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RESEARCH ARTICLE

A Sector Prioritization Index with Carbon Emission Intensity Considerations

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Globalization has influenced the production processes. The varying degree of regulation on carbon emissions has caused some economies to continue with their production practices which can cause them to miss their commitments to international organizations. Previous literature has developed prioritization and vulnerability indices for sectors that account for the socioeconomic metrics, but they were unable to integrate the environmental effects that sectors generate. This study proposed a sector prioritization index with carbon emission intensity considerations to include the environmental effects based on a multiregional input-output model. The results show that electricity sectors, services sectors, transport sectors, and energy-intensive industries in selected regions are among the sectors that should be prioritized after considering economic impact, economic distance, sector size, and carbon emission intensity. The sector prioritization index developed in this paper can be used for climate financing and green recovery.

Keywords: input-output analysis, prioritization index, emission multiplier, multidimensional index

JEL Classification: C67, Q56

Global carbon emissions continue to rise as economic activities continue to increase over time. Although the pandemic has caused the largest decline in annual global emission change in 2020, the rebound observed in 2021 is also the largest increase in annual global carbon emission change (International Energy Agency [IEA], 2022). Countries have struggled to meet their commitments to the Paris Agreement as a result of the pandemic. Instead of shifting towards low-carbon alternatives, coal accounted for 40% of the increase in carbon emissions in 2021 (IEA, 2022). In addition, the Russia-Ukraine war has affected energy prices and derailed decarbonization efforts around the world (Tollefson, 2022). In addition to the pandemic and the war, the occurrence of natural hazards causes major disruptions to the global economy. In 2021 alone,

there were 432 occurrences of natural hazards across the globe (Centre for Research on the Epidemiology of Disasters [CRED], 2022). The highest of which were in the United States, India, China, and the Philippines.

Globalization has exposed other economies to vulnerabilities that may not necessarily occur within their territorial borders. The COVID-19 pandemic caused the unprecedented closure of borders that triggered global supply chain disruptions (Yu & Aviso, 2020). The closure of ports has hampered the international trade of goods for intermediate and final consumption (Sarkar et al., 2021). Despite the increased demand for electronics, the shortage in essential technology metals resulting from the mining operation shutdown has affected the production and distribution of electronic products (Yu et al., 2020). Furthermore, political tensions between countries will result in developing supply chain alternatives, leading to economic losses and increased levels of emissions (Shi et al., 2021). Countries have been informed about taking advantage of the COVID-19 recovery packages to promote green recovery (International Monetary Fund, 2019). However, Nahm et al. (2022) found that the economic stimulus packages implemented by the G20 continued to support emission-intensive industries. Shan et al. (2021) used a multiregional input-output model to show that economic stimulus plans can indeed increase emissions, but directing fiscal stimuli to the right industries can result in emission reduction.

With the dual threat of the pandemic and climate change, economic planning plays a central role in ensuring that systems are prepared for disruptions. There are numerous definitions of vulnerability. For this study, vulnerability is defined as the measure of a system is negatively affected from the occurrence of a hazardous event (Timmerman, 1981, p.18). Although a system can be geographically exposed to extreme events, it is also plausible to reduce its vulnerability through its capacity to absorb the effects of such disruptions. Cutter et al. (2003) identified three aspects of vulnerability research: (a) Human or place vulnerability to external shocks or events, (b) vulnerability as a social condition used to measure societal resilience, and (c) the consolidation of location-based potential risk exposures and societal resilience. This can also be applied in economic systems where vulnerability is a function of the inherent sensitivity of the economic sectors and the interdependencies among these sectors.

Different measures of vulnerability have been developed. At the national level, Briguglio (1995) introduced a composite vulnerability index for small island developing countries that accounts for the remoteness of the economies relative to their trading partners. Easter (1999) developed the Commonwealth Vulnerability Index for small Commonwealth states that lack diversification, trade dependence, and impact of natural disasters as determinants. At the regional level, data envelopment analysis (DEA) can provide alternative measures to generate vulnerability indices by identifying population and gross domestic product as input variables, and the number of people affected and the total cost of the damage as output variables (Wei et al., 2003). An expanded DEA model that includes indicators of the dangerousness of regional hazards, exposure to the regional socioeconomic system, and regional natural disaster losses have also been used to assess the regional vulnerability in China (Huang et al., 2013). Localized vulnerability indices have also been used to assess and compare the vulnerability of local government units. Cutter et al. (2003) pioneered the work of creating a multidimensional Social Vulnerability Index (SoVI) with 11 subcomponents that include socioeconomic factors, built environment, and infrastructure dependence. The SoVI has been implemented in the Yangtze River Delta Region (Chen et al., 2013) and Beijing-Tianjin-Hebei Region in China (Huang et al., 2015). A composite place-based vulnerability index was constructed by integrating the SoVI with the hazard vulnerability index and built environment vulnerability index wherein the weighted average of the components was based on the observed variance of each component (Piegorsch et al., 2021). Ahsan and Warner (2014) developed a vulnerability index that considered the social, economic, and physical aspects and exposure to risks to estimate the overall vulnerability of coastal unions in Bangladesh. Another alternative to assess local vulnerability is to consider the difference between households near the district headquarters and away from the district headquarters (Pandey & Jha, 2012). Considering the availability of capital goods, geographic location, demographic characteristics, environmental factors, economic and livelihood, policy and institutional support, and food security, Orencio and Fujii (2013) were able to determine the community-specific vulnerability of some communities in the Philippines.

Sectoral vulnerability assessment frameworks have also emerged. Optimization models have been used in combination with input-output models to assess the vulnerability of the economy to loss of agricultural land (Tan et al., 2015), storm damage (Aviso et al., 2015), and electricity shortages (Yu et al., 2016). Using input-output (IO) model-derived metrics, Yu et al. (2014) developed a vulnerability index for post-disaster key sector prioritization that considered economic impact, diversity of reach, and economic size. Go et al. (2019) formulated a sector prioritization index that factored in the degree of influence, structural significance, degree of interconnectedness, dependence on domestic economy, and contribution to the risk of inoperability, and established the weight of each criterion through an analytic hierarchy process. Foong et al. (2022) built upon Yu et al. (2014) and included human resource-related metrics to factor in workforce disruptions that may result from a pandemic. IO analysis has been used to assess the environmental impact of the pandemic on the economy (Lenzen et al., 2020). It can provide information on the carbon emission contribution of the various sectors and countries towards the production of goods (Su & Ang, 2011; Meng et al., 2018) through the use of global multiregional input-output models (Minx et al., 2009; Dietzenbacher et al., 2013; Lenzen et al., 2017). Although several studies have been done to assess the efforts toward achieving the Paris Agreement commitments (Salem et al., 2021; Shan et al., 2021, Lenzen et al., 2022), there are no studies that include the carbon emission impacts with vulnerability. This study aims to address this gap by developing a vulnerability index based on Yu et al. (2014) that considers production emission intensities.

The remainder of the paper is organized as follows: Section 2 provides a discussion of the index and its components as derived from the IO model. Section 3 introduces a case study to illustrate the use of the index. Section 4 presents the conclusions and recommendations for future work.

Sector Prioritization Index with Carbon Emission Intensities (SPICE)

The Sector Prioritization Index with Carbon Emission Intensities (SPICE) is based on metrics that can be derived from IO models that measure economic impact through gains and losses (C1), economic distance to other sectors (C2), sector size (C3), and carbon emission intensities (C4). Equation 1 shows how the SPICE for each sector is computed:

$$SPICE_i^r = w_1 C_{i1}^r + w_2 C_{i2}^r + w_3 C_{i3}^r + w_4 C_{i4}^r \qquad (1a)$$

Where $SPICE_i^r$ is the sector prioritization index with emission intensities for sector in region *r;* w_1, w_2, w_3, and w_4 are the weights that are assigned to each component. The sum of the weights should be equal to 1. C_{ik}^r is the value of the th sector's performance in terms of the th component in region .

The components of the SPICE are based on the IO model, which captures the interdependencies between economic sectors quantify the ripple effects across the entire economic system (Leontief, 1936). The values are then normalized to ensure that the components have desirable properties (Eichhorn, 1967). The individual components are discussed in this section.

Component 1: Economic Impact

Economic impact is measured through the ratio of gain and risk that the sector can contribute to the entire system. This is specified as:

$$C_{i1}^r = \frac{O_i^r / \gamma_i^r}{\sum_{i=1}^n O_i^r / \gamma_i^r} \qquad (2)$$

where O_i^r is the output multiplier of sector *i* in region *r* and γ_i^r is the inoperability multiplier of sector *i* in region *r*. The output multiplier is derived from the Leontief Inverse (Miller & Blair, 2009), whereas the inoperability multiplier is derived from the inoperability input-output model (Santos & Haimes, 2004). When the output multiplier of sector in region is greater than the inoperability multiplier of sector *i* in region *r*, this means that there are higher gains relative to the risk that ripples through the economy. On the other hand, when the output multiplier of sectorb *i* in region *r* is less than the inoperability multiplier of sector *i* in region *r*, the gains are not commensurate to the risk that the sector is exposed to. Thus, as the value of C_{i1}^r approaches one, this means that it should be prioritized.

Component 2: Economic Distance

Economic distance is measured through the average propagation length (APL) index, which integrates the significant connections of sector *i* in region *r* as a producer of inputs for other sectors and consumer of output of other sectors. This metric is based on the APL as defined in Dietzenbacher et al. (2005) and is specified as:

$$C_{i2}^r = \frac{\sum_{l=1}^n s_{li}^{rs} + \sum_{l=1}^n s_{il}^{rs} - 2s_{ii}^{rr}}{\sum_{i=1}^n \left(\sum_{l=1}^n s_{li}^{rs} + \sum_{l=1}^n s_{il}^{rs} - 2s_{ii}^{rr}\right)} \qquad (3)$$

where $\sum_{l=1}^n s_{li}^{rs}$ is the backward APL of sector *i* in region *r* or the number of inter-industry interactions resulting from a change in final demand for sector *i's* output in region *r*, $\sum_{l=1}^n s_{il}^{rs}$ is the forwards APL of sector *i* in region *r* or the number of inter-industry interactions resulting from a change in primary cost for sector *i* in region *r*, and $2s_{ii}^{rr}$ is two times the element along the diagonal of the APL matrix. By subtracting $2s_{ii}^{rr}$, we eliminate the initial effect of an exogenous change in the sector to itself. As the value of C_{i2}^r approaches unity, the number of connections that sector *i* in region *r* has relative to all other sectors becomes higher and thus increases its vulnerability to external shocks.

Component 3: Sector Size

Sector size is the relative contribution of sector in region to the entire economy. This component is specified as:

$$C_{i3}^r = \frac{x_i^r}{\sum_{i=1}^n x_i^r} \qquad (4)$$

As the value of C_{i3}^r approaches unity, the share of sector *i* in region *r's* contribution to gross output increases.

Component 4: Carbon Emission Intensity

The carbon emission multiplier is used to measure the emission intensity of each sector in each region. This component is specified as:

$$C_{i1}^r = \frac{e_i^r}{\sum_{i=1}^n e_i^r} \qquad (5)$$

Where e_i^r is the carbon emission multiplier of sector *i* in region *r* provides information on the carbon emissions resulting from the change in final demand for the output of sector i in region *r* (Statistics Canada, 2019). As this component approaches unity, this means that the share of sector in region contribution to total carbon emissions increases.

Case Study

This study will consider a case study that focuses on the Association of South East Asian Nations (ASEAN). With a regional contribution of 3.6% to the world's total GDP in 2019, they are the fifth largest economy in the world (The ASEAN Secretariat, 2020). ASEAN has facilitated easier intra- and inter-regional trade, easing barriers to trade among member-states, lowering business costs, and creating economies of scale. Hence, the export industry contributed an average of 65% to the ASEAN GDP in the last five years.

ASEAN members are all signatories to the 2015 Paris Agreement and have enacted domestic policies and measures aimed at reducing carbon emissions within their respective countries by 2030. Their commitments are disclosed in the Nationally Determined Contributions, submitted by countries to the United Nations Framework Convention on Climate Change (UNFCCC) last 2021. Table 1 shows the commitment of the AMS to cut carbon emissions from the projected 2030 Business-as-usual (BAU) scenario. Using the GHG emission data from a specified base year, countries identified the estimated 2030 million tons of carbon dioxide and identified a target reduced carbon emission for 2030, measured as the percentage reduction commitment. The Philippines committed the highest carbon reduction at 75%. However, 72.29% of this is on a conditional basis, entailing that the country would need international assistance and support to implement its commitments, as stipulated in the Paris Agreement. On the other hand, Malaysia and Cambodia have the highest unconditional reduction commitment, which focuses on the creation of domestic policies and measures to mobilize resources to achieve their commitments.

Table 1. *Consolidated ASEAN Carbon Reduction Commitments Indicated in Each Country's Nationally Determined Contribution to the UNFCCC (2021)*

Country	Reduction Commitment (**conditional)	Base Year	Projected 2030 BAU scenario	Source
Philippines	75%** (**72.29%)	2010	3340.3 Mt CO2	Philippine Nationally Determined Contribution (2021)
Indonesia	70%** (**41%)	2010	2869 Mt CO2	Updated Nationally Determined Contribution Republic of Indonesia (2021)
Malaysia	45%	2005	undisclosed	Malaysia's Update of its first Nationally Determined Contribution (2021)
Cambodia	42%	2016	155 Mt CO2	Cambodia's Updated Nationally Determined Contribution (2020).
Singapore	36%	2005	65 Mt CO2	Singapore's update of its first Nationally Determined Contribution (NDC) and Accompanying Information (2020)
Myanmar	35%	2014	297 Mt CO2	Myanmar Nationally Determined Contributions (2021).
Lao PDR	34%	2000	104 Kt CO2	Lao People's Democratic Republic Nationally Determined Contribution (NDC) (2021)
Viet Nam	33%** (25%)	2010	787.4 Mt CO2	Viet Nam Updated Nationally Determined Contribution (NDC) (2020)
Brunei	20%	2015	29.5 Mt CO2	Brunei Darussalam Nationally Determined Contribution (NDC) 2020
Thailand	20%	2005	555 Mt CO2	Thailand's Updated Nationally Determined Contribution (NDC) (2020)

Table 2. *Region Disaggregation*

Code	Region
R01	Brunei
R02	Cambodia
R03	Indonesia
R04	Lao PDR
R05	Malaysia
R06	Philippines
R07	Singapore
R08	Thailand
R09	Vietnam
R10	Rest of South East Asia
R11	East Asia
R12	Rest of the World

Table 3. *Sectoral Disaggregation*

Code	Sector
S01	Agriculture Fishery and Forestry
S02	Mining
S03	Food
S04	Transport
S05	Energy Intensive Industries
S06	Non-Energy Intensive Industries
S07	Services
S08	Electricity

A 12-region 8-sector specification of the Global Trade Analysis Project 10 (GTAP10) was used for this study. Table 2 shows the regional disaggregation, and Table 3 shows the sectoral disaggregation adapted for this study. R01-R09 are ASEAN member states. R11 represents East Asia which is composed of China, South Korea, and Japan. In terms of sectoral disaggregation, the 8-sector disaggregation was based on the similarities in terms of energy intensities as published in the GTAP10 database.

Table 4. *Top 10 Sectors for Each Component and SPICE Values*

Rank	Economic Impact		Economic Distance		Sector Size		Carbon Emission Intensity		Overall Index	
	C1		C2		C3		C4		SPICE	
1	0.0629	R01 S08	0.0914	R11 S04	0.3738	R12 S07	0.1758	R03 S08	0.1110	R12 S07
2	0.0418	R10 S08	0.0692	R12 S07	0.1129	R12 S05	0.1335	R11 S08	0.0536	R03 S08
3	0.0309	R10 S02	0.0631	R11 S02	0.1022	R11 S07	0.0886	R06 S08	0.0392	R11 S08
4	0.0275	R07 S01	0.0616	R11 S05	0.0861	R12 S04	0.0747	R09 S08	0.0388	R11 S07
5	0.0239	R04 S02	0.0551	R01 S08	0.0560	R11 S05	0.0711	R05 S08	0.0382	R12 S05
6	0.0212	R05 S08	0.0495	R11 S07	0.0523	R11 S04	0.0515	R07 S08	0.0374	R11 S04
7	0.0193	R07 S03	0.0470	R12 S04	0.0334	R12 S03	0.0457	R12 S08	0.0355	R12 S04
8	0.0189	R10 S06	0.0374	R12 S05	0.0268	R12 S06	0.0329	R08 S08	0.0326	R01 S08
9	0.0185	R01 S06	0.0333	R03 S08	0.0246	R12 S02	0.0245	R09 S06	0.0320	R11 S05
10	0.0185	R02 S02	0.0268	R10 S08	0.0192	R12 S01	0.0197	R02 S08	0.0260	R06 S08

Table 4 presents the 10 sectors from all regions that have the highest index values for each component and the overall SPICE values. By analyzing this for each component, the underlying reason for the value and rank of the overall SPICE is easier to understand. It should be noted that there are 96 region-sector entries for each component. For example, In terms of economic impact or the gain relative to risk that the sector in a country is exposed to, the highest value is for the electricity sector in Brunei. This is followed by the electricity sector of the rest of South East Asia and the mining sector of the rest of South East Asia. It is interesting to note that the region-sector pairs for the economic impact component are composed of sectors from relatively smaller economies. This may largely be due to the law of diminishing marginal product. Because these sectors in the smaller economies have not reached their efficient production, higher gains can be achieved or the risk that the sectors in these economies are exposed to are smaller compared; thus, the gains relative to risk are still larger.

In terms of economic distance, the transport sector of East Asia (R11-S04) is the highest, followed by the services sector of the rest of the World (R12-S07) and the mining sector of East Asia (R11-S02). The economic distance metric shows the relative number of significant connections that the region-sector has with the rest of the economy. Given that China is part of the East Asian region, it is assumed that this is the reason why its transport sector predominantly has the highest value in this range. During the height of the pandemic lockdowns, disruptions to China's transportation domestically and internationally have indeed led to shortages around the world. The service sector of the rest of the world is also a key sector in terms of economic distance. With globalization going beyond trade in goods but also includes trade in services, the services sector of the rest of the world ranking second in this aspect is reasonable. In this aspect, East Asia and the rest of the world are the leading regions in terms of this metric.

Similarly, given the size of the aggregation of the economies, the largest sector sizes can be observed for sectors that belong to the rest of the world and East Asia. In particular, the sectors are the services sector, transport sector, and energy-intensive industries.

The carbon emission intensity metric shows the relative levels of emission that ripples through the global economy as a result of activity in the region-sector. It can be noted that nine of the 10 region-sector pairs identified belong to the electricity sector. This means that the highest contributors to carbon emissions are related to electricity generation. This can be expected as the electricity sector is largely dependent on fossil fuels. The only outlier is the non-energy-intensive industries sector of Vietnam (R09-S06), which is quite interesting as non-energy-intensive industries require fewer activities that can generate carbon emissions. However, it might be the case that when this industry uses energy, the carbon emissions generated might be higher than usual as the energy source may not be clean energy.

The overall SPICE is computed based on all components having equal weights. The region-sector pairs with the highest SPICE values are the rest of the world services sector (R12-S07), Indonesia's electricity sector (R03-S08), and East Asia's electricity sector (R11-S08). Aside from the electricity sectors and services sectors, the transport sector and energy-intensive industries in the rest of the world and East Asia. Other individual countries that are included in the 10 highest region-sector pairs are Brunei's electricity sector and the Philippines' electricity sector. The SPICE provides insights on which region-sectors should be prioritized in terms of economic impact, its influence on other sectors, its contribution to the global economy, and emissions. With countries struggling to achieve higher post-pandemic growth, the SPICE can complement other tools to achieve green recovery.

Conclusions

This study developed a novel sector prioritization index with carbon emission considerations (SPICE) based on the foundations of input-output analysis. Most indices only account for economic impact and social impact but do not include the aspect of environmental impact. Although individual countries have their own vulnerability assessment measures and prioritization efforts, a multiregional prioritization index is integral for international policymaking. With the current initiatives to promote green pandemic recovery plans, the SPICE provides insights into region-sectors that need to be prioritized to achieve environmental commitments while accounting for economic performance measures on the production side. This can also serve as an input in climate financing policies.

Future work can include other metrics, including aspects that have not been included in this study. The SPICE is composed of metrics that focus on the production side. Although consumption-based emissions may be calculated using the IO model, including this in the SPICE is not coherent with the structure of the index. Integrating production-based with consumption-based metrics of the IO model can be further explored. In addition, future studies can explore the application of the analytic hierarchy process and other multicriteria decision analysis models to determine the component weights. Lastly, a different specification of the data can be used to draw out insights that are fitter for the needs of the decision-maker.

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