., 2019]. The EIO-SIA method also includes a method for industry cluster derivation that was utilized first, to combine industries into larger sectors, and second, to derive the Advanced Manufacturing (AM) cluster described in section 4.5.2. The data used in the EIO-SIA model and cluster derivation calculations were accessed from a research platform for disaggregated national and modeled multiregional economic data.

4.4.1 Multiregional economic data

The input output (IO) economic data tables informing the subsequent analysis were accessed through the Input Output - State and National Analysis Program (IO-Snap) from West Virginia University [Jackson & Court, 2019]. The IO data were retrieved from the IO-Snap program, and were available in 67 industry combinations of Make, Use, Final Demand, and Value Added tables. By contrast, the national IO tables from the U.S. Bureau of Economic Analysis (BEA) are offered in 71 industry sets. The variation can be explained by reporting of government sectors (combined into 2 entries in IO-Snap from the 5 entries in the BEA tables) and the IO-Snap Real estate industry from the combination of two BEA industries, HS - Housing Services and ORE - Other Real Estate. For the IO-Snap to BEA, and industry to sector mapping, see Table C.2.

The IO-Snap model has a unique adaptation compared to traditional IO tables. Convention dictates that imports are handled as a reduction to Final Demand and exist as a column in the Use table (common with mostly negative entries). In contrast, imports are identified to lack a comparable domestic industry and therefore moved to the payments quadrant, i.e., removed from Final Demand in the Use tables, then subsequently transposed and added to the Make table. The entire import operation must be reversed for the IO tables to be used in the EIO-SIA method. Some pre-processing of the data with basic matrix algebra coerced the extracted tables into the traditional form for the Make and Use tables.

In addition to extracting IO-Snap data and engaging the EIO-SIA method, quantified SI data is required to inform industry social performance. The SI data focuses on a main stakeholder group impacted by industrial activity: the employee.

4.4.2 Employee-need metrics

The employee/worker is the stakeholder who may be most impacted by operations of industry. Following this premise, Richter et al. [Richter et al., Manuscript in preparation] suggested five quantitative metrics to address employees/workers and the associated need levels [Maslow, 1943, 1958] that can be affected by industrial activity. Tying the created metrics to industrial economic activity not only links two pillars of sustainability, but also intimately relates economic activity to societal impacts that have long been considered externalities of industrial activity. The five employee-need metrics can be seen in Figure 4.2, and were evaluated as U.S. national totals for each employee-need metric.

Figure 4.2 - Social impact metrics for the employee stakeholder at five need levels (italicized) used to evaluate regional social competitiveness in the EIO-SIA model [Richter et al., Manuscript in preparation].

Each metric was designed to have a clear relationship with industrial economic activity at the national level, thus providing the basis for scalability utility at the regional level. All five metrics were shown to have a positively increasing relationship with economic output, i.e., as output increases, so do the values for each metric. The scalability assumption is explained next.

4.4.3 Assumptions

While much of the prior literature assumes that impacts from economic activity are scalar, this is rarely proven to be true. Instead, Richter et al. [Richter et al., Manuscript in preparation] suggest that a measurable connection between economic activity and the desired social impact can aid in predicting social outcomes given a change in economic output. Simply stated, more industrial activity leads to greater social impact. The same can be stated about a decrease, i.e., less activity leads to a predictable reduction in social impact. The positively increasing relationship between economic output and social impact metric forms the basis for the assumption that social impacts per US$ of output at the national level will inform the R matrix required for regional application of the EIO-SIA method.

An additional assumption from the ELW metric requires attention. The ELW metric suggest three different household sizes, 1 Adult, 2 Adult, and 2 Adult, 1 Working, 1 Child. These household sizes assume the entirety of the U.S. is made up of that particular household size. Demographic analysis provides a heterogeneous composition of households throughout the U.S., but such analysis and data allocation will be a product of future work. Some further explanation of limitations follows.

4.4.4 Model, data, and other limitations

The EIO-SIA model utilizes national level economic and social data to offer a prediction regarding the subsequent SIs at the regional level. The scalability assumption suggests that all regions (and states) will operate with the same production mix as does the nation, e.g., AM represents about 10% of the national total commodity output. As a result, the model can identify regions, if any, that may not fit the scalability assumption. Potential regions outside the scalability assumption then may require a deeper investigation into the data causing the variation. In addition, the model is limited due to the absence of region-level data for many social impacts. Without greater granularity of social impact data, e.g., state-industry or county-sector, the top-down approach to social impact prediction is the best available method.

With data, methods, assumptions, and limitations established, an exploration of the results will provide some insight into the social competitiveness of AM in regions of the United States.

4.5 Results and Discussion

The employee-need metrics used in the EIO-SIA model are set to inform the baseline of social performance for industries and regions across the U.S. While the total output of each metric across regions is advantageous for future work, it provides little insight into regional social competitiveness when normalization is not considered. For simplification of the discussion, all metrics were subjected to the simple normalizing step of dividing the total regional SI metric by the total number of employees in each sector per region, e.g., approximately 1.49 million workers were employed in the Advanced Manufacturing cluster the Great Lakes region in 2012. Such a basic normalization step allows the unit of each SI metric to be reported as “unit per employee,” and the following discussion will then explore how Advanced Manufacturing compares to the Rest of Manufacturing for the five SI metrics in the eight BEA regions of the U.S.

Beginning with employee basic needs, the trend seen in the maps of Figure 4.3 is that 31R has a consistently higher fraction of total employees below the living wage than does AM. The 1 Adult households (Figure 4.3Figure 4.3A-B) for 31R show a range of ELW from 14% (approx. 39,000 employees) in the New England region up to 38% (over 200,000 employees) in the Southwest region. By contrast, the highest ELW for AM with same household size only reaches 10% in the Great Lakes region. Considering the total number of employees in the Great Lakes region, this is still quite a large quantity of employees who are unable to earn a living wage, at over 150,000 employees. In the grand scheme of the national total ELW for 1 Adult households, 31R and AM contribute 4.0% and 1.6%, respectively, amounting to over 1.8 million employees below the living wage collectively.

A similar comparison can be seen in the maps of Figure 4.3C-D for the 2 Adult household as well. The 2 Adult household, where both adults are wage earners, show a reduced percentage of ELW for both 31R and AM. While the Southwest region is still highest in percentage of ELW at 22% (over 115,000 employees), the Southeast region at 12% ELW has the highest total of employees below a living wage at approximately 204,000 employees. Similar to the 1 Adult households, the Great Lakes region presents both the highest percentage (5%) and total ELW (approximately 72,000 employees). Notable however, is the Southwest and Far West regions also show 5% of employees (41,000 and 30,000, respectively) earning below a living wage. For the national total ELW of 2 Adult households, 31R and AM contribute 4.2% and 1.4%, amounting to over 990,000 employees living below the living wage collectively.

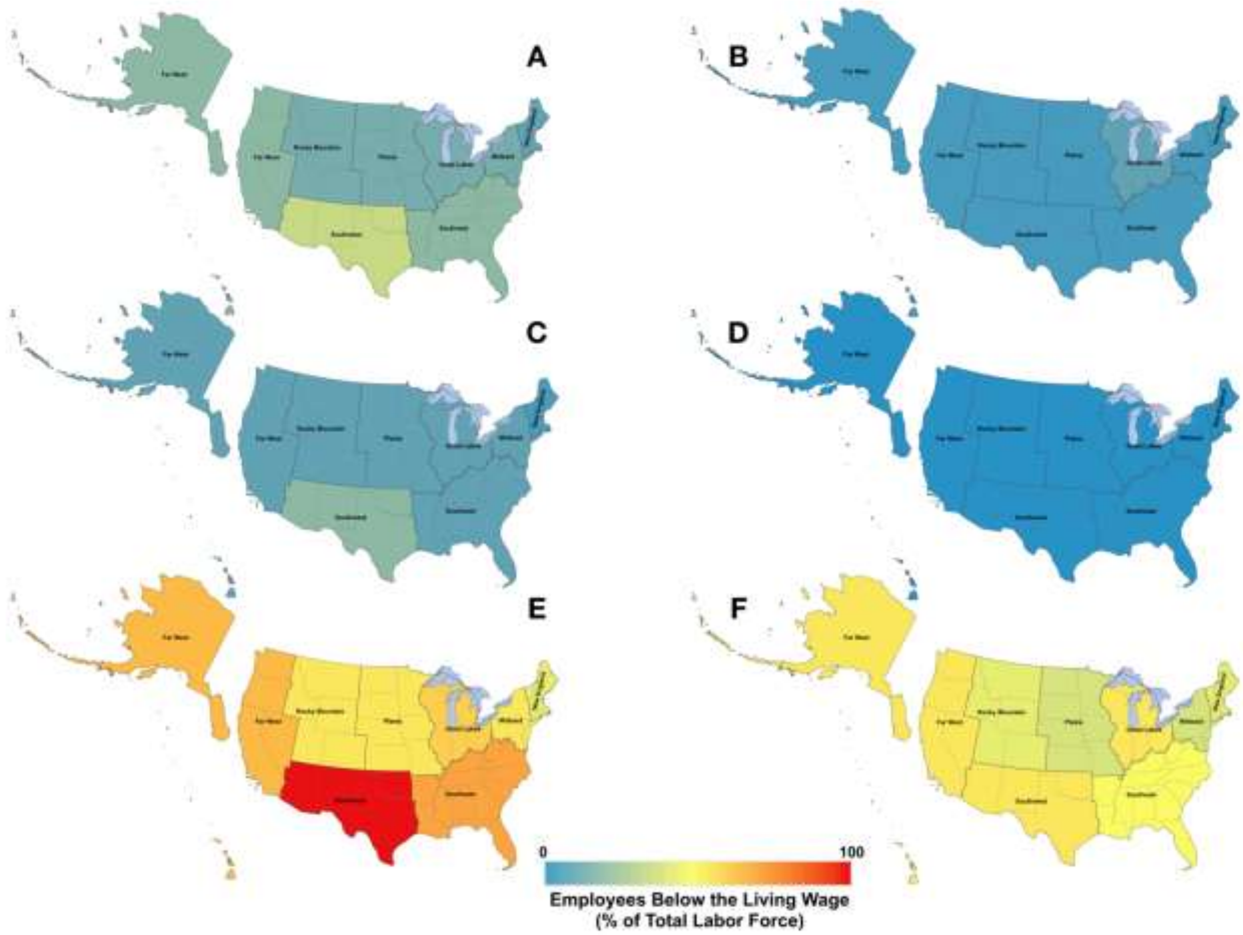

Figure 4.3 - Comparison of three household sizes [1 Adult (A, B), 2 Adult (C, D), and 2 Adult, 1 Working, 1 Child (E, F)], two manufacturing clusters [31R-Rest of Manufacturing (A, C, E) and AM-Advanced Manufacturing (B, D, F)], across eight regions of the United States for percent of Employees Below the Living Wage (ELW).

The final household size of 2 Adults, 1 Working, 1 Child, introduces additional expenditures to the household by way of one worker earning for two dependents. A drastic increase in fraction of ELW is expected, and is exactly what is observed in Figure 4.3E-F. Both 31R and AM encroach, and for some regions surpass, the 50% employees earning below a living wage. Looking first at 31R, the standout observation is that the Southwest region shows 100% ELW. In actuality, the results of the model predict that 124% of the employees in 31R are earning below the living wage for this household size. While this is clearly not a possibility, the model does highlight that this region presents a complication for the model and does not completely fit the scalability assumption. The complication is identified within two industries that supply 40% of total manufacturing output and 64% of 31R output in the region: 324-Petroleum and coal products, and 325-Chemical products. These two industries are clearly very large producers in the area, and the national model does not suitably capture the dependence on such industries for this region. In this instance, the model does exactly as it should, and identifies where further development is needed.

To complete the discussion on the 2 Adult, 1 Working, 1 Child household ELW results, 31R in all regions except New England (46%) exceed 50%, with the Southeast as high as 70% (approximately 1,150,000 employees). AM, by comparison, has 4 of the 8 regions above 50% with the highest still being the Great Lakes region, and all regions above 40% employees earning below a living wage. Consider the reality of over 4.1 million employees in 31R and over 3.0 million employees in AM across the country unable to earn a living wage. This may speak to the significance of the cost of living around the nation, but also may speak to the continuous struggle to earn wages suitable for a modern life. For the national total ELW of 2 Adult, 1 Working, 1 Child households, 31R and AM contribute 4.9% and 3.5%, amounting to over 7,180,000 employees living below the living wage collectively. The following discussion will explore the four remaining employee-need metrics in summary of region for highest, lowest, and industry cluster compared to the national totals.

The next metric in hierarchy of employee-needs is COI. This metric captures the cost of time lost to injury and is the lowest of the cost-related metrics. As discussed earlier, the Southwest region may not be an ideal fit using the national model, but can be seen to contribute the highest cost of injuries per employee of all eight regions, seen in Figure 4.4A. For all but the New England region, 31R is predicted to have greater COI than AM would. Overall, the lowest COI is the Mideast region for AM at US$177.50 per employee and the Plains region is a close second lowest at US$186 per employee. COI at the highest is predicted in 31R in the Southwest region exceeding US$505 per employee. The next highest COI can be seen in the Southeast at US$286 per employee. For the national total COI, 31R and AM contribute 11.2% and 8.5%, amounting to over US$2.995 billion collectively. This is not an insignificant amount but considering that the total national output exceeded US$30 trillion in 2012, COI may seem a lower priority than the next metric, Cost of Turnover.

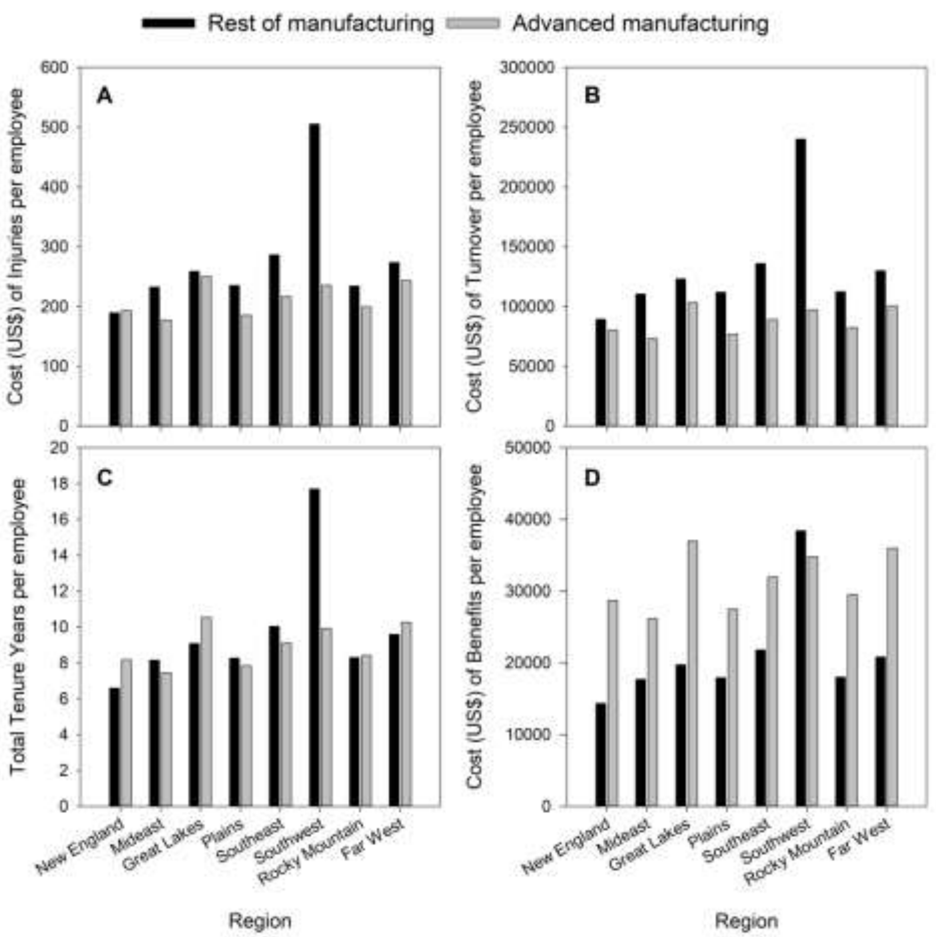

Figure 4.4 - Employee-need metrics comparing Rest of Manufacturing (black) and Advanced Manufacturing (gray) for the eight BEA regions in the U.S. All metrics normalized for number of employees in sector in region. A) Cost of Injuries; B) Cost of Turnover; C) Total Tenure Years; and D) Cost of Benefits.

The next metric in hierarchy of employee-needs is COT. This metric captures the cost of job separations by way of quits, terminations, and other losses. Similar to the occurrences before, the Southwest region can be seen to contribute the highest cost of injuries per employee of all eight regions, seen in Figure 4.4B. In all eight regions, 31R is predicted to have greater COT than expected of AM. Overall, the lowest COT is the Mideast region for AM at just over US$73,000 per employee and the Plains region is a close second lowest costing nearly $77,000 per employee. COT at the highest is predicted in 31R in the Southwest region exceeding $240,000 per employee. The next highest COT can be seen in the Far West at over US$130,000 per employee. For the national total COT, 31R and AM contribute 8.1% and 5.3%, amounting to over US$1.34 trillion collectively. A predicted COT extending into the cost territory of the total national output might create a cause for concern with industries seeking to attract and retain talent. Losing employees is clearly a highly expensive endeavor, but there is hope for certain regions that are fairly successful at retaining talent, as seen in the next metric, Total Tenure Years.

The next metric in hierarchy of employee-needs is TTY. This metric captures the time that employees spend in an industry. As seen with earlier metrics, the Southwest region is predicted to have the highest total tenure years per employee of all eight regions, seen in Figure 4.4C. This metric sees an observable shift in the trend of regions in 31R predicted to be higher than AM. Four of the eight regions are higher for AM than 31R, and more specifically the shift happens in the New England, Great Lakes, Rocky Mountain, and Far West regions. Overall, the lowest TTY is the New England region for 31R at 6.6 years per employee and the Mideast region for AM is a close second lowest at 7.5 years per employee. TTY at the highest is predicted in 31R in the Southwest region exceeding 17.7 years per employee and nearly three times the lowest TTY. The next highest TTY can be seen in the Great Lakes region for AM at 10.5 years per employee. For the national total TTY, 31R and AM contribute 7.1% and 6.5%, amounting to over 114 million tenure years collectively. It can be argued that if an employee is willing to commit extended periods of time to an industry, the value of that employee would increase with expanded knowledge and experience. A high TTY could then be suggested to identify the successful, and potentially efficient and effective industries. To get employees to make a long-term commitment to an industry, it is often argued that an industry most provide benefits to enable employees to be more successful. The final metric, Cost of Benefits, identifies the cost of that enabling behavior.

The highest order employee-need metric in hierarchy is COB. This metric captures the cost of benefits offered to employees in attempt to enable employees to become the best they can be. As expected, the Southwest region is predicted to contribute the highest cost of benefits per employee of all eight regions, seen in Figure 4.4D. Different in this metric however, is in seven of the eight regions the AM cluster far exceeds the COB per employee in 31R. Overall, the lowest COB is the New England region for 31R at just over $14,000 per employee and the Mideast region for 31R is a distant second lowest costing nearly $18,000 per employee. COB at the highest is predicted in 31R in the Southwest region exceeding $38,000 per employee. The next three highest regions for COB can be seen in the Great Lakes, Far West, and Southwest for AM at US$37,000, US$36,000, and US$35,000 per employee, respectively. For the national total COB, 31R and AM contribute 5.1% and 7.5%, amounting to over US$320 billion collectively. High COB may be associated with happier, more fulfilled, and more productive employees, enabling an employee to reduce stress and worry and become a more productive version of their best self.

As employee-needs are the focus of the metrics, manufacturing sectors are the focus of comparison, and regions are the focus of competitiveness utilized in this work, much work remains in exploring how social impact models can better create social impact predictions. The following section will summarize the work done here and provide some guidance of future work.

4.6 Summary and Conclusions

This work set forth to apply the EIO-SIA model using national level data to predict regional outcomes for various social impacts. Where the model offered reasonable outcomes for most regions, the model also identified a region that did not align with the national expectation. This, in fact, is what a model is supposed to do, i.e., highlight areas of the data that need deeper exploration. Using economic data to predict social impacts is not without limitations, but in the absence of micro level, e.g., county, state, or region, social impact data, the EIO-SIA model presents a reasonable prediction for the social impacts of industrial economic activity.

The predicted SI values will be used to begin the creation of a database informing baseline values for various SIs, ultimately leading to a more descriptive understanding of industrial social performance. Where discussion of total SI values is meaningless without context of comparison, regional total values for each SI were the goal of this work from the very beginning. The total values for each employee-need metric will be used to inform future work that then will inform benchmarking for social performance. At present, baselines for comparison do not yet exist. Only when a baseline is created can the comparative understanding of social performance, i.e., the knowledge of good, bad, good enough, and superior performance, truly influence decisions.

4.7 Acknowledgments

The authors would also like to thank Dr. Randall Jackson of West Virginia University for granting access to regional input-output data from the IO-Snap model.

CHAPTER 5. SUMMARY AND CONCLUSIONS

The entirety of this work began with a goal to understand, and quantitatively describe, how people are affected by industrial and economic activity. While impacts on humans are commonly measured, they are often considered external to the bottom line of industrial and economic production. It has been suggested that people are integral, and intimately tied, to the success or failure of economies, but recent research advances have only begun to address how economic and industrial activity affect people. After much development, iteration, failure, and adaptation, the results from exploring how people are affected by industrial activity suggested the initial goal was shortsighted and needed strengthening. The initial goal is subsequently enhanced by the need to influence industrial behavior change for the betterment of impacted stakeholders. Through this effort it is shown that an industry can have profound impacts on a single stakeholder, that in turn can result in significant impacts back to the industry.

In total, this work describes a quantitative path forward for predicting social impacts due to changes in economic and industrial activity. Through the course of this work, four novel contributions can be identified. The first includes a framework that suggests the transformation of data, or measures, to meaning through creation of metrics. The second includes creation of five employee-need metrics to further the development of baselines for understanding true social performance, e.g., good, bad, or good enough, applied to various spatial scales. Additionally, this work develops a multidisciplinary quantitative method that links society to economy. The final contribution suggests that an economy can also be explored in valuable detail by extracting high performance industrial clusters. Collectively these contributions can be used to further the understanding of industrial social performance.

While two pillars of sustainability, economy and society, are addressed here, a full elaboration of sustainability, including environment, is necessary if we are to find a just and safe operating space for humanity. Previous work attempting to connect economy, society, and environment in a measurable way has been limited mostly to the economy-environment relationship. In the search for sustainable solutions, solely focusing on decreasing resource consumption, improving efficiency, and reducing environmental damage, while common operational practice, is insufficient. Social impacts associated with industrial activity require increasing consideration but remain difficult to measure. The three pillars of sustainability (economy, environment, and society) together require a common platform for evaluation and a method that has clear operational and functional applicability. The quantifiable method linking economy to society described through this work enables a larger overall assessment of the anthropocentric effects of industrial production activity and the resulting societal effects.

The suggested method, integrated economic input-output social impact analysis, EIO-SIA, can be used to estimate SIs across several spatial scales, within industrial sectors, or throughout industrial sector relationships. While this work is explicitly attentive to the U.S. economy, the expanded EIO-SIA method is also capable of describing SIs for important industrial subsectors in any country with developed economic input-output accounts. Parallel to economic accounts that may require coordination, the SI data may also require transformation.

While challenging to quantify, SIs can be evaluated using readily available public data. The social data alone do not tell the story of employee-related SIs, but after considerable transformation, does begin to identify the effect that industrial activity has on the employee stakeholder group. Employees also have needs that can be met by the industry in which they work. Each need level presents a different challenge that may include data representativeness, industry coverage, and distribution across workers in a given sector. The SI metrics established in this work were created from the transformation of social data and represent each level of employee need. The employee-needs metrics begin to establish a baseline of understanding, that then informs the employee-needs indicators suggested by Hutchins et al. [2019]. The developmental path from measure transformed to metric and in turn, from metric creating a baseline for social performance indicator, further suggests that social performance of industrial activity can be measured, assessed, and predicted.

SIs at various scales can be predicted by the EIO-SIA model. Using national level data enabled prediction of regional outcomes for various social impacts. Where the model offered reasonable outcomes for most regions, the model also identified a region that did not align with the national expectation. This, in fact, is what a model is supposed to do, i.e., highlight areas of the data that need deeper exploration. Using economic data to predict social impacts is not without limitations, but in the absence of micro level, e.g., county, state, or region, social impact data, the EIO-SIA model presents a reasonable prediction for the social impacts of industrial economic activity.

The predicted SI values will be used to begin the creation of a database informing baseline values for various SIs, ultimately leading to a more descriptive understanding of industrial social performance. The total values for each employee-need metric will be used to inform future work that then will inform benchmarking for social performance. At present, baselines for comparison do not yet exist. Only when a baseline is created can the comparative understanding of social performance, i.e., the knowledge of good, bad, good enough, and superior performance, truly influence decisions of change. Baselines will require extensive processing of temporal data beyond the single year focus of this work. Decadal analysis (where data available) and changes over time for the employee-need metrics proposed in this work are highly interesting and worth significant future consideration. An expansion on this idea includes addressing the entirety of the stakeholder-needs categorization suggested by [Hutchins et al., 2010] with data. The measures from data would then be transformed into relevant metrics, each building the foundation of understanding for baseline industrial social performance in all thirty categories in the framework. An ideal scenario would be transformation into common units for each metric enabling a composite social performance evaluation index. As Rome was not built in a day, I am reminded that evaluating social impacts may take a similar amount of time.

In closing, it can be seen that the impact of industrial activity on people is significant and should no longer be ignored. Potential future work could also explore specific demographic data within each SI metric, including gender, race, and ethnicity, where available.

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APPENDIX A. SUPPLEMENTAL MATERIAL FOR CHAPTER 2

Section A.1 - Acronyms

Table A.1 - Notations and Descriptions.

Notation	Description
AM	Advanced Manufacturing
BEA	Bureau of Economic Analysis (U.S.)
BLS	Bureau of Labor Statistics (U.S.)
bn	billion
COI	Cost of Injuries
ELW	Employees below a Living Wage
EIO	Economic Input-Output
IA	Impact Assessment
IO	Input-Output
LCA	Life Cycle Assessment
MMIs	Measures, Metrics, and Indicators
NAICS	North American Industrial Classification System
SI	Social Impact
SIA	Social Impact Assessment
SLCIA or S-LCIA	Social Life Cycle Impact Assessment

Section A.2 - Review of Economic Input-Output Model

An example economy is depicted in **Table A.2** with three industrial sectors, all requiring resources from the others to operate. This scenario assumes there are no external inputs, or simply, no imports from outside the economy. O_{ij} represents the output of sector *i* consumed by sector *j*. Combining all inputs across industrial sectors (*j*) for a commodity producing sector (*i*), generates the intermediate output (*O*) for sector *i*. Adding *O* to final demand (*F*), where *F* represents the quantity requested by consumers of the final commodity from that industrial sector, results in total commodity output (*X*) for sector *i*.

Table A.2 - Input-output depiction of economy use table with industry sector interactions.

		Industrial Sector (j) "to" or "consuming"			Intermediate Output (O)	Final Demand (F)	Total Commodity Output (X)
		1	2	3			
Industrial Commodity (i) "from" or "producing"	1	O_{11}	O_{12}	O_{13}	O_1	F_1	X_1
	2	O_{21}	O_{22}	O_{23}	O_2	F_2	X_2
	3	O_{31}	O_{32}	O_{33}	O_3	F_3	X_3
	Intermediate Input (I)	I_1	I_2	I_3			
	Value Added (V)	V_1	V_2	V_3		GDP	
	Total Industry Output (X)	X_1	X_2	X_3			

The equation that describes the output from sector X_1 is

$$O_{11} + O_{12} + O_{13} + \ldots + O_{1n} + F_1 = O_1 + F_1 = X_1 \tag{A.1}$$

or in general for the ith sector output, X_i, as

$$O_{i1} + \ldots + O_{ij} + \ldots O_{in} + D_i = O_i + F_i = X_i \tag{A.2}$$

Expressing all intermediate outputs, O_{ij}, as a fraction of total industrial sector output, X_j, identifies the amount of commodity inputs required by an industry to produce each dollar of output. While commodity producing sector *i* and consuming sector *j* can be the same industrial sector, e.g., O_{22}, the fundamental difference is that *i* produces commodities and *j* is agnostic of product or service differentiation. The resulting values (quotients) are commonly considered the direct coefficients, viz.,

$$A_{ij} * X_j = O_{ij} \tag{A.3}$$

and thus,

$$A_{ij} = O_{ij}/X_j \tag{A.4}$$

Entering Eq. (A.3) into Eq. (A.2), the system becomes

$$A_{i1}X_1 \ldots + A_{ij}X_j + \ldots + A_{in}X_n + F_i = X_i \quad \text{(A.5)}$$

All the direct coefficients may be summarized with a matrix, **A**, often referred to as the direct requirements matrix. In matrix notation, the example economy becomes

$$\mathrm{AX} + \mathrm{F} = \mathrm{X} \quad \text{(A.6)}$$

Using matrix algebra, the resulting equation reorganizes to

$$\mathrm{X} - \mathrm{AX} = \mathrm{F} \quad \text{(A.7)}$$

or,

$$[\mathbf{I} - \mathbf{A}]\mathrm{X} = \mathrm{F} \quad \text{(A.8)}$$

where I is an identity matrix. Solving for X, Eq. (A.8) becomes:

$$[\mathbf{I} - \mathbf{A}]^{-\mathbf{1}}\mathrm{F} = \mathrm{X} \quad \text{(A.9)}$$

also known as the Leontief inverse equation. The Leontief inverse is valuable for explaining individual or aggregated sector contributions to the final output of every other industrial sector.

Section A.3 – Industrial sector numbering and nomenclature

Table A.3 - North American Industrial Classification System sector codes used by the U.S. Bureau of Economic Analysis (NAICS codes used by the U.S. BEA). Shaded sectors are those in the Advanced Manufacturing cluster as the final entries in the table.

IO Code	Industrial Sector Name	IO Code	Commodities/Industries Name
11	Agriculture, forestry, fishing, and hunting	111CA	Farms
		113FF	Forestry, fishing, and related activities
21	Mining	211	Oil and gas extraction
		212	Mining, except oil and gas
		213	Support activities for mining
22	Utilities	22	Utilities
23	Construction	23	Construction
31G	Manufacturing	321	Wood products
		327	Nonmetallic mineral products
		331	Primary metals
		332	Fabricated metal products
		333	Machinery
		334	Computer and electronic products
		335	Electrical equipment, appliances, and components
		3361MV	Motor vehicles, bodies and trailers, and parts
		3364OT	Other transportation equipment
		337	Furniture and related products
		339	Miscellaneous manufacturing
		311FT	Food and beverage and tobacco products
		313TT	Textile mills and textile product mills
		315AL	Apparel and leather and allied products
		322	Paper products
		323	Printing and related support activities
		324	Petroleum and coal products
		325	Chemical products
		326	Plastics and rubber products
42	Wholesale trade	42	Wholesale trade
44RT	Retail trade	441	Motor vehicle and parts dealers
		445	Food and beverage stores
		452	General merchandise stores
		4A0	Other retail
48TW	Transportation and warehousing	481	Air transportation
		482	Rail transportation
		483	Water transportation
		484	Truck transportation
		485	Transit and ground passenger transportation
		486	Pipeline transportation
		487OS	Other transportation and support activities
		493	Warehousing and storage

Table A.3 -*Continued*

IO Code	Industrial Sector Name	IO Code	Commodities/Industries Name
51	Information	511	Publishing industries, except internet (includes software)
		512	Motion picture and sound recording industries
		513	Broadcasting and telecommunications
		514	Data processing, internet publishing, and other info services
FIRE	Finance, insurance, real estate, rental, and leasing	521CI	Federal Reserve banks, credit intermediation, and related activities
		523	Securities, commodity contracts, and investments
		524	Insurance carriers and related activities
		525	Funds, trusts, and other financial vehicles
		HS	Housing
		ORE	Other real estate
		532RL	Rental and leasing services and lessors of intangible assets
PROF	Professional and business services	5411	Legal services
		5415	Computer systems design and related services
		5412OP	Miscellaneous professional, scientific, and technical services
		55	Management of companies and enterprises
		561	Administrative and support services
		562	Waste management and remediation services
6	Educational services, health care, and social assistance	61	Educational services
		621	Ambulatory health care services
		622	Hospitals
		623	Nursing and residential care facilities
		624	Social assistance
7	Arts, entertainment, recreation, accommodation, and food services	711AS	Performing arts, spectator sports, museums, and related activities
		713	Amusements, gambling, and recreation industries
		721	Accommodation
		722	Food services and drinking places
81	Other services, except government	81	Other services, except government
G	Government	GFGD	Federal general government (defense)
		GFGN	Federal general government (nondefense)
		GFE	Federal government enterprises
		GSLG	State and local general government
		GSLE	State and local government enterprises
Used	Scrap, used and secondhand goods	Used	Scrap, used and secondhand goods
Other	Noncomparable imports and rest-of-the-world adjustment	Other	Noncomparable imports and rest-of-the-world adjustment
AM	**Advanced Manufacturing**	331	Primary metals
		332	Fabricated metal products
		333	Machinery
		334	Computer and electronic products
		335	Electrical equipment, appliances, and components
		3361MV	Motor vehicles, bodies and trailers, and parts
		3364OT	Other transportation equipment

Section A.4 – Variable descriptions

Table A.4 - Description and assumptions for equation variables and parameters.

Description variables and parameters	**Description/definition**	**Assumptions/references**
O_{ij}^{target}	Value of the commodity input for the specific industry of interest (from the 71-industry tables) to be used in the 15-sector input-output model.	Example: Advanced Manufacturing (AM) cluster of industries (331, 332, 333, 334, 335, 3361MV, and 3364OT) are all in sector Manufacturing (31G).
$O_{ij}^{expansion}$	Value of the commodity input for the specific industrial sector requiring expansion (from the 15-sector tables).	Example: Industries 331, 332, 333, 334, 335, 3361MV, and 3364OT are each individual industries in the AM cluster.
$O_{ij}^{rest\ of\ main\ sector}$	Value of the total commodity input for the remaining industries (from the 71-industry tables) within the main sector that the target industry/cluster was derived from.	Example: Main sector 31G has 19 industries (See A.3). Rest of main sector is industries remaining in sector 31G after removing AM (7 industries), referred to as 31R in the text.
$O_{ij}^{main\ sector}$	Value of the commodity input from the specific sector (from the 15-sector tables) that the target industry/cluster is derived from.	Example: Manufacturing (31G)
B_{ij} or **B**	Elements of the rectangular direct requirements matrix (**B**), derived from the input-output Use tables.	Miller, R. E., & Blair, P. D. (2009). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press. Chap. 5.6, p.511-13.
X_i, X_j or X	Elements of the total commodity output vector (X) from the Use table.	Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic System of the United States. *Review of Economic Statistics*, 18(3), 105-125.
D_{ij} or **D**	Elements of the rectangular market shares matrix (**D**), derived from the input-output Make tables.	Miller, R. E., & Blair, P. D. (2009). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press. Chap. 5.6, p.511-13.
V_{ij} or V	Elements of the value added vector (V) from the Use tables, equaling the total value an industry adds to the inputs.	Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic System of the United States. *Review of Economic Statistics*, 18(3), 105-125.
Q_j or Q	Elements of the total commodity output vector (Q) from the Make table.	Miller, R. E., & Blair, P. D. (2009). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press. Chap. 5.6, p.511-13.
I	The identity matrix where the value 1 is present on the diagonal and all other values are 0.	Not cited in text: Strang, G. (2006). *Linear Algebra and Its Applications*. Cengage Learning; 4th ed.

Table A.4 - *Continued*

Description variables and parameters	**Description/definition**	**Assumptions/references**
F	The final demand vector of commodities required by consumers in the economy.	Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic System of the United States. *Review of Economic Statistics*, 18(3), 105-125.
R	Diagonal matrix of sector-related social impacts per dollar of economic output.	Referenced from the environmental aspects attributable to: Leontief, W. W. (1986). *Input-output economics*. Oxford University Press on Demand.
COI_j	Cost of injuries from industrial activity incurred in sector j, based on time away from work and the cost of the lost productivity. Eq. (7)	All industries work the same number of days per year, i.e., 50 weeks * 5 days per week. This value is represented in the denominator of Eq. (7). All employees in a sector are equally productive.
EMP_j	Number of employees in industrial sector j.	Count is static for 1 year.
$DAFW_j$	Count of the days away from work in industrial sector j.	The data provide a good estimate of the actual values across all industries.
$DAFWr_{LB}$	The lower bound of the range for days away from work.	The lower bound of the range, e.g., 6-9 days, is a conservative estimate and does not account for extreme outliers.
ELW_j	The number of employees below a regional living wage in industrial sector j. Eq. (8)	The employee is the wage earner in the household of 2 Adults with 1 child, where only 1 adult is working. This household size is representative of all U.S. households.
$pnorm_j$	The fraction of total employees below the regional living wage threshold in industrial sector j. This fraction results from a statistical curve fit of sectoral/industrial wage quantile data compared against the Living Wage threshold for a given area.	The wage data assumes median values for all wage quantiles. The Living Wage threshold assumes 2 Adults, 1 working, with 1 child households are representative of all households in the U.S.

APPENDIX B. SUPPLEMENTAL MATERIAL FOR CHAPTER 3

Table B.1 - Industrial sector totals for each employee-needs social impact (SI) metric. Included are percentages of national totals for which each sector is responsible. Top 4 sectors are colored in gray.

NAICS	Name	Total Commodity Output		Employees		Employee-Needs Metrics													
						Basic						Safety / Security		Affiliation		Esteem		Self-Actualization	
						ELW1A		ELW2A		ELW2A1W1C		COI		COT		TTY		COB	
		$	%	Emp	%	Emp	%	Emp	%	Emp	%	$	%	$	%	Years	%	$	%
11	Agriculture, forestry, fishing, and hunting	449,367	2	394,090	0.3	281,570	0.9	210,485	1.2	374,780	0.4	318	2	180,752	2	18,074,850	3	70,348	3
21	Mining	473,878	2	783,110	0.6	46,318	0.1	24,166	0.1	323,115	0.4	310	2	229,050	2	1,934,800	0.3	20,344	0.8
22	Utilities	530,814	2	552,790	0.4	8,994	0.0	3,717	0.0	129,106	0.2	238	2	168,248	2	7,757,700	1.1	24,530	1.0
23	Construction	1,152,064	4	5,612,000	4	556,081	1.7	247,391	1.4	3,141,204	3.7	868	6	797,336	8	30,705,010	4	140,291	6
31G	Manufacturing	5,680,251	20	11,866,570	9	1,814,024	5.6	990,652	5.6	7,184,820	8.4	2,979	20	1,342,499	13	73,548,600	10	279,924	11
42	Wholesale trade	1,406,469	5	5,623,530	4	927,673	2.9	535,052	3.0	3,199,694	3.7	818	5	370,156	4	31,993,500	5	100,792	4
44RT	Retail trade	1,331,838	5	14,982,740	12	6,478,891	20	3,742,429	21	14,092,936	16	550	4	607,663	6	51,807,030	7	108,446	4
48TW	Transportation and warehousing	999,613	3	5,014,650	4	584,713	1.8	258,789	1.5	3,052,259	3.6	1,368	9	354,906	4	28,329,030	4	109,587	4
51	Information	1,158,103	4	2,688,390	2	295,371	0.9	164,972	0.9	1,156,477	1.3	448	3	326,963	3	15,316,020	2	77,406	3
FIRE	Finance, insurance, real estate, rental, and leasing	4,864,050	17	7,463,990	6	1,101,565	3.4	604,912	3.4	4,061,176	4.7	1,329	9	1,370,467	14	42,495,500	6	196,851	8
PROF	Professional and business services	3,563,675	12	17,755,300	14	3,429,749	11	1,959,898	11	10,241,005	12	610	4	2,008,577	20	76,798,760	11	333,990	13
6	Educational services, health care, and social assistance	2,440,382	9	30,403,910	23	5,521,889	17	3,246,597	18	18,037,357	21	1,119	7	612,173	6	96,786,360	14	297,919	12
7	Arts, entertainment, recreation, accommodation, and food services	1,166,448	4	13,613,460	10	9,355,652	29	4,712,208	26	13,321,126	15	370	2	740,562	7	34,927,200	5	50,719	2
81	Other services, except government	727,937	3	3,809,400	3	1,229,213	3.8	757,144	4.2	3,020,492	3.5	245	2	417,148	4	24,665,040	4	69,353	3
G	Government	2,704,063	9	9,716,020	7	775,869	2.4	358,486	2.0	4,618,665	5.4	3,596	24	440,837	4	166,209,420	24	611,758	25
TOT	All U.S. industrial sectors	28,648,952	100	130,279,950	100	32,407,569	100	17,816,898	100	85,954,212	100	15,164	100	9,967,336	100	701,348,820	100	2,492,257	100

$ - Million $US; Emp - Number of employees; ELW - Employees below the Living Wage; 1A - 1 Adult household; 2A - 2 Adult wage earning household; 2A1W1C - 2 Adult, 1 Working, 1 Child household; COI - Cost of Injuries; COT - Cost of Turnover; TTY - Total Tenure Years; COB - Cost of Benefits.

Table B.2 - Web links to data reliability estimates for public data informing social impact metrics.

Employee-need metric	**Dataset (Acronym)**	**Web link address**
Employees below a Living Wage (ELW)	Occupational Employment Statistics (OES)	www.bls.gov/oes/current/oes_research_estimates.htm
Cost of Injuries (COI)	Injuries, Illnesses, and Fatalities (IIF)	www.bls.gov/iif/osh_rse.htm
Cost of Turnover (COT)	Job Openings and Labor Turnover Survey (JOLTS)	www.bls.gov/jlt/jltreliability.htm
Total Tenure Years (TTY)	Employee Tenure through the Current Population Survey (CPS)	www.bls.gov/news.release/archives/tenure_09182012.htm
Cost of Benefits (COB)	Employer Costs for Employee Compensation (ECEC)	www.bls.gov/web/ecec/ecsuprse.txt www.bls.gov/opub/mlr/cwc/measuring-trends-in-the-structure-and-levels-of-employer-costs-for-employee-compensation.pdf

APPENDIX C. SUPPLEMENTAL MATERIAL FOR CHAPTER 4

Table C.1 - Mapping of the 50 U.S. States (including Washington D.C.) to the U.S. Bureau of Economic Analysis (BEA) regions.

State	BEA Regions							
	NE	ME	GL	PLN	SE	SW	RM	FW
	New England	Mideast	Great Lakes	Plains	Southeast	Southwest	Rocky Mountain	Far West
Alabama					x			
Alaska								x
Arizona						x		
Arkansas					x			
California								x
Colorado							x	
Connecticut	x							
Delaware		x						
D.C.		x						
Florida					x			
Georgia					x			
Hawaii								x
Idaho							x	
Illinois			x					
Indiana			x					
Iowa				x				
Kansas				x				
Kentucky					x			
Louisiana					x			
Maine	x							
Maryland		x						
Massachusetts	x							
Michigan			x					

Table C.1 - *Continued*

State	**BEA Regions**							
	NE	**ME**	**GL**	**PL**	**SE**	**SW**	**RM**	**FW**
	New England	**Mideast**	**Great Lakes**	**Plains**	**Southeast**	**Southwest**	**Rocky Mountain**	**Far West**
Minnesota				x				
Mississippi					x			
Missouri				x				
Montana							x	
Nebraska				x				
Nevada								x
New Hampshire	x							
New Jersey		x						
New Mexico						x		
New York		x						
North Carolina					x			
North Dakota				x				
Ohio			x					
Oklahoma						x		
Oregon								x
Pennsylvania		x						
Rhode Island	x							
South Carolina					x			
South Dakota				x				
Tennessee					x			
Texas						x		
Utah							x	
Vermont	x							
Virginia					x			
Washington								x
West Virginia					x			
Wisconsin			x					
Wyoming							x	

Table C.2 - Mapping of the 15 NAICS sectors to IO-Snap Codes and Names to the 71 NAICS industry codes used in the BEA Input-Output Use Tables.

NAICS	**Name**		**IO-Snap Code and Entry Name**	**NAICS**	**Name**
11	Agriculture, forestry, fishing, and hunting		1. Farms	111CA	Farms
			2. Forestry, fishing, and related activities	113FF	Forestry, fishing, and related activities
21	Mining		3. Oil and gas extraction	211	Oil and gas extraction
			4. Mining, except oil and gas	212	Mining, except oil and gas
			5. Support activities for mining	213	Support activities for mining
22	Utilities		6. Utilities	22	Utilities
23	Construction		7. Construction	23	Construction
31G	Manufacturing		8. Wood products	321	Wood products
			9. Nonmetallic mineral products	327	Nonmetallic mineral products
		Advanced Manufacturing	10. Primary metals	331	Primary metals
			11. Fabricated metal products	332	Fabricated metal products
			12. Machinery	333	Machinery
			13. Computer and electronic products	334	Computer and electronic products
			14. Electrical equipment, appliances, and components	335	Electrical equipment, appliances, and components
			15. Motor vehicles, bodies and trailers, and parts	3361MV	Motor vehicles, bodies and trailers, and parts
			16. Other transportation equipment	3364OT	Other transportation equipment
			17. Furniture and related products	337	Furniture and related products
			18. Miscellaneous manufacturing	339	Miscellaneous manufacturing
			19. Food and beverage and tobacco products	311FT	Food and beverage and tobacco products
			20. Textile mills and textile product mills	313TT	Textile mills and textile product mills
			21. Apparel and leather and allied products	315AL	Apparel and leather and allied products
			22. Paper products	322	Paper products
			23. Printing and related support activities	323	Printing and related support activities
			24. Petroleum and coal products	324	Petroleum and coal products
			25. Chemical products	325	Chemical products
			26. Plastics and rubber products	326	Plastics and rubber products

Table C2 - *Continued*

NAICS	Name	IO-Snap Code and Entry Name	NAICS	Name
42	Wholesale trade	27. Wholesale trade	42	Wholesale trade
44RT	Retail trade	28. Motor vehicle and parts dealers	441	Motor vehicle and parts dealers
		29. Food and beverage stores	445	Food and beverage stores
		30. General merchandise stores	452	General merchandise stores
		31. Other retail	4A0	Other retail
48TW	Transportation and warehousing	32. Air transportation	481	Air transportation
		33. Rail transportation	482	Rail transportation
		34. Water transportation	483	Water transportation
		35. Truck transportation	484	Truck transportation
		36. Transit and ground passenger transportation	485	Transit and ground passenger transportation
		37. Pipeline transportation	486	Pipeline transportation
		38. Other transportation and support activities	487OS	Other transportation and support activities
		39. Warehousing and storage	493	Warehousing and storage
51	Information	40. Publishing industries, except internet (includes software)	511	Publishing industries, except internet (includes software)
		41. Motion picture and sound recording industries	512	Motion picture and sound recording industries
		42. Broadcasting and telecommunications	513	Broadcasting and telecommunications
		43. Data processing, internet publishing, and other information services	514	Data processing, internet publishing, and other information services
FIRE	Finance, Insurance. real estate, rental, and leasing	44. Federal Reserve banks, credit intermediation, and related activities	521CI	Federal Reserve banks, credit intermediation, and related activities
		45. Securities, commodity contracts, and investments	523	Securities, commodity contracts, and investments
		46. Insurance carriers and related activities	524	Insurance carriers and related activities
		47. Funds, trusts, and other financial vehicles	525	Funds, trusts, and other financial vehicles
		48. Real estate	HS	Housing Services
			ORE	Other Real Estate
		49. Rental and leasing services and lessors of intangible assets	532RL	Rental and leasing services and lessors of intangible assets

Table C.2 - *Continued*

NAICS	Name	IO-Snap Code and Entry Name	NAICS	Name
PROF	Professional and business services	50. Legal services	5411	Legal services
		51. Computer systems design and related services	5415	Computer systems design and related services
		52. Miscellaneous professional, scientific, and technical services	5412OP	Miscellaneous professional, scientific, and technical services
		53. Management of companies and enterprises	55	Management of companies and enterprises
		54. Administrative and support services	561	Administrative and support services
		55. Waste management and remediation services	562	Waste management and remediation services
6	Educational services. health care. and social assistance	56. Educational services	61	Educational services
		57. Ambulatory health care services	621	Ambulatory health care services
		58. Hospitals	622	Hospitals
		59. Nursing and residential care facilities	623	Nursing and residential care facilities
		60. Social assistance	624	Social assistance
7	Arts, entertainment, recreation, accommodation, and food services	61. Performing arts, spectator sports, museums, and related activities	711AS	Performing arts, spectator sports, museums, and related activities
		62. Amusements, gambling, and recreation industries	713	Amusements, gambling, and recreation industries
		63. Accommodation	721	Accommodation
		64. Food services and drinking places	722	Food services and drinking places
81	Other services, except government	65. Other services, except government	81	Other services, except government
G	Government	66. Federal general government defense	GFGD	Federal general government (defense)
		67. Total Government	GFGN	Federal general government (nondefense)
			GFE	Federal government enterprises
			GSLG	State and local general government
			GSLE	State and local government enterprises
Used	Scrap, used and secondhand goods	68. Scrap, used, and secondhand goods	Used	Scrap, used and secondhand goods
Other	Noncomparable imports and rest-of-the-world adjustment	69. Noncomparable imports and rest of world adjustment	Other	Noncomparable imports and rest-of-the-world adjustment
V001	Compensation of employees	Compensation of employees	V001	Compensation of employees
V002	Taxes on production and imports, less subsidies	Taxes on production and imports, less subsidies	V002	Taxes on production and imports, less subsidies
V003	Gross operating surplus	Gross operating surplus	V003	Gross operating surplus
TIO	Total industry output	Column Sum		Total Industry Output

APPENDIX D. PUBLISHED ARTICLES

Li, Z. G., & Richter, J. S. (2015). Problem and Countermeasure on Promoting the Plastic Bag Ban of USA. *Applied Mechanics and Materials*, 768, 787-796. doi:10.4028/www.scientific.net/AMM.768.787

Sutherland, J. W., Richter, J. S., Hutchins, M. J., Dornfeld, D., Dzombak, R., Mangold, J., Robinson, S., Hauschild, M. Z., Bonou, A., Schönsleben, P., & Friemann, F. (2016). The role of manufacturing in affecting the social dimension of sustainability. *CIRP Annals - Manufacturing Technology*, 65(2), 689-712. doi:10.1016/j.cirp.2016.05.003

Hutchins, M. J., Richter, J. S., Henry, M. L., & Sutherland, J. W. (2019). Development of indicators for the social dimension of sustainability in a U.S. business context. *Journal of Cleaner Production*, 212, 687-697. doi:10.1016/j.jclepro.2018.11.199

Richter, J. S., Mendis, G. P., Nies, L., & Sutherland, J. W. (2019). A method for economic input-output social impact analysis with application to U.S. advanced manufacturing. *Journal of Cleaner Production*, 212, 302-312. doi:10.1016/j.jclepro.2018.12.032