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Triple Bottom Line Analysis of the Decline in Foreign Tourist Demand in Japan due to the COVID-19 Pandemic

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https://hdl.handle.net/2324/7443233

出版情報：Kyushu University, 2025, 博士（経済学）, 課程博士
バージョン：
権利関係：

KYUSHU UNIVERSITY

Triple Bottom Line Analysis of the Decline in Foreign Tourist Demand in Japan due to the COVID-19 Pandemic

A Dissertation Submitted in Partial Fulfillment of the Requirement of the Degree of Ph.D. in Economics

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Chapter 1. Introduction

1.1. The beginning of global warming and the growth of the tourism

Following World War II, the global expansion of fossil fuel consumption, including coal and oil, and the widespread adoption of electricity were accompanied by a marked rise in the Earth's surface temperature. Around the 1960s, this problem has come to be discussed globally as “global warming”, one of the world’s major problems (Manabe and Wetherald, 1967; Keeling, 1960; President’s Science Advisory Committee, 1965).

The global warming is expected to lead to various adverse impacts, including sea-level rise, ecosystem collapse, health risks, and food insecurity (IPCC, 2023). Therefore, to address the global warming, international organizations (i.e., Intergovernmental Panel on Climate Change (IPCC), United Nations (UN)) formulated policy directions (IPCC, 2023; United Nations Framework Convention on Climate Change (UNFCCC), 2015). Because the main cause of global warming is the increase in greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2), reducing GHG emissions from economic activities is the primary approach mitigation.

The Paris Agreement represents a prominent example. This international framework was adopted at the 21st Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCCC), with the objective of

limiting the increase in global mean temperature to approximately 1-1.5 ℃ by the year 2100 (UNFCCC, 2015). Under the agreement, 145 countries have announced to make effort to achieve net zero emissions (Climate Action Tracker, 2023). Japan has demonstrated its commitment to this framework by setting national targets to reduce GHG emissions by 50% relative to the fiscal year 2013 level by 2030, and to achieve carbon neutrality by 2050 (Government of Japan, 2021). However, according to the IPCC, current national efforts are far from sufficient to achieve the 1.5 °C goal (IPCC, 2023).

Tourism industry has expanded rapidly alongside global economic growth, but it also contributes to climate change. According to the World Travel & Tourism Council (WTTC), the tourism sector accounted for 10.3% of global GDP and 330 million jobs (10.4% of total employment) in 2019 (WTTC, 2020). Sun *et al.* (2024) showed that GHG emissions from global tourism demand induced 5.2 Gt-CO_2e through industrial supply chains, accounting for 8.8% of total global GHG emissions in the same year.

According to the World Economic Forum (2025), travel & tourism is expected to expand at about 1.5 times as fast as the global economy (3.7% vs. 2.4% real growth), reaching around 16 trillion USD (11% of global GDP) by 2034 (WEF, 2025; Betti and Zuazua, 2025). Tourism plays a vital economic and social role; however, sustaining its development will inevitably require compatibility with decarbonization (World Tourism Organization (UNWTO), 2018). WTTC (2021a and 2024) presented a roadmap toward net-zero emissions for the global travel and

tourism sector and pointed out several challenges, including weak government-industry coordination and low tourist awareness of climate change. This, in turn, calls for technological innovation to reduce environmental impacts and systems that align the behavior of consumers and appliers. To this end, more proactive government-led initiatives are required—for example, fostering technological innovation to reduce environmental impacts and establishing mechanisms that align the behavior of consumers and suppliers.

1.2. A further challenge for tourism: vulnerability to disasters

In 2020, the COVID-19 pandemic posed an unprecedented challenge to the tourism sector. Although tourism had expanded steadily since the late twentieth century (UNWTO, 2019), the industry—being inherently dependent on human mobility—was hit hard by lockdowns imposed to curb the spread of infection. According to the WTTC, travel and tourism's share of global gross domestic product (GDP) declined from 10.4% to 5.5%, and employment in the sector fell by about 62million jobs (WTTC, 2021b). From an environmental perspective, global tourism-related GHG emissions declined from 5.2 to 2.2 $GtCO_2e$ between 2019 and 2020—a drop of about 58%—due to the COVID-19 pandemic's disruption of travel (Sun *et al.*, 2024).

As of 2025, the acute phase of the COVID-19 pandemic has ended. Nevertheless, several studies and official reports state that the risk of similar pandemics remains (Marani *et al.*, 2021; Carlson *et al.*, 2022; Intergovernmental

Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2020; Sánchez *et al.*, 2022). It is essential to remain vigilant about the potential reemergence of novel pandemics and design tourism recovery policies for such scenarios. Moreover, because tourism is inherently dependent on human mobility, the sector is vulnerable to other disasters (e.g., earthquakes, tsunamis, and typhoons) (Granvorka and Strobl, 2013; IPCC, 2021; Organisation for Economic Co-operation and Development (OECD), 2024; Reiner *et al.*, 2024; Ritchie and Jiang., 2019). For the continued expansion of tourism, implementing countermeasures against these disasters is equally important.

As with COVID-19, these disasters can affect the economic, social, and environmental dimensions via the tourism sector, which is inherently dependent on human mobility. In formulating tourism recovery policies for disaster contexts, it is essential to quantify the impacts of disaster induced contractions in tourism demand. For this purpose, the triple-bottom-line (TBL) framework provides an appropriate basis for evaluation. TBL framework was originally proposed to assess corporate sustainability across the economic, social, and environmental dimensions (Elkington, 1997, 2018). In 2016, the "wedding-cake model," which organizes the 17 SDGs into the biosphere, society, and economy layers, further generalized this perspective, turning it into a widely used guide for sustainability assessment across fields (Stockholm Resilience Centre, 2016). For the tourism industry—which faces the dual challenges of pursuing sustainable growth while remaining vulnerable to disasters—evaluating disaster impacts through the TBL lens is therefore a key requirement.

1.3. Japan's inbound tourism market during the COVID-19 pandemic: a case study

The situation described above also applies to Japan. Since 2003, the Japanese government has pursued policies to expand inbound tourism (Ministry of Land, Infrastructure, Transport and Tourism (MLIT), 2003; Japan Tourism Agency (JTA), MLIT, 2021a); as a result, the number of international arrivals rose to 31.9 million in 2019, roughly six times the 2003 level (JTA, MLIT, 2025a). However, because of the COVID-19 pandemic, arrivals fell to 4.1 million (an 87% decline from 2019) (JTA, MLIT, 2025a). For Japan, inbound travel revenue in 2019 were equivalent to roughly 24% of the current-account surplus (Ministry of Finance Japan (MFJ), 2025), highlighting inbound tourism as a policy-responsive channel for earning foreign currency in the short to medium term. Following the end of the COVID-19 pandemic, Japan's inbound tourism has gradually recovered, and by 2024 it recorded all-time highs in both the number of foreign tourists and inbound tourism expenditure (JTA, MLIT, 2025a, 2025b). However, as in the global tourism industry, it remains essential to formulate recovery policies for a potential pandemic recurrence and other disasters remains indispensable.

This doctoral thesis takes Japan as a case study—for two reasons explained below—and analyzes how the COVID-19 pandemic affected Japan via its inbound tourism market in 2020. First, as an island nation where more than 90% of foreign tourists enter by air, Japan was particularly exposed to the effects of travel restrictions and border controls (including lockdowns). Consequently, the decline in

the number of foreign tourists was especially pronounced. Second, as noted earlier, Japan's inbound market was on a steep growth trajectory; absent the pandemic, 2020 was expected to set a new record for both arrivals and inbound expenditure. It is therefore appropriate to assess the impact using a with- and without-pandemic counterfactual scenario comparison.

This thesis aims to evaluate, in TBL terms, the economic, social, and environmental impacts—both direct and indirect— of the COCID-19-induced stagnation in inbound tourism demand to Japan. To this end, a novel analytical framework for tourism under disaster conditions is developed, integrating consumption-endogenous input-output analysis, counterfactual scenarios, structural decomposition analysis (SDA), and structural path decomposition (SPD).

1.4. Structure of this thesis

This doctoral thesis consists of five chapters (Figure 1-1). Chapter 2 presents a comprehensive literature review covering: (i) the development of input–output analysis and its evolution into environmentally extended input–output analysis (EEIOA); (ii) applications of input–output analysis to environmental and disaster studies with a focus on tourism; and (iii) advanced IO-based methods developed for more detailed attribution and factor decomposition—namely, consumption-endogenous input–output analysis, structural decomposition analysis (SDA), structural path analysis (SPA), and structural path decomposition (SPD) analysis. Within the context of the reviewed literature, Chapter 2 identifies the research gaps

addressed by this dissertation and clarifies its contributions and novelty.

Chapter 3 applies a consumption-endogenous input–output framework to analyze the 2020 collapse of Japan's inbound tourism and augments it with a counterfactual structural decomposition analysis (SDA). This approach enables the evaluation of direct and indirect impacts—namely, value-added losses, employment losses, and reductions in CO_2 emissions—caused by COVID-19 through inbound tourism, and decomposes these impacts into six contributing factors. The chapter derives policy implications, recommending targeted government interventions such as subsidies for sectors experiencing the largest value-added and employment losses, alongside support schemes for sectors capable of mitigating environmental impacts so as to preserve the environmental gains observed during the pandemic.

Chapter 4 extends the analysis by implementing a counterfactual structural path decomposition (SPD) based on a consumption-endogenous input–output model to identify the supply-chain hotspot paths through which the COVID-19 shock to inbound demand propagated across Japan's industrial supply chain. The chapter further contrasts with- and without-pandemic scenarios to isolate the contributions of six drivers (including final demand, input structure, and income-induced consumption), and discusses policy guidance for building disaster-resilient and sustainable inbound tourism—for example, by targeting support to supply-chain hotspots while embedding incentives for decarbonization and labor transitions in face-to-face service linkages.

Chapter 5 concludes the dissertation by integrating the results of Chapters 3 and 4 within a triple bottom line (TBL) framework and addressing two key themes: optimal recovery strategies for inbound tourism during the COVID-19 pandemic, and policy measures the tourism sector should adopt to prepare for future disasters.

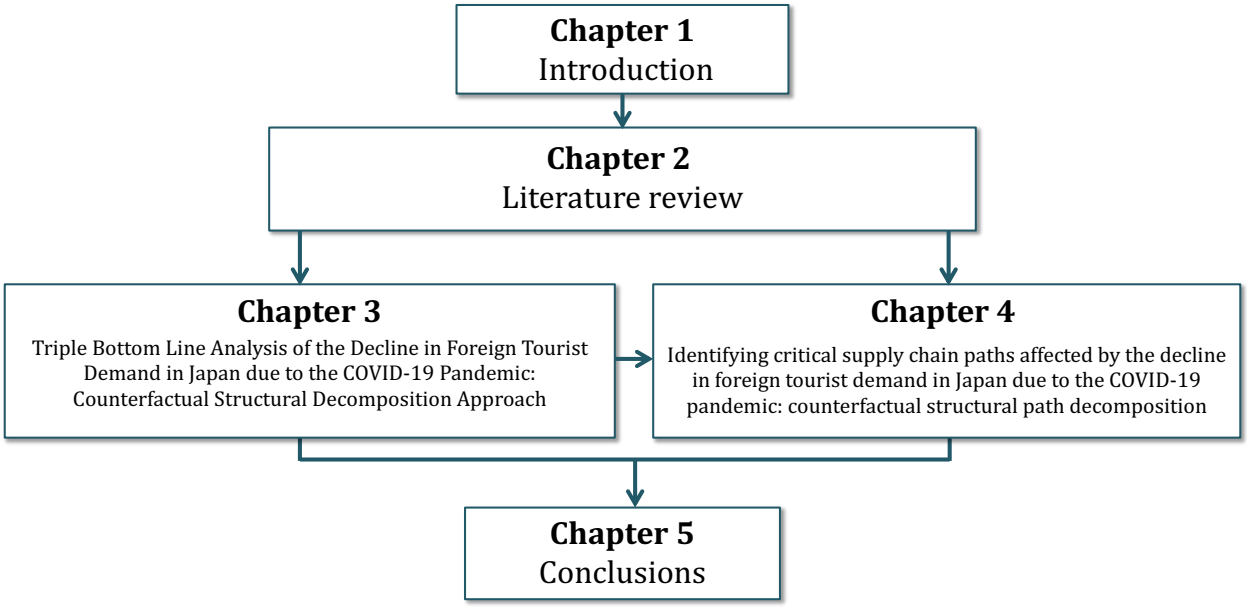


Figure 1-1. Structure of this thesis

Chapter 3 has been published in a peer-reviewed journal, and the manuscript derived from Chapter 4 is currently under review.

Chapter 3:

Oga, Y. & Kagawa, S. (2025). Triple bottom line analysis of the decline in foreign tourist demand in Japan due to the COVID-19 pandemic: Counterfactual structural decomposition approach, *Journal of Industrial Ecology*, 29(2), pp. 518-530.

Chapter 4:

Oga, Y. (2025). Identifying Critical Supply Chain Paths Affected by the Decline in Foreign Tourist Demand in Japan due to the COVID-19 Pandemic: Counterfactual Structural Path Decomposition, *Structural Change and Economic Dynamics*, under review.

Chapter 2. Literature review

2.1. The beginning of input–output analysis: its evolution into quantitative footprint accounting methods

Since the early 1900s, as economies expanded and became more complex, several macroeconomic analytical frameworks were developed to systematically represent the economy as a whole, including general equilibrium models (Arrow and Debreu, 1954; Johansen, 1974; Scarf, 1967; Shoven and Whalley, 1992), the Social Accounting Matrix approach (Stone, 1962; Pyatt and Thorbecke, 1976; Pyatt and Round, 1979), and the System of National Accounts (SNA) (Meade and Stone, 1941; UN, 1953; European Commission *et al*., 2009).

Input–output analysis (Leontief, 1936, 1941, 1953, 1966; Miller and Blair, 2009) is one of these approaches. Using an input–output table that summarizes, by industry within a given region and period, the cost and sales structures, final demand, and value added, it enables the estimation of the total volume of interindustry transactions indirectly induced by a unit change in final demand—that is, the economy-wide ripple effects.

Since its inception, input–output analysis has diversified along multiple fronts: from early cross-country comparisons by Chenery and Watanabe (1958) to interregional and international input–output systems (Isard, 1951; Leontief *et al*.,

1974), the formulation of backward and forward linkage indices (Rasmussen, 1956; Hirschman, 1958), and later methodological extensions such as structural decomposition (Dietzenbacher and Los, 1997, 1998) and structural path analysis (Defourny and Thorbecke, 1984; Lenzen, 2003).

The applications of input–output analysis have extended beyond economics. Since the 1960s—against the backdrop of pollution problems that emerged as the cost of rapid growth—researchers began developing environmentally extended input–output (EEIO) models that combine IO frameworks with physical data on resource use and waste generation (Daly, 1968; Isard *et al*., 1968; Ayres and Kneese, 1969; Leontief, 1970; Victor, 1972). Leontief (1970) and Leontief and Ford (1972) incorporated pollution emissions and pollution-abatement activities into input–output tables, modeling the relationship between industrial production and the emission or removal of environmental pollutants within the economic system. These studies laid the foundations of EEIO, providing the methodological groundwork for later footprint accounting.

Following Wackernagel and Rees (1996), who emphasized the importance of the Ecological Footprint—quantifying the productive land and sea area required to support human consumption—environmentally extended input–output (EEIO) analysis has become widely used in footprint studies (Kitzes, 2013; Wiedmann, 2009; Miller and Blair, 2009). In particular, alongside life cycle assessment (LCA)—which comprehensively quantifies life-cycle environmental flows such as energy use and greenhouse gas (GHG) emissions across the cradle-to-grave stages of production,

use, and end-of-life (Hunt, 1992; Fava, 1994; Klöpffer, 1997; ISO, 2006a, 2006b; Guinée, 2002)—EEIO is now one of the standard approaches in the field.

Within the UN Sustainable Development Goals (SDGs), official indicators such as the Material Footprint for Goals 8.4 and 12.2 are compiled on the basis of multi-regional input–output (MRIO) models (Lenzen *et al*., 2013, 2017a, 2017b; Malik *et al*., 2019; Stadler *et al*., 2018; Tukker and Dietzenbacher, 2013; Wiedmann *et al*., 2015), demonstrating the institutional use of input–output analysis (UN Statistics Division, 2025; UNEP, 2023b). Goal 12 explicitly calls for management across the life cycle, and UNEP's Life Cycle Initiative positions LCA as guidance for policy, public procurement, and product assessment (UNEP Life Cycle Initiative, 2023). Accordingly, IO and LCA have become standard tools within public policy frameworks such as the SDGs.

2.2. Application of environmentally extended input–output analysis to tourism

Input–output analysis has evolved into a tool for quantifying consumption-based footprints across multiple domains—including carbon footprints (CF) (Davis and Caldeira, 2010; Davis *et al*., 2011; Kanemoto *et al*., 2016; Minx *et al*., 2008, 2009; Nansai *et al*., 2012; Peters, 2008), air-pollutant footprints (Zhang *et al*., 2017; Lin *et al*., 2014), water footprints (Hoekstra and Mekonnen, 2012; Zhao *et al*., 2015), and material footprints (Wiedmann *et al*., 2015; International Resource Panel (IRP), 2019).

Combining input–output analysis with Tourism Satellite Accounts (TSA), a large body of work has quantified the CF attributable to tourism consumption worldwide (Lenzen *et al*., 2018; Munday *et al*., 2013; Sun *et al*., 2014, 2020; Sharp *et al*., 2016; Becken and Patterson, 2009; Cadarso *et al*., 2015, 2016; Demeter *et al*., 2021; Jones, 2024; Shi *et al*., 2024; Sun, 2020; Hu *et al*., 2022). Most notably, Lenzen *et al*. (2018) linked tourism final demand to a global MRIO model and found that tourism-related GHG emissions accounted for about 8% of the global total in 2013, highlighting the dominance of indirect emissions. Similar frameworks have been implemented at national and regional levels—for China (Hu *et al*., 2022), Taiwan (Sun *et al*., 2014), the UK/Wales (Munday *et al*., 2013), Scotland (Sharp *et al*., 2016), New Zealand (Becken and Patterson, 2009), and Spain (Cadarso *et al*., 2015).

Munday *et al*. (2013) linked a regional IO table with a TSA to estimate Wales's tourism CF, finding that indirect emissions exceeded direct, in-destination emissions, with substantial contributions from accommodation, food services, and retail trade in addition to transport. Sharp *et al*. (2016) decomposed Scotland's tourism spending by sector and showed that upstream food and retail sectors, not only aviation, are key mitigation targets. Hu *et al*. (2022) traced Chinese tourism demand through a China MRIO model and demonstrated that interprovincial carbon transfers and visitor origin–destination pairings strongly shape the spatial distribution of emissions. Overall, while transport (aviation, railway, and road transport) accounts for a large share of tourism-related GHG emissions, on-site consumption and its embedded supply chains are also significant—implying the need to manage long-haul international tourism (inbound and outbound) while

decarbonizing procurement and upstream production.

For water footprints (WF), IO applications have likewise advanced (Cazcarro *et al*., 2014; Lee *et al*., 2021). Cazcarro *et al*. (2014) estimated Spain's tourism-embodied blue and green water footprints using EEIO analysis and pointed to the externalization of demand to already water-stressed regions. Lee *et al*. (2021) assessed China's tourism WF using MRIO with SDA to attribute changes to income, consumption demand, and technology/efficiency effects, quantifying the contribution of efficiency improvements. Together, these studies argue for integrating carbon and water accounting in tourism strategy and for explicitly considering basin-level water stress.

2.3. Input–output analysis for disaster impact assessment

Over the years, input–output analysis has been widely applied to investigate the economic and social consequences of various types of disasters (Okuyama, 2007; Okuyama and Santos, 2014; Oosterhaven, 2017; Galbusera and Giannopoulos, 2018; Steenge and Bočkarjova, 2007; Bočkarjova *et al*., 2004; Li *et al*., 2013; Schulte in den Bäumen *et al*., 2015; Reiner *et al*., 2024). Through literature reviews of studies analyzing the economic impacts of disasters using IO, SAM, and computable general equilibrium (CGE) models, Okuyama (2007) and Okuyama and Santos (2014) summarized the advantages and limitations of employing input–output analysis. Its advantages include the ability to comprehensively assess both direct shocks (e.g., abrupt changes in final demand or supply outages) and indirect impacts transmitted

through supply chains, allowing a systematic estimation of upstream–downstream effects. Its limitations are that a simple IO model cannot capture short-run dynamics or recovery trajectories, and—unless factors such as inventories, substitution, spare capacity, and policy interventions are explicitly incorporated—the results may be biased upward or downward.

To the best of the author's knowledge, before the COVID-19 pandemic, relatively few studies had assessed the tourism industry's disaster impacts using input–output analysis. Among them, Reiner *et al*. (2024) examined the "Black Summer" wildfires in Australia (2019–2020) and estimated that the halt in tourism reduced total output by about 2.8 billion Australian dollars (AUD) and caused a loss of roughly 7,300 jobs. In contrast, since the onset of COVID-19—given its profound global impact on tourism—numerous studies have analyzed its effects through the tourism sector (Kitamura *et al*., 2020b; Lee *et al*., 2024; Osorio *et al*., 2023; Vayá *et al*., 2024; Yeh and Liou, 2025; Sun *et al*., 2021; Tsutsumi *et al*., 2024). The COVID-19 pandemic, through lockdown measures that restricted human mobility, arguably represented the first disaster to cause a clearly observable, worldwide standstill in tourism. At the same time, it spurred progress in developing impact-analysis frameworks for disaster recovery in the tourism industry—an area that had previously received limited attention. Refining such frameworks will contribute to risk management and the design of recovery policies for future tourism stagnations caused by large-scale disasters, whether pandemic-related or otherwise.

2.4. Consumption-endogenous input–output analysis

Input–output analysis estimates economic ripple effects by multiplying a final demand column vector (i.e., direct effects) by the Leontief inverse, which incorporates the input-coefficient matrix. The input-coefficient matrix represents, for each industry, the monetary shares of goods and services purchased as intermediate inputs from all industries (including itself) to produce one unit of output.

In the standard input–output setting, household consumption and labor income are treated as exogenous, which precludes the estimation of induced effects on income and consumption. This shortcoming is addressed by the Leontief–Miyazawa model, which endogenizes household consumption and labor income in an extended input–output model (Miyazawa, 1960; Miyazawa and Masegi, 1963; Miyazawa, 1976). In reality, consumption depends on income and income depends on production; therefore, in principle, both can be endogenized within Leontief's system. To implement this, Miyazawa developed a consumption-endogenous input–output model by embedding the inter-relational income multiplier—based on Keynes's and Kalecki's consumption functions (Keynes, 1936; Kalecki, 1954)—into the Leontief inverse, thereby enabling quantitative estimation of the production → income → consumption feedback loop.

The Leontief–Miyazawa model has been widely employed for multiplier studies (Lager, 1988; Rose and Beaumont, 1988; Rose *et al.*, 1989; Sonis and

Hewings, 1993, 1995; Cloutier and Thomassin, 1994; Trigg and Madden, 1994; Batey and Madden, 1999; Rose and Li, 1999; Hewings *et al*., 2001; Lenzen and Schaeffer, 2004; Kagawa, 2005; Nagashima, 2018). Consumption-endogenous input–output analysis is particularly well suited to accounting for the temporary changes in household consumption and labor income observed during the COVID-19 pandemic.

2.5. Structural decomposition analysis

Since input–output analysis began to be widely applied to economic and environmental issues, there has been a growing practical demand to decompose changes in economic growth and environmental burdens into activity effects (changes in the overall level of final demand), composition effects (shifts in the mix of products and sectors), and technology effects (changes in technical coefficients or intensities) (Chenery *et al*., 1962; Bullard and Herendeen, 1975; Rose and Casler, 1996). Structural decomposition analysis (SDA) emerged precisely to meet this demand. It attributes the change in an aggregate variable between two periods—e.g., output, energy use, or CO_2 emissions—to underlying drivers within the IO identity (typically $E = \mathbf{e}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}$), allowing observed differences to be expressed as the contributions of (i) technological change (e.g., changes in value-added or emission intensities), (ii) production-structure change, and (iii) final-demand change.

Methodologically, SDA was systematized by Dietzenbacher and Los (1997, 1998, 2000), who formalized the treatment of the non-uniqueness problem (different factor orderings yield different results) via polar decompositions and

averaging over permutations, and clarified additive vs. multiplicative forms, reference-period choices, and extensions to environmentally extended and multi-regional IO settings. Since then, SDA has been widely applied in economic and environmental analyses—to disentangle changes in energy use, CO_2 emissions, material and water footprints, value added, and employment—while preserving system-wide accounting consistency (Peters *et al*., 2011; Kagawa and Inamura, 2001; Arto and Dietzenbacher, 2014; Wiedmann *et al*., 2015; Feng *et al*., 2014; Zhang *et al*., 2012). When analyzing how the COVID-19 pandemic or other disasters have affected the tourism industry, identifying the contributing drivers is crucial for formulating well-targeted policy recommendations.

2.6. Further analysis at the industrial supply-chain level

Whereas SDA decomposes the change in a target variable (e.g., output, CO_2, or water use) over a given period into the contributions of underlying drivers, structural path analysis (SPA) was developed to quantify the direct and indirect effects computed in input–output analysis at the level of individual supply-chain transactions (Defourny and Thorbecke, 1984; Lenzen, 2003). SPA expands the Leontief inverse into supply-chain paths by order of propagation and quantifies the target variable at the level of industrial supply-chain paths. Specifically, SPA expands $(\mathbf{I}-\mathbf{A})^{-1}$ as $\mathbf{I}+\mathbf{A}+\mathbf{A}^2+\mathbf{A}^3+\cdots$, mapping products of input coefficients to ordered paths (e.g., fishery → transport services → eating services), thereby attributing impacts to concrete upstream linkages rather than aggregate sectors. This enables actionable “hotspotting” for policy and management by identifying

which supply chains dominate a footprint and to what extent. SPA was first formalized in an IO setting by Defourny and Thorbecke (1984) and subsequently adapted to environmentally extended IO for footprint tracing and trade-embodiment studies (e.g., Lenzen, 2003; Peters and Hertwich, 2006).

As a complement to SPA, structural path decomposition (SPD) compares two points in time and decomposes the change along each structural path into contributions from relevant drivers—technology, production structure, and final demand (Wood and Lenzen, 2009). SPD effectively extends SDA's driver attribution to the path level; for example, it pinpoints which supply-chain paths improved—and by how much—due to technological changes that contributed to CO_2-emission reductions. Methodologically, SPD builds on SPA's path expansion and applies decomposition rules to each term (Wood and Lenzen, 2009), with subsequent work extending SPD to multi-regional settings and various indicators (carbon, energy, materials, water) (Oshita, 2012; Yang *et al*., 2015; Tian *et al*., 2018; Su *et al*., 2019; Zhang *et al*., 2021; Lin and Teng, 2022).

Structural path decomposition (SPD) is well suited to disaster analysis because it can both identify supply-chain hotspots heavily affected by disasters (e.g., pandemics) and decompose their underlying drivers. To the best of our knowledge, however, it has not yet been explicitly applied to disaster contexts in the literature.

2.7. Contribution of this thesis

This Chapter has reviewed previous studies on the origins of input-output analysis and its development into environmentally extended models, as well as applications to tourism and disaster analysis. Building on the above, input-output models that analyze impacts transmitted through the tourism industry under disaster conditions face at least three challenges.

First, applications of TBL analysis—jointly addressing the economic, social and environmental dimensions—are scarce, and there remains considerable scope for methodological improvement. To the best of author's knowledge, Kitamura *et al*. (2020b) is, to the best of our knowledge, the only empirical study that quantifies COVID-19's impacts transmitted via Japan's tourism sector across the economic (domestic output), social (employment) and environmental (CO_2) dimensions. That study (Kitamura *et al*., 2020b) was published less than a year after the pandemic began, providing a rapid, policy-relevant contribution at a time when COVID-19 countermeasures were not yet established. However, its recovery scenarios rely on only eight months of post-outbreak data, which limits their accuracy.

Second, it does not consider the changes in income and household consumption caused by the disaster. As shown by Okuyama (2007) and Okuyama and Santos (2014), applying input–output analysis to disaster impact assessment requires explicit consideration of factors such as inventories, substitution, spare capacity, and policy interventions. Under a large-scale pandemic like COVID-19, which severely restricts mobility, household incomes and consumption behavior (including propensities to consume) can shift markedly; hence, there is a need to

develop more refined models that can endogenize and reflect these changes.

A third challenge is that we still lack a framework capable of fine-grained analysis of the main drivers of pandemic-era changes and the propagation of impacts through supply chains. The impacts of COVID-19 transmitted through the tourism industry manifest in multiple ways—via changes in industrial structure (e.g., value added shares and production efficiency), declines in final demand. They can also concentrate along particular supply-chain paths. Enhancing the precision of the input-output analytical framework and identifying the drivers of change and supply-chain hotspots will support the design of more detailed and actionable recovery measures.

The objective of this study is to develop a new analytical framework that address the shortcomings of input-output-based approaches to assessing disaster-era impacts transmitted through tourism industry. Specifically, we integrate a consumption-endogenous input-output model, structural decomposition analysis (SDA), and structural path decomposition (SPD) to provide a comprehensive and granular assessment of how declines in tourism demand propagate through industrial supply chains to affect economic, social, and environmental outcomes. I also review previous studies on each of these methods to position my approach within the existing literature.

Chapter 3. Triple bottom line analysis of the decline in foreign tourist demand in Japan due to the COVID-19 pandemic: Counterfactual structural decomposition approach

3.1. Introduction

Since 2012, Japan has adopted policies to attract foreign tourists, including visa easing and expanding shipping routes (Cabinet Secretariat, Government of Japan, 2016). These policies doubled the number of foreign visitors to Japan and their consumption during travel from 2012 to 2015 (Cabinet Secretariat, Government of Japan, 2016). Japan's inbound revenue is expected to grow further by 2020 and 2030 (Cabinet Secretariat, Government of Japan, 2016). The Japanese government has also planned large-scale investments to develop its tourism infrastructure (Cabinet Secretariat, Government of Japan, 2016).

Since 2020, inbound travel has been more tightly regulated than domestic travel because of entry restrictions in Japan due to the COVID-19 pandemic. Consequently, the total number of foreign tourists was only four million in 2020 and 13% of the total number of foreign tourists in 2019 (Japan National Tourism Organization, 2022). The total number of domestic tourists was 290 million in 2020, of which half occurred in 2019 (JTA, MLIT, 2021a). Accordingly, the Japanese inbound market has shrunk considerably.

Tourism is closely connected to multiple industries through supply chains,

including food services. Therefore, tourism revenue (i.e., the final consumption expenditure of domestic and foreign tourists) contributes to the revenue of other domestic industries. JTA reported that 14 trillion JPY (approximately 99 billion U.S.$ at an exchange rate of 141 JPY per U.S.$) in direct tourism value added in 2019 generated an additional 14 trillion JPY (99 billion U.S.$) in indirect tourism value added to GDP. These direct and indirect value-added effects accounted for 5.1% of Japan's GDP in 2019 (JTA, MLIT, 2023). However, Japanese tourism revenue in 2020 was only 11 trillion JPY (78 billion U.S.$), a significant decrease from 2019 (JTA, MLIT, 2023). Thus, Japan has experienced substantial economic losses owing to an 'exogenous' factor: a reduction in tourism demand.

The COVID-19 pandemic has directly affected the Japanese economy by altering household consumption and labor income. According to Japan's input–output tables for 2019 and 2020 (Cabinet Office, 2021, 2022a), household consumption decreased by 18.2 trillion JPY between 2019 and 2020, a decline of 5.9%. Labor income fell by 3.5 trillion JPY during the same period, a reduction of 1.2% compared with 2019. The Household Survey (Ministry of Internal Affairs and Communications (MIC), 2020b, 2021) indicated that the disposable income ratio, defined as the ratio of disposable household income to labor income, decreased from 67.3% to 60.7% between 2019 and 2020, a decrease of 6.6%. These economic factors are important contributors to the economic losses during the pandemic period. Therefore, this study incorporates labor income and household consumption into our analytical framework.

Economic loss affects society (i.e., job opportunities) and the environment (i.e., CO_2 emissions). In 2019, tourism-related job opportunities accounted for approximately 10% of the total Japanese labor force (6,570,000 people) (JTA, MLIT, 2021b). By 2020, these jobs had decreased by 310,000 (JTA, MLIT, 2023). In 2020, CO_2 emissions in Japan were 5.1% lower than in 2019 owing to the economic downturn, showing the largest decrease since the 2009 financial crisis (Ministry of the Environment, 2021). Kitamura *et al*. (2020a) reported that tourism activities in Japan (including domestic, inbound, and outbound tourism) emitted 136 million t-CO_2 in 2017, accounting for 10.5% of the nation's greenhouse gas (GHG) emissions. Additionally, Lenzen *et al*. (2018) revealed that the CF of tourism increased to account for 8% of the global total in 2013, highlighting that tourism to small island nations is one of the most emission-intensive forms of the per capita destination-based footprint. These findings suggest that Japan should put effort into promoting sustainable tourism. Therefore, local countermeasures should not only focus on the recovery of Japan's inbound markets but also on mitigating CO_2 emissions resulting from the recovery of Japan's inbound markets.

When policymakers consider countermeasures against the COVID-19 pandemic, they should comprehensively evaluate the economic, social, and environmental impacts of the pandemic and efficiently allocate limited resources to important stakeholders. However, there are challenges in evaluating the specific impact of the pandemic and identifying stakeholders indirectly affected by inbound markets because industries are closely connected in multiple markets.

Input-output analyses can model inter-industry deliveries in markets (Leontief, 1953) and have been used in previous studies to estimate direct and indirect economic impacts or CO_2 emissions through the tourism supply chain in the U.K. (Munday *et al*., 2013), Taiwan (Sun ,2014), Iceland (Sharp *et al*.,2016), New Zealand (Becken and Patterson, 2009), and Spain (Cadarso *et al*., 2015 and Cadarso *et al*., 2016). Output analyses have also been used to estimate the effects of the COVID-19 pandemic in different countries. Lenzen *et al*. (2020), using this analysis, identified the socioeconomic losses and environmental benefits worldwide. Similarly, input-output analyses have been applied to observe the economic impacts of COVID-19 in Indonesia (Sun *et al*., 2021).

Kitamura *et al*. (2020b) used a 'consumption-exogenous' input-output analysis to determine the impacts of COVID-19 in Japan through tourism activities and estimated the economic, environmental, and social impacts of the Japanese tourism industry from January 2020 to August 2020. Although the study by Kitamura *et al*. (2020b) is useful for understanding the rapid economic changes resulting from the pandemic, it did not identify important stakeholders with detailed sector resolutions (i.e., key industrial sectors) in the supply chains associated with inbound final demand. Additionally, Kitamura *et al*. (2020b) did not suggest specific policies to both recover the economic activities of the key sectors largely affected by the pandemic and mitigate CO_2 emissions associated with tourism supply chains.

This study aimed to estimate the economic, environmental, and social impacts of the COVID-19 pandemic. We developed an analysis framework that combines a

'consumption-endogenous' input-output analysis (Miyazawa, 1960) with a counterfactual final demand estimation model that determines inbound final demands with and without the pandemic. Based on the analysis framework, this study determined the final demand by foreign tourists during the pandemic and a counterfactual case without the pandemic and quantified direct and indirect economic losses, employment loss, and CO_2 reductions caused by the decline in the number of foreign visitors to Japan due to the pandemic. Key economic, social, and environmental sectors were identified. This study also discusses policies that support the identified key sectors in the tourism industry and allows policymakers to identify industries that have experienced hidden indirect damages from the COVID-19 pandemic, thereby recommending the improvement of recovery policies.

Policymakers ought to empirically investigate the factors influencing changes in economic, social, and environmental multiplier effects arising from the COVID-19 pandemic. While the structural decomposition analysis (SDA) framework is a useful methodology for exploring the effects of structural changes that occur within the national economy and environment (see e.g., Dietzenbacher and Los, 1997, 1998; Kagawa, 2011; Lenzen, 2016), it is important to note that we cannot directly observe the economic structure in 2020 without the pandemic. Therefore, the SDA framework cannot be straightforwardly applied to investigate the effects of the 'counterfactual' yearly structural change in 2020 due to the COVID-19 pandemic. This study proposes a new counterfactual SDA framework based on a consumption-endogenous input-output analysis. This assumes that the economic structure in 2020, without the pandemic, can be approximated as that of 2019.

In a recent study, Magacho and Rocha (2022) introduced a SDA framework based on a consumption-endogenous input-output analysis and investigated the factors contributing to changes in gross output in Brazil during the 2010s. While their SDA framework shares similarities with our framework, it is worth noting that they did not endogenously identify the labor income coefficient vector and household expenditure coefficient vector, in contrast to the consumption-endogenous input-output model we employ. Additionally, Magacho and Rocha (2022) primarily focused on 'empirical' structural changes, while this study centers around 'counterfactual' structural changes. We also discuss policies to support the major factors influencing changes in economic, social, and environmental multiplier effects arising from the pandemic.

The remainder of this chapter is organized as follows. Section 3.2 describes the methodology and data used in this study, Section 3.3 presents the empirical results, Section 3.4 outlines the data employed, Section 3.5 discusses the limitations of this study, and Section 3.6 provides the conclusion.

3.2. Methodology

3.2.1. Counterfactual scenario setting

To determine the economic, social, and environmental impacts of the COVID-19 pandemic, we defined two scenarios: with-COVID scenario and non-COVID

scenario. The with-COVID scenario shows the number of foreign visitors to Japan in 2020 during the pandemic. By contrast, the non-COVID scenario shows the *estimated* number of foreign visitors to Japan in 2020 in the counterfactual case, assuming that the pandemic did not occur that year. Japan has experienced structural changes in inbound tourism through policies such as easing visas. Following these structural changes, the number of foreign visitors rapidly increased until the end of the pandemic. Therefore, this structural break must be considered within an analytical framework. When the number of foreign visitors from country c to Japan in year t is defined as $\bar{n}_t^c$, the linear trend model can be formulated as:

$$\begin{cases} \bar{n}_t^c = \alpha_1^c + \beta_1^c t + e_{1,t}^c \quad (t = 2003, 2004, \dots, b^c - 1) \\ \bar{n}_t^c = \alpha_2^c + \beta_2^c t + e_{2,t}^c \quad (t = b^c, b^c + 1, \dots, 2019) \end{cases} \tag{1}$$

where α^c and β^c represent parameters showing the intercept and slope in the linear trend model, respectively, e_t^c represent independent and identically distributed error terms, and b^c represents the year of the structural break for country c during the period between 2003 and 2019. Subscripts 1 and 2 in Eq. (1) represent the parameters before and after a structural break, respectively.

We conducted two regression analyses as shown in Eq. (1), repeatedly changing the specific year of structural change (i.e., b^c), and compared the *F*-values between the null hypothesis ($\alpha_1^c = \alpha_2^c$ and $\beta_1^c = \beta_2^c$) and the alternative hypothesis. By identifying the year with the highest *F*-value, defined as:

$$F = \left\{ \sum_{t=2003}^{2019} (u_t^c)^2 - \sum_{t=2003}^{b_c-1} \left(u_{1,t}^c\right)^2 - \sum_{t=b_c}^{2019} \left(u_{2,t}^c\right)^2 \right\} \Big/ \left\{ \sum_{t=2003}^{b_c-1} \left(u_{1,t}^c\right)^2 + \sum_{t=b_c}^{2019} \left(u_{2,t}^c\right)^2 \right\} \Big/ (17-2) \tag{2}$$

where u_t^c represents the error term obtained from the regression analysis without considering the structural change year, and 17 and 2 represent the number of observations and parameters in Eq. (1), respectively. In this study, a linear trend model was developed using the ordinary least-squares (OLS) method.

Accordingly, we have:

$$\tilde{n}_t^c = \tilde{\alpha}_2^c + \tilde{\beta}_2^c t \tag{3}$$

where $\tilde{n}_t^c$ is the predicted number of foreign visitors from country *c* to Japan in year *t* after the structural break and $\tilde{\alpha}_2^c$ and $\tilde{\beta}_2^c$ represent the estimated intercept and slope parameters, respectively. The extrapolation method, based on the specified linear trend model in Eq. (3) yields the forecast number of foreign visitors from country *c* to Japan in 2020 following the linear time trend between the *estimated* structural break $\tilde{b}^c$ and 2019 before the COVID-19 pandemic, as follows:

$$\tilde{n}_{2020}^c = \tilde{\alpha}^c + \tilde{\beta}^c \times 2020 \tag{4}$$

When the actual number of foreign visitors from a specific country *c* to Japan in 2020 *with* the pandemic is defined as $\bar{n}_{2020}^c$ and the forecasted number of foreign visitors

from a specific country *c* to Japan in 2020 *without* the COVID-19 pandemic is defined as $\tilde{n}^c_{2020}$, the pandemic could reduce the number of foreign visitors from a specific country *c* in 2020 by $\Delta n^c_{2020} = \tilde{n}^c_{2020} - \bar{n}^c_{2020}$. It should be noted that the tilde ($\sim$) and bar ($-$) denote the non-COVID scenario and with-COVID scenario, respectively.

3.2.2. Direct, indirect, and income-induced economic effects triggered by travel consumption by foreign visitors in 2020

In this study, the *actual* travel consumption of foreign visitors from Country *c* during the COVID-19 pandemic was calculated as follows:

$$\bar{\mathbf{f}}^c_{2020} = \bar{n}^c_{2020}\bar{\mathbf{d}}^c_{2020} \tag{5}$$

where $\bar{\mathbf{f}}^c_{2020}$ represents the final demand column vector of commodities consumed by foreign visitors in Japan in 2020 and $\bar{\mathbf{d}}^c_{2020}$ represents a column vector showing the per capita commodity consumption for foreign visitors from a specific country *c*.

Based on an input-output analysis (Miller and Blair, 2009), we estimated the direct and indirect economic effects triggered by foreign visitors' travel consumption in 2020 as follows:

$$\bar{\mathbf{x}}^c_{1,2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\right\}^{-1}\bar{\mathbf{f}}^c_{2020} = \bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^c_{2020} \tag{6}$$

where $\bar{\mathbf{x}}_{1,2020}^{c}$ represents a vector of industrial commodity outputs directly and indirectly induced by the *actual* inbound final demand of country c in 2020, $\bar{\mathbf{L}}_{1,2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\right\}^{-1}$ is a non-competitive import-type Leontief inverse matrix showing intermediate inputs from industry i directly and indirectly required to produce one unit in industry j, $\hat{\bar{\mathbf{M}}}_{2020}$ is the diagonal import coefficient matrix in 2020, whose diagonal element shows a portion of imported commodity i to the domestic demand of commodity i, $\bar{\mathbf{A}}_{2020}$ is the input coefficient matrix in 2020, showing intermediate inputs from industry i directly required to produce one unit in industry j, and $\mathbf{I}$ is the identity matrix.

Based on Miyazawa (1960) and Miyazawa and Masegi (1963), we formulate the consumption-endogenous input-output model as follows:

$$\bar{\mathbf{x}}_{2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right\}^{-1}\bar{\mathbf{f}}_{2020}$$

$$= \bar{\mathbf{L}}_{2,2020}\bar{\mathbf{f}}_{2020} = \underbrace{\bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}_{2020}}_{\bar{\mathbf{x}}_{1,2020}} + \underbrace{\bar{\mathbf{L}}_{1,2020}\left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\bar{\mathbf{L}}_{2,2020}\bar{\mathbf{f}}_{2020}}_{\bar{\mathbf{x}}_{2,2020}} \quad (7)$$

where $\bar{\mathbf{x}}_{2,2020}$ denotes the gross output vector showing the gross outputs of industry i induced by the exogenous final demand (i.e., exogenous final consumptions of foreign tourists) in 2020 of $\bar{\mathbf{f}}_{2020}$, $\bar{\mathbf{w}}_{2020}$ represents the actual labor income coefficient row vector in 2020 showing labor income per unit of output

of industry j, $\bar{\mu}_{2020}$ actual household disposable income ratio in 2020, and $\bar{\mathbf{h}}_{2020}$ actual household expenditure coefficient column vector in 2020 showing the household expenditure of commodity i per unit of labor income. $\bar{\mathbf{L}}_{2,2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right\}^{-1}$ is the Leontief-Miyazawa inverse matrix showing intermediate inputs from industry i associated with household consumption *endogenously* derived by the labor income necessary for producing one unit in industry j.[1] Here, it should be noted that $\bar{\mathbf{x}}_{2,2020}$ expresses the additional commodity output effects derived from labor income induced by the exogenous final demand in 2020.

By using the second term in Eq. (7), we estimate the additional commodity output effects derived from the labor income induced by the *actual* inbound final demand of country *c* in 2020 during the COVID-19 pandemic as follows:

$$\bar{\mathbf{x}}^{c}_{2,2020} = \bar{\mathbf{L}}_{1,2020}\left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\bar{\mathbf{L}}_{2,2020}\bar{\mathbf{f}}^{c}_{2020} \tag{8}$$

[1] The consumption-endogenous input-output system can be written as $\bar{\mathbf{x}}_{2020} = \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\bar{\mathbf{x}}_{2020} + \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\bar{\mathbf{x}}_{2020} + \bar{\mathbf{f}}_{2020}$ (see Miyazawa and Masegi, 1963). Solving this endogenous input-output system yields $\bar{\mathbf{x}}_{2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\right\}^{-1}\bar{\mathbf{f}}_{2020} + \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\right\}^{-1}\left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\bar{\mathbf{x}}_{2020} = \bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}_{2020} + \bar{\mathbf{L}}_{1,2020}\left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\bar{\mathbf{L}}_{2,2020}\bar{\mathbf{f}}_{2020}$. It is important to note that Miyazawa and Masegi (1963) did not exclude the imported intermediate and final products in the inter-industry transactions.

3.2.3. Economic, social, and environmental effects triggered by travel consumption by foreign visitors in 2020

To evaluate the economic impacts of the *actual* inbound final demand during the 2020 COVID-19 pandemic, we focus on the industrial value added to the economy. When the diagonal value-added coefficient matrix, whose diagonal elements show the value-added coefficient indicating the value added directly generated by producing one unit of output by industry i is defined as $\hat{\bar{\mathbf{v}}}_{2020}$, the direct value-added effects $\bar{\mathbf{V}}^{c}_{1,2020}$, indirect value-added effects $\bar{\mathbf{V}}^{c}_{2,2020}$, and income-induced value-added effects $\bar{\mathbf{V}}^{c}_{3,2020}$ are estimated as follows[2]:

$$\bar{\mathbf{V}}^{c}_{1,2020} = \hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{f}}^{c}_{2020} \tag{9}$$

$$\bar{\mathbf{V}}^{c}_{2,2020} = \hat{\bar{\mathbf{v}}}_{2020}(\bar{\mathbf{x}}^{c}_{1,2020} - \bar{\mathbf{f}}^{c}_{2020}) \tag{10}$$

$$\bar{\mathbf{V}}^{c}_{3,2020} = \hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{x}}^{c}_{2,2020} \tag{11}$$

[2]The input-output system can be written as $\bar{\mathbf{x}}^{c}_{1,2020} = \bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^{c}_{2020}$. Based on the Taylor series expansion of the Leontief inverse matrix, we have $\bar{\mathbf{x}}^{c}_{1,2020} = \bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^{c}_{2020} = \Big[\mathbf{I} + \Big(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020} + \Big\{\Big(\mathrm{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020}\Big\}^{2} + \cdots\Big]\bar{\mathbf{f}}^{c}_{2020} = \Big\{\mathbf{I} + \Big(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020}\bar{\mathbf{L}}_{1,2020}\Big\}\bar{\mathbf{f}}^{c}_{2020} = \bar{\mathbf{f}}^{c}_{2020} + \Big(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020}\bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^{c}_{2020}$. Therefore, when multiplying this equation by the diagonal matrix of value-added coefficients ($\hat{\bar{\mathbf{v}}}_{2020}$), the equation can be rewritten as $\hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{x}}^{c}_{1,2020} = \underbrace{\hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{f}}^{c}_{2020}}_{\bar{\mathbf{V}}^{c}_{1,2020}} + \underbrace{\hat{\bar{\mathbf{v}}}_{2020}\Big(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020}\bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^{c}_{2020}}_{\bar{\mathbf{V}}^{c}_{2,2020}}$. Therefore, the indirect value-added effects can be obtained as $\bar{\mathbf{V}}^{c}_{2,2020} = \hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{x}}^{c}_{1,2020} - \hat{\bar{\mathbf{v}}}_{2020}\bar{\mathbf{f}}^{c}_{2020} = \hat{\bar{\mathbf{v}}}_{2020}\Big(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\Big)\bar{\mathbf{A}}_{2020}\bar{\mathbf{L}}_{1,2020}\bar{\mathbf{f}}^{c}_{2020}$.

The overall economic impact on tourists from N foreign countries on Japan is calculated as follows:

$$\bar{V}_{2020} = \sum_{c=1}^{N} \mathbf{i}\left(\bar{\mathbf{V}}_{1,2020}^{c} + \bar{\mathbf{V}}_{2,2020}^{c} + \bar{\mathbf{V}}_{3,2020}^{c}\right) \tag{12}$$

where $\mathbf{i}$ is the row vector whose elements are one.

When we define the diagonal employment input coefficient matrix for 2020, showing the employment input in persons required to produce one unit of output in industry i as $\hat{\bar{\mathbf{s}}}_{2020}$, the direct, indirect, and income-induced employment opportunities can be estimated as follows:

$$\bar{\mathbf{S}}_{1,2020}^{c} = \hat{\bar{\mathbf{s}}}_{2020}\bar{\mathbf{f}}_{2020}^{c} \tag{13}$$

$$\bar{\mathbf{S}}_{2,2020}^{c} = \hat{\bar{\mathbf{s}}}_{2020}(\bar{\mathbf{x}}_{1,2020}^{c} - \bar{\mathbf{f}}_{2020}^{c}) \tag{14}$$

$$\bar{\mathbf{S}}_{3}^{c} = \hat{\bar{\mathbf{s}}}_{2020}\bar{\mathbf{x}}_{2,2020}^{c} \tag{15}$$

The overall social impact of tourists from N foreign countries on Japan was calculated as:

$$\bar{S}_{2020} = \sum_{c=1}^{N} \mathbf{i}\left(\bar{\mathbf{S}}_{1,2020}^{c} + \bar{\mathbf{S}}_{2,2020}^{c} + \bar{\mathbf{S}}_{3,2020}^{c}\right) \tag{16}$$

When we define the diagonal CO_2 emission coefficient matrix showing the

direct CO_2 emissions generated by producing one unit of output in industry i as $\hat{\bar{\mathbf{e}}}_{2020}$, the direct, indirect, and income-induced CO_2 emissions can be estimated as follows:

$$\bar{\mathbf{E}}_{1,2020}^{c} = \hat{\bar{\mathbf{e}}}_{2020}\bar{\mathbf{f}}_{2020}^{c} \tag{17}$$

$$\bar{\mathbf{E}}_{2,2020}^{c} = \hat{\bar{\mathbf{e}}}_{2020}(\bar{\mathbf{x}}_{1,2020}^{c} - \bar{\mathbf{f}}_{2020}^{c}) \tag{18}$$

$$\bar{\mathbf{E}}_{3}^{c} = \hat{\bar{\mathbf{e}}}_{2020}\bar{\mathbf{x}}_{2,2020}^{c} \tag{19}$$

The overall environmental impact of tourists from N foreign countries on Japan was calculated as follows:

$$\bar{E}_{2020} = \sum_{c=1}^{N} \mathbf{i}\left(\bar{\mathbf{E}}_{1,2020}^{c} + \bar{\mathbf{E}}_{2,2020}^{c} + \bar{\mathbf{E}}_{3,2020}^{c}\right) \tag{20}$$

3.2.4. Economic, social, and environmental effects triggered by travel consumption by foreign tourists in 2020 under the non-COVID scenario

It is noteworthy that Eq. (4) provides $\tilde{n}_{2020}^{c}$ showing the predicted number of foreign tourists from country *c* to Japan in 2020 under the non-COVID scenario. Accordingly, the *unobservable* travel consumption by foreign visitors from Country *c* in 2020 in the non-COVID scenario can be estimated as follows:

$$\tilde{\mathbf{f}}_{2020}^{c} = \tilde{n}_{2020}^{c}\tilde{\mathbf{d}}_{2020}^{c} \tag{21}$$

where $\tilde{\mathbf{d}}_{2020}^{c}$ represents a column vector showing *unobservable* per-capita commodity consumption of foreign tourists from Country *c*.

The direct and indirect economic effects triggered by foreign visitors' travel consumption in 2020 under the non-COVID scenario can be estimated as follows:

$$\tilde{\mathbf{x}}_{1,2020}^{c} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\right\}^{-1}\tilde{\mathbf{f}}_{2020}^{c} \tag{22}$$

where $\hat{\tilde{\mathbf{M}}}_{2020}$ is the *unobservable* diagonal import coefficient matrix in 2020 under the non-COVID scenario and $\tilde{\mathbf{A}}_{2020}$ is the *unobservable* input coefficient matrix in 2020 under the non-COVID scenario.

Furthermore, the additional commodity output effects derived from labor income induced by the inbound final demand of country *c* in 2020 under the non-COVID scenario can be estimated as follows:

$$\tilde{\mathbf{x}}_{2}^{c} = \tilde{\mathbf{L}}_{1,2020}\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}\tilde{\mathbf{L}}_{2,2020}\tilde{\mathbf{f}}_{2020}^{c} \tag{23}$$

Here, we have $\tilde{\mathbf{L}}_{1,2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\right\}^{-1}$ and $\tilde{\mathbf{L}}_{2,2020} = \left\{\mathbf{I} - \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020} - \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}\right\}^{-1}$ where $\tilde{\mathbf{w}}_{2020}$ represents the unobservable labor income coefficient row vector in 2020, $\tilde{\mu}_{2020}$ unobservable

household disposable income ratio in 2020, and $\tilde{\mathbf{h}}_{2020}$ unobservable household expenditure coefficient column vector in 2020.

The output effects in Eq. (21), (22), and (23) can be inserted into the variables of $\mathbf{f}_{2020}^{c}$, $\mathbf{x}_{1}^{c}$, and $\mathbf{x}_{2}^{c}$ in the impact analysis framework formulated in Section 3.2.3: The overall economic, social, and environmental effects triggered by foreign tourist travel consumption in 2020 in the non-COVID scenario were estimated to be $\tilde{V}$, $\tilde{S}$, and $\tilde{E}$, respectively. A comparison of the economic, social, and environmental impacts of the with-COVID and non-COVID scenarios revealed economic and social losses and environmental benefits resulting from the pandemic.

$$\Delta V_{2020} = \bar{V}_{2020} - \tilde{V}_{2020} \tag{24}$$

$$\Delta S_{2020} = \bar{S}_{2020} - \tilde{S}_{2020} \tag{25}$$

$$\Delta E_{2020} = \bar{E}_{2020} - \tilde{E}_{2020} \tag{26}$$

By focusing on the triple bottom-line effects driven by the inbound demand of foreign visitors to Japan, we can decompose the changes between each scenario into key factors: changes in the value-added coefficient vector, changes in the input coefficient matrix (i.e., production technology), changes in household expenditure coefficients (i.e., consumption patterns), changes in the household disposable income coefficient (i.e., disposable income level), changes in the labor income

coefficient vector (i.e., labor income), and changes in the final demand of foreign visitors (i.e., inbound demand).

3.2.5. Decomposing the economic multiplier

Focusing on the economic multiplier effects driven by the inbound demand of foreign visitors to Japan, we can break down the changes between each scenario into key factors. It is important to note that the following two relationships exist for the consumption-endogenous input-output systems under the with-COVID and non-COVID scenarios, respectively:

$$\mathbf{i}\left(\mathbf{I}-\widehat{\overline{\mathbf{M}}}_{2020}\right)\overline{\mathbf{A}}_{2020}+\overline{\mathbf{w}}_{2020}+\overline{\mathbf{v}}_{2020}+\overline{\mathbf{m}}_{2020}=\mathbf{i} \tag{27}$$

$$\mathbf{i}\left(\mathbf{I}-\widehat{\widetilde{\mathbf{M}}}_{2020}\right)\widetilde{\mathbf{A}}_{2020}+\widetilde{\mathbf{w}}_{2020}+\widetilde{\mathbf{v}}_{2020}+\widetilde{\mathbf{m}}_{2020}=\mathbf{i} \tag{28}$$

where $\mathbf{i}$ represents the summation row vector of ones, and $\overline{\mathbf{m}}_{2020}=\mathbf{i}\widehat{\overline{\mathbf{M}}}_{2020}\overline{\mathbf{A}}_{2020}$ and $\widetilde{\mathbf{m}}_{2020}=\mathbf{i}\widehat{\widetilde{\mathbf{M}}}_{2020}\widetilde{\mathbf{A}}_{2020}$ represent the import coefficient row vectors, defined as the column sums of the import coefficient matrices $\widehat{\overline{\mathbf{M}}}_{2020}\overline{\mathbf{A}}_{2020}$ and $\widehat{\widetilde{\mathbf{M}}}_{2020}\widetilde{\mathbf{A}}_{2020}$, respectively. Dietzenbacher and Los (2000) pointed out that the four structural determinants $\left(\mathbf{I}-\widehat{\overline{\mathbf{M}}}_{2020}\right)\mathbf{A}_{2020}$, $\mathbf{w}_{2020}$, $\mathbf{v}_{2020}$, $\mathbf{m}_{2020}$ in Eqs. (27) and (28) are interdependent. For example, a decrease in the value-added coefficient row vector ($\mathbf{v}_{2020}$) may lead to an increase in the input coefficient matrix ($\mathbf{A}_{2020}$), or a decrease

in the value-added coefficient row vector($\mathbf{v}_{2020}$) may result in an increase in the labor income coefficient row vector ($\mathbf{w}_{2020}$).

In this study, we employed the structural decomposition method with dependent determinants developed by Dietzenbacher and Los (2000). Following their approach, we define the following 'adjusted' augmented input coefficient matrices under the with-COVID and non-COVID scenarios, respectively:

$$\bar{\mathbf{C}}_{2020} = \bar{\mathbf{B}}_{2020}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020} \tag{29}$$

$$\tilde{\mathbf{C}}_{2020} = \tilde{\mathbf{B}}_{2020}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020} \tag{30}$$

where $\bar{\mathbf{B}}_{2020} = \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020} + \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}$ and $\tilde{\mathbf{B}}_{2020} = \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020} + \left(\mathbf{I} - \hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}$, respectively, and $\hat{\bar{\mathbf{r}}}_{2020}$ and $\hat{\tilde{\mathbf{r}}}_{2020}$ represent the diagonal matrices of the column sum vectors of $\bar{\mathbf{B}}_{2020}$ and $\tilde{\mathbf{B}}_{2020}$, respectively. Here, the column sum vector of the 'adjusted' augmented input coefficient matrix under the with-COVID scenario $\bar{\mathbf{C}}_{2020}$ is equal to the column sum vector of the 'observed' augmented input coefficient matrix under the non-COVID scenario $\tilde{\mathbf{B}}_{2020}$, while the column sum vector of the 'observed' augmented input coefficient matrix under the with-COVID scenario $\bar{\mathbf{B}}_{2020}$ is equal to the column sum vector of the 'adjusted' augmented input coefficient matrix under the non-COVID scenario $\tilde{\mathbf{C}}_{2020}$. In other words, $\bar{\mathbf{C}}_{2020}$ (or $\bar{\mathbf{B}}_{2020}$) and $\tilde{\mathbf{B}}_{2020}$ (or $\tilde{\mathbf{C}}_{2020}$) are independent of each other, allowing us to compare their two determinants over time.

We further define the 'adjusted' augmented Leontief inverse matrices under the with-COVID and non-COVID scenarios, respectively:

$$\bar{\mathbf{D}}_{2020} = (\mathbf{I} - \bar{\mathbf{C}}_{2020})^{-1} \tag{31}$$

$$\tilde{\mathbf{D}}_{2020} = \left(\mathbf{I} - \tilde{\mathbf{C}}_{2020}\right)^{-1} \tag{32}$$

It is important to note that the 'adjusted' augmented Leontief inverse matrix under the with-COVID scenario ($\bar{\mathbf{D}}_{2020}$) is comparable to the 'observed' augmented Leontief inverse matrix under the non-COVID scenario ($\tilde{\mathbf{L}}_{2020}$), while the 'adjusted' augmented Leontief inverse matrix under the non-COVID scenario ($\tilde{\mathbf{D}}_{2020}$) is comparable to the 'observed' augmented Leontief inverse matrix under the with-COVID scenario ($\bar{\mathbf{L}}_{2020}$). Thus, the change in value-added impacts between the with-COVID and non-COVID scenarios can be decomposed as follows:

$$\Delta V_{2020} = \bar{V}_{2020} - \tilde{V}_{2020} = \sum_{c=1}^{N} \Delta\left(\mathbf{v}_{2020}\mathbf{L}_{2,2020}\mathbf{f}_{2020}^{c}\right)$$

$$= \sum_{c=1}^{N} \frac{1}{2}\left\{\Delta\left(\mathbf{v}_{2020}\mathbf{L}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \left(\bar{\mathbf{v}}_{2020}\,\bar{\mathbf{L}}_{2020} + \tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2020}\right)\Delta\mathbf{f}_{2020}^{c}\right\}$$

$$= \underbrace{\sum_{c=1}^{N} \frac{1}{2}\left\{\left(\bar{\mathbf{v}}_{2020}\tilde{\mathbf{D}}_{2020} - \tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta\hat{V}_{2020}^{va}}$$

$$+\underbrace{\sum_{c=1}^{N}\frac{1}{2}\left\{\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020}-\bar{\mathbf{v}}_{2020}\widetilde{\mathbf{D}}_{2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c}+\tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta V_{2020}^{ps}}$$

$$+\underbrace{\sum_{c=1}^{N}\frac{1}{2}\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020}+\tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\Delta\mathbf{f}_{2020}^{c}}_{\Delta V_{2020}^{fd}}$$

(33)

Alternatively, we have the following decomposition equation.

$$\Delta V_{2020}=\bar{V}_{2020}-\tilde{V}_{2020}=\sum_{c=1}^{N}\Delta\left(\mathbf{v}_{2020}\mathbf{L}_{2,2020}\mathbf{f}_{2020}^{c}\right)$$

$$=\sum_{c=1}^{N}\frac{1}{2}\left\{\Delta\left(\mathbf{v}_{2020}\mathbf{L}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c}+\tilde{\mathbf{f}}_{2020}^{c}\right)+\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2020}+\tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2020}\right)\Delta\mathbf{f}_{2020}^{c}\right\}$$

$$=\underbrace{\sum_{c=1}^{N}\frac{1}{2}\left\{\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020}-\tilde{\mathbf{v}}_{2020}\overline{\mathbf{D}}_{2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c}+\tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta V_{2020}^{va}}$$

$$+\underbrace{\sum_{c=1}^{N}\frac{1}{2}\left\{\left(\tilde{\mathbf{v}}_{2020}\overline{\mathbf{D}}_{2020}-\tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c}+\tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta V_{2020}^{ps}}$$

$$+\underbrace{\sum_{c=1}^{N}\frac{1}{2}\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020}+\tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\Delta\mathbf{f}_{2020}^{c}}_{\Delta V_{2020}^{fd}}$$

(34)

This study uses an 'average' decomposition equation derived from two decomposition equations, Eqs. (33) and (34), resulting in the following three decomposition effects:

$$\Delta V_{2020}^{va} = \frac{1}{4}\sum_{c=1}^{N}\left\{\left(\bar{\mathbf{v}}_{2020}\tilde{\mathbf{D}}_{2020} - \tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020} - \tilde{\mathbf{v}}_{2020}\bar{\mathbf{D}}_{2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\} \tag{35}$$

$$\Delta V_{2020}^{ps} = \frac{1}{4}\sum_{c=1}^{N}\left\{\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020} - \bar{\mathbf{v}}_{2020}\tilde{\mathbf{D}}_{2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \left(\tilde{\mathbf{v}}_{2020}\bar{\mathbf{D}}_{2020} - \tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\} \tag{36}$$

$$\Delta V_{2020}^{fd} = \frac{1}{2}\sum_{c=1}^{N}\left(\bar{\mathbf{v}}_{2020}\,\overline{\mathbf{L}}_{2,2020} + \tilde{\mathbf{v}}_{2020}\tilde{\mathbf{L}}_{2,2020}\right)\Delta\mathbf{f}_{2020}^{c} \tag{37}$$

Equation (35) represents the economic effect of changes in the value-added coefficients of industries, Equation (36) represents the economic effect of changes in the production structure, and Equation (37) represents the economic effect of changes in the final demand from foreign visitors to Japan. We further decompose the economic effect of changes in the production structure into three effects: changes in the input coefficient matrix (i.e., production technology), changes in household expenditure coefficients (i.e., consumption patterns), and changes in the household disposable income coefficient (i.e., disposable income level). The supplemental information includes the detailed structural decomposition analysis

of the economic, social, and environmental impacts between the with-COVID and non-COVID scenarios.

From equations (29) and (30), we further rewrite the following 'adjusted' input coefficient matrices under the with-COVID and non-COVID scenarios, respectively.

$$\begin{aligned}\bar{\mathbf{C}}_{2020} &= \left\{\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}+\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right\}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020} \\ &= \left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020}+\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020} \\ &= \bar{\mathbf{G}}_{2020}+\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{h}}_{2020}\bar{\mu}_{2020}\bar{\mathbf{y}}_{2020}\end{aligned} \tag{38}$$

$$\begin{aligned}\tilde{\mathbf{C}}_{2020} &= \left\{\left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}+\left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}\right\}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020} \\ &= \left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020}+\left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020} \\ &= \tilde{\mathbf{G}}_{2020}+\left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{h}}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{y}}_{2020}\end{aligned} \tag{39}$$

where we have: $\bar{\mathbf{G}}_{2020}=\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\bar{\mathbf{A}}_{2020}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020}$, $\tilde{\mathbf{G}}_{2020}=\left(\mathbf{I}-\hat{\tilde{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020}$, $\bar{\mathbf{y}}_{2020}=\bar{\mathbf{w}}_{2020}\hat{\bar{\mathbf{r}}}_{2020}^{-1}\hat{\tilde{\mathbf{r}}}_{2020}$, and $\tilde{\mathbf{y}}_{2020}=\tilde{\mathbf{w}}_{2020}\hat{\tilde{\mathbf{r}}}_{2020}^{-1}\hat{\bar{\mathbf{r}}}_{2020}$, respectively. The 'adjusted' input coefficient matrix under the with-COVID scenario ($\bar{\mathbf{G}}_{2020}$) is comparable to the 'observed' input coefficient matrix under the non-

COVID scenario ($\left(\mathbf{I}-\widehat{\widetilde{\mathbf{M}}}_{2020}\right)\widetilde{\mathbf{A}}_{2020}$), while the 'adjusted' input coefficient matrix under the non-COVID scenario ($\widetilde{\mathbf{G}}_{2020}$) is comparable to the 'observed' input coefficient matrix under the non-COVID scenario ($\left(\mathbf{I}-\widehat{\overline{\mathbf{M}}}_{2020}\right)\overline{\mathbf{A}}_{2020}$). Similarly, the 'adjusted' labor income coefficient vector under the with-COVID scenario ($\bar{\mathbf{y}}_{2020}$) is comparable to the 'observed' input coefficient matrix under the non-COVID scenario ($\widetilde{\mathbf{w}}_{2020}$), while the 'adjusted' labor income coefficient vector under the non-COVID scenario ($\tilde{\mathbf{y}}_{2020}$) is comparable to the 'observed' input coefficient matrix under the non-COVID scenario ($\overline{\mathbf{w}}_{2020}$).

Based on the inverse matrix decomposition method (e.g., Lin and Polenske, 1995), we can further decompose the augmented Leontief-Miyazawa inverse matrix as follows:

$$\Delta\mathbf{L}_{2,2020} = \tilde{\mathbf{L}}_{2,2020}\Delta\mathbf{A}^{d}_{2020}\overline{\mathbf{D}}_{2020} + \tilde{\mathbf{L}}_{2,2020}\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)\overline{\mathbf{D}}_{2020}$$

$$= \tilde{\mathbf{L}}_{2,2020}\left\{\overline{\mathbf{G}}_{2020} - \left(\mathbf{I}-\widehat{\widetilde{\mathbf{M}}}_{2020}\right)\widetilde{\mathbf{A}}_{2020}\right\}\overline{\mathbf{D}}_{2020} + \tilde{\mathbf{L}}_{2,2020}\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)\overline{\mathbf{D}}_{2020} \quad (40a)$$

$$= \tilde{\mathbf{L}}_{2,2020}\left\{\left(\mathbf{I}-\widehat{\overline{\mathbf{M}}}_{2020}\right)\overline{\mathbf{A}}_{2020} - \widetilde{\mathbf{G}}_{2020}\right\}\overline{\mathbf{D}}_{2020} + \tilde{\mathbf{L}}_{2,2020}\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)\overline{\mathbf{D}}_{2020} \quad (40b)$$

where we define $\mathbf{A}^{d}_{2020} = \left(\mathbf{I}-\widehat{\mathbf{M}}_{2020}\right)\mathbf{A}_{2020}$ and $\mathbf{h}^{d}_{2020} = \left(\mathbf{I}-\widehat{\mathbf{M}}_{2020}\right)\mathbf{h}_{2020}$, respectively. The second term of Eqs. (40a) and (40b) can be decomposed as follows.

$\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)$

$$= \frac{1}{6}(2\Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020})$$

$$+\frac{1}{6}\left(2\tilde{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)$$

$$+\frac{1}{6}\{2\tilde{\mathbf{h}}^d_{2020}\tilde{\mu}_{2020}(\bar{\mathbf{y}}_{2020} - \tilde{\mathbf{w}}_{2020}) + \tilde{\mathbf{h}}^d_{2020}\bar{\mu}_{2020}(\bar{\mathbf{y}}_{2020} - \tilde{\mathbf{w}}_{2020}) + \bar{\mathbf{h}}^d_{2020}\tilde{\mu}_{2020}(\bar{\mathbf{y}}_{2020} - \tilde{\mathbf{w}}_{2020}) + 2\bar{\mathbf{h}}^d_{2020}\bar{\mu}_{2020}(\bar{\mathbf{y}}_{2020} - \tilde{\mathbf{w}}_{2020})\} \quad (41)$$

or

$$\Delta(\mathbf{h}^d_{2020}\mu_{2020}\mathbf{w}_{2020})$$

$$= \frac{1}{6}(2\Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020})$$

$$+\frac{1}{6}\left(2\tilde{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^d_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)$$

$$+\frac{1}{6}\{2\tilde{\mathbf{h}}^d_{2020}\tilde{\mu}_{2020}(\bar{\mathbf{w}}_{2020} - \tilde{\mathbf{y}}_{2020}) + \tilde{\mathbf{h}}^d_{2020}\bar{\mu}_{2020}(\bar{\mathbf{w}}_{2020} - \tilde{\mathbf{y}}_{2020}) + \bar{\mathbf{h}}^d_{2020}\tilde{\mu}_{2020}(\bar{\mathbf{w}}_{2020} - \tilde{\mathbf{y}}_{2020}) + 2\bar{\mathbf{h}}^d_{2020}\bar{\mu}_{2020}(\bar{\mathbf{w}}_{2020} - \tilde{\mathbf{y}}_{2020})\} \quad (42)$$

where $\Delta\mathbf{h}^d_{2020} = \bar{\mathbf{h}}^d_{2020} - \tilde{\mathbf{h}}^d_{2020}$ and $\Delta\mu_{2020} = \bar{\mu}_{2020} - \tilde{\mu}_{2020}$.

By inserting Eqs. (41) and (42) into the second term on the right-hand side of Eq. (40a), we obtain the following two decomposition equations, respectively.

$$\Delta\mathbf{L}_{2,2020} = \bar{\mathbf{D}}_{2020} - \tilde{\mathbf{L}}_{2,2020} = \underbrace{\tilde{\mathbf{L}}_{2,2020}\left\{\bar{\mathbf{G}}_{2020} - \left(\mathbf{I} - \hat{\bar{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\right\}\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{a*}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}(2\Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020} + \Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^d_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020})\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{h}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020}+\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}+\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020}+2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{\mu}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left\{2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020}+\tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020}+\bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020}+2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020}\right\}\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{w*}_{2,2020}}$$

(43a)

and

$$\Delta\mathbf{L}_{2,2020}=\bar{\mathbf{D}}_{2020}-\tilde{\mathbf{L}}_{2,2020}=\underbrace{\tilde{\mathbf{L}}_{2,2020}\left\{\bar{\mathbf{G}}_{2020}-\left(\mathbf{I}-\hat{\bar{\mathbf{M}}}_{2020}\right)\tilde{\mathbf{A}}_{2020}\right\}\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{a*}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020}+\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020}+\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020}+2\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right)\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{h}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020}+\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}+\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020}+2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{\mu}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left\{2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020}+\tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020}+\bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020}+2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020}\right\}\bar{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{w**}_{2,2020}}$$

(43b)

where $\Delta\mathbf{w}^{\#}_{2020}=\bar{\mathbf{y}}_{2020}-\tilde{\mathbf{w}}_{2020}$ and $\Delta\mathbf{w}^{\#\#}_{2020}=\bar{\mathbf{w}}_{2020}-\tilde{\mathbf{y}}_{2020}$.

Similarly, inserting Eqs. (41) and (42) into the second term on the right-hand side of Eq. (40b) gives the following two decomposition equations, respectively.

$$\Delta\mathbf{L}_{2,2020} = \overline{\mathbf{L}}_{2,2020} - \widetilde{\mathbf{D}}_{2020} = \underbrace{\tilde{\mathbf{L}}_{2,2020}\left\{\left(\mathbf{I} - \widehat{\overline{\mathbf{M}}}_{2020}\right)\overline{\mathbf{A}}_{2020} - \tilde{\mathbf{G}}_{2020}\right\}\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{a**}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\widetilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\overline{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\widetilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\overline{\mathbf{w}}_{2020}\right)\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{h}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\widetilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\overline{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\widetilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\overline{\mathbf{w}}_{2020}\right)\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{\mu}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left\{2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#}_{2020}\right\}\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{w*}_{2,2020}}$$

(43c)

and

$$\Delta\mathbf{L}_{2,2020} = \overline{\mathbf{L}}_{2,2020} - \widetilde{\mathbf{D}}_{2020} = \underbrace{\tilde{\mathbf{L}}_{2,2020}\left\{\left(\mathbf{I} - \widehat{\overline{\mathbf{M}}}_{2020}\right)\overline{\mathbf{A}}_{2020} - \tilde{\mathbf{G}}_{2020}\right\}\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{a**}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\widetilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\overline{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\widetilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\overline{\mathbf{w}}_{2020}\right)\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{h}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\widetilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\overline{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\widetilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\overline{\mathbf{w}}_{2020}\right)\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{\mu}_{2,2020}}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left\{2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}^{\#\#}_{2020}\right\}\overline{\mathbf{D}}_{2020}}_{\Delta\mathbf{L}^{w**}_{2,2020}}$$

(43d)

Inserting Eqs. (43a), (43b), (43c), and (43d) into the right-hand side of Eq. (36) and taking an average of the four decomposition equations, the economic impact of changes in the production structure owing to the pandemic as:

$$\Delta V_{2020}^{ps} = \frac{1}{4}\sum_{c=1}^{N}\left\{\tilde{\mathbf{v}}_{2020}\left(\bar{\mathbf{D}}_{2020} - \tilde{\mathbf{L}}_{2,2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \bar{\mathbf{v}}_{2020}\left(\bar{\mathbf{L}}_{2,2020} - \tilde{\mathbf{D}}_{2020}\right)\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\}$$

$$= \underbrace{\frac{1}{4}\sum_{c=1}^{N}\left\{\tilde{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{a*}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \bar{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{a**}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta V_{2020}^{a}}$$

$$+ \underbrace{\frac{1}{4}\sum_{c=1}^{N}\tilde{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{h}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)}_{\Delta V_{2020}^{h}}$$

$$+ \underbrace{\frac{1}{4}\sum_{c=1}^{N}\tilde{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{\mu}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)}_{\Delta V_{2020}^{\mu}}$$

$$+ \underbrace{\frac{1}{4}\sum_{c=1}^{N}\left\{\tilde{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{w*}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right) + \bar{\mathbf{v}}_{2020}\Delta\mathbf{L}_{2,2020}^{w**}\left(\bar{\mathbf{f}}_{2020}^{c} + \tilde{\mathbf{f}}_{2020}^{c}\right)\right\}}_{\Delta V_{2020}^{w}} \quad (44)$$

where the first term on the right side of Eq. (44) (ΔV_{2020}^{a}) is economic impacts of changes in the intermediate input coefficients due to the COVID-19 pandemic, the second term on the right-hand side of Eq. (44) (ΔV_{2020}^{h}) is economic impacts of changes in the household expenditure coefficients due to the pandemic, the third term (ΔV_{2020}^{μ}) is economic impacts of changes in the household disposable income

ratio due to the pandemic, and the fourth term (ΔV^{w}_{2020}) expresses economic impacts of changes in the labor income coefficients due to the pandemic.

3.2.6. Decomposing the social and environmental multipliers

Focusing on the social multiplier effects induced by the inbound demand of foreign visitors to Japan, the change in social impacts between the with-COVID and non-COVID scenarios can be decomposed as follows:

$$\begin{aligned}\Delta S_{2020} &= \bar{S}_{2020} - \tilde{S}_{2020} \\ &= \textstyle\sum_{c=1}^{N} \mathbf{i}\left(\Delta \mathbf{S}^{c}_{1,2020} + \Delta \mathbf{S}^{c}_{2,2020} + \Delta \mathbf{S}^{c}_{3,2020}\right) \\ &= \textstyle\sum_{c=1}^{N} \Delta\left(\mathbf{s}_{2020}\mathbf{L}_{2,2020}\mathbf{f}^{c}_{2020}\right) \\ &= \underbrace{\sum_{c=1}^{N}\frac{1}{6}\left(2\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020} + \tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}_{2,2020}\bar{\mathbf{f}}^{c}_{2020} + \bar{\mathbf{s}}_{2020}\Delta\mathbf{L}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020} + 2\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}\right)}_{\Delta S^{ps}_{2020}} \\ &\quad + \underbrace{\sum_{c=1}^{N}\frac{1}{6}\left(2\tilde{\mathbf{s}}_{2020}\tilde{\mathbf{L}}_{2,2020}\Delta\mathbf{f}^{c}_{2020} + \tilde{\mathbf{s}}_{2020}\bar{\mathbf{L}}_{2,2020}\Delta\mathbf{f}^{c}_{2020} + \bar{\mathbf{s}}_{2020}\tilde{\mathbf{L}}_{2,2020}\Delta\mathbf{f}^{c}_{2020} + 2\bar{\mathbf{s}}_{2020}\bar{\mathbf{L}}_{2,2020}\Delta\mathbf{f}^{c}_{2020}\right)}_{\Delta S^{fd}_{2020}}\end{aligned} \tag{45}$$

where it should be noted that we used the perfect structural decomposition method based on the two scenarios in 2020 (see Dietzenbacher and Los, 1997, 1998) and here we have $\Delta\mathbf{s}_{2020} = \bar{\mathbf{s}}_{2020} - \tilde{\mathbf{s}}_{2020}$, $\Delta\mathbf{L}_{2,2020} = \bar{\mathbf{L}}_{2,2020} - \tilde{\mathbf{L}}_{2,2020}$, and $\Delta\mathbf{f}_{2020} = \bar{\mathbf{f}}_{2020} - \tilde{\mathbf{f}}_{2020}$, respectively. The first terms on the right side of Eq. (45) (ΔS^{ps}_{2020}) represents the social impact of changes in the production structure due to the pandemic, and the second term (ΔS^{fd}_{2020}) expresses the social impact of changes in

the final demand for foreign visitors due to the pandemic. It is important to note that this study assumes the employment coefficient vector $\mathbf{s}_{2020}$ remained unchanged between the with-COVID and non-COVID scenarios. Therefore, we cannot estimate the social impact of changes in the employment intensities of sectors.

We can further decompose the Leontief-Miyazawa inverse matrix as follows:

$$\Delta\mathbf{L}_{2,2020} = \tilde{\mathbf{L}}_{2,2020}\Delta\mathbf{A}^{d}_{2020}\bar{\mathbf{L}}_{2,2020} + \tilde{\mathbf{L}}_{2,2020}\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)\bar{\mathbf{L}}_{2,2020} \quad (46)$$

Noting that $\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)$ is further decomposed as:

$$\begin{aligned}
&\Delta\left(\mathbf{h}^{d}_{2020}\mu_{2020}\mathbf{w}_{2020}\right)\\
&= \frac{1}{6}\left(2\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right)\\
&+ \frac{1}{6}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)\\
&+ \frac{1}{6}\left(2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}_{2020}\right),
\end{aligned} \quad (47)$$

here we have $\Delta\mathbf{w}_{2020} = \bar{\mathbf{w}}_{2020} - \tilde{\mathbf{w}}_{2020}$. We have the following decomposition formula of the Leontief-Miyazawa inverse matrix:

$$\begin{aligned}
\Delta\mathbf{L}_{2,2020} = &\underbrace{\tilde{\mathbf{L}}_{2,2020}\Delta\mathbf{A}^{d}_{2020}\bar{\mathbf{L}}_{2,2020}}_{\Delta\mathbf{L}^{a}_{2,2020}}\\
&+ \underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\tilde{\mu}_{2020}\bar{\mathbf{w}}_{2020} + \Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\tilde{\mathbf{w}}_{2020} + 2\Delta\mathbf{h}^{d}_{2020}\bar{\mu}_{2020}\bar{\mathbf{w}}_{2020}\right)\bar{\mathbf{L}}_{2,2020}}_{\Delta\mathbf{L}^{h}_{2,2020}}\\
&+ \underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + \tilde{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020} + \bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\tilde{\mathbf{w}}_{2020} + 2\bar{\mathbf{h}}^{d}_{2020}\Delta\mu_{2020}\bar{\mathbf{w}}_{2020}\right)\bar{\mathbf{L}}_{2,2020}}_{\Delta\mathbf{L}^{\mu}_{2,2020}}
\end{aligned}$$

$$+\underbrace{\frac{1}{6}\tilde{\mathbf{L}}_{2,2020}\left(2\tilde{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}_{2020}+\tilde{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}_{2020}+\bar{\mathbf{h}}^{d}_{2020}\tilde{\mu}_{2020}\Delta\mathbf{w}_{2020}+2\bar{\mathbf{h}}^{d}_{2020}\bar{\mu}_{2020}\Delta\mathbf{w}_{2020}\right)\bar{\mathbf{L}}_{2,2020}}_{\Delta\mathbf{L}^{w}_{2,2020}}$$

(48)

Finally, when we insert Eq. (48) into the first term of Eq. (45), the social impact of changes in the production structure owing to the pandemic can be further decomposed into the following four factors:

$$\Delta S^{ps}_{2020}=\underbrace{\frac{1}{6}\sum_{c=1}^{N}\left(2\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{a}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{a}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}+\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{a}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+2\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{a}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}\right)}_{\Delta S^{a}_{2020}}$$

$$+\underbrace{\frac{1}{6}\sum_{c=1}^{N}\left(2\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{h}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{h}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}+\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{h}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+2\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{h}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}\right)}_{\Delta S^{h}_{2020}}$$

$$+\underbrace{\frac{1}{6}\sum_{c=1}^{N}\left(2\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{\mu}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{\mu}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}+\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{\mu}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+2\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{\mu}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}\right)}_{\Delta S^{\mu}_{2020}}$$

$$+\underbrace{\frac{1}{6}\sum_{c=1}^{N}\left(2\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{w}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+\tilde{\mathbf{s}}_{2020}\Delta\mathbf{L}^{w}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}+\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{w}_{2,2020}\tilde{\mathbf{f}}^{c}_{2020}+2\bar{\mathbf{s}}_{2020}\Delta\mathbf{L}^{w}_{2,2020}\bar{\mathbf{f}}^{c}_{2020}\right)}_{\Delta S^{w}_{2020}}$$

(49)

where the first term on the right side of Eq. (49) (ΔS^{a}_{2020}) is social impacts of changes in the intermediate input coefficients due to the COVID-19 pandemic, the second term on the right-hand side of Eq. (49) (ΔS^{h}_{2020}) is social impacts of changes in the household expenditure coefficients due to the pandemic, the third term (ΔS^{μ}_{2020}) is social impacts of changes in the household disposable income ratio due to the pandemic, and the fourth term (ΔS^{w}_{2020}) expresses social impacts of changes in the labor income coefficients due to the pandemic. Similarly, we can decompose the

environmental multiplier effects. It is important to note that this study assumes the emission coefficient vector $\mathbf{e}_{2020}$ remained unchanged between the with-COVID and non-COVID scenarios. Therefore, we cannot estimate the environmental impact of changes in the emission intensities of sectors.

3.3. Data

To estimate the linear trend model, the number of foreign visitors to Japan between 2003 and 2019, before the COVID-19 pandemic, was obtained from the Japan National Tourism Organization (JNTO, 2025a). The per capita travel consumption of visitors from 21 countries and regions to Japan in 2020 during the COVID-19 pandemic was estimated using data from the Survey of Foreign Visitor Spending Trends, provided by the Japan Tourism Agency (JTA, MLIT, 2025b). An important issue is that it is very difficult to obtain data on the unobservable per capita commodity consumption of foreign visitors in 2020 under a non-COVID scenario. In this study, we assumed that the per capita commodity consumption of foreign visitors in 2020 under a non-COVID scenario was the same as in 2019, before the COVID-19 pandemic (JTA, MLIT, 2025b). Additionally, based on the detailed commercial and transportation margin table for 2015 provided by the Ministry of Internal Affairs and Communications (MIC, 2019a), we converted the per capita commodity consumption for foreign visitors from purchaser prices to producer prices.

To estimate the economic, social, and environmental multiplier effects in 2020 under the COVID-19 pandemic, we used the 2020 input-output table covering 94 sectors from the Cabinet Office of Japan (Cabinet Office of Japan, 2022a). It is important to note that it is very difficult to acquire data on the unobservable input-output table for 2020 under a non-COVID scenario. Regarding this problem, we assumed that the input-output table for 2020 under a non-COVID scenario was the same as that of the previous year, 2019, before the COVID-19 pandemic (Cabinet Office of Japan, 2021). It is important to note that the input-output tables for 2019 and 2020 were deflated using 2015 prices.

We also used the disposable income ratio of the average working household in 2020, which was obtained as $\bar{\mu}_{2020} = 0.607$ from the household survey report of the Ministry of Internal Affairs and Communications (MIC, 2021). The disposable income ratio in 2020 under a non-COVID scenario was assumed to be the same as in 2019, set as $\tilde{\mu}_{2020} = 0.673$ (MIC, 2020b).

Data on sectoral employment and sectoral CO_2 emissions for the years 2019 and 2020 were not available. In order to assess the social impacts, we computed employment input coefficients using sectoral employment data from 2015 (MIC, 2019b). Thus, this study assumes that the employment input coefficient vectors for both the non-COVID scenario and the with-COVID scenario remain the same as the employment input coefficient vector in 2015.

For quantifying the environmental impact, we utilized sectoral CO_2 emission

data for Japan derived from the input-output table (3EID) of 2015 (Nansai, 2019; Nansai *et al.*, 2020). This study also assumes that the CO_2 emission coefficient vectors for both the non-COVID and with-COVID scenarios remain consistent with the CO_2 emission coefficient vector in 2015.

3.4. Results

3.4.1. Decrease in the number of foreign tourists due to the COVID-19 pandemic

The total number of foreign tourists from 21 major countries visiting Japan was approximately 32 million in 2019, which sharply decreased by 89% in 2020 owing to severe entry restrictions (Table 3-1). Importantly, the linear trend model forecasts the total number of foreign tourists in 2020 under the counterfactual non-COVID scenario to be 36 million people, a 12% increase in the number of foreign tourists from 2019 to 2020 (Table 3-1). Therefore, the pandemic has caused a significant decrease in the number of foreign tourists to approximately 32 million by 2020. This rapid decrease in the number of foreign tourists has directly and indirectly affected the Japanese economy via inbound markets.

Table 0-1. The number of foreign visitors to Japan in 2019 and 2020 in persons.

	2019	2020	
		Non-COVID scenario	With-COVID scenario
Australia	621,771	684,007	143,508
Canada	375,262	412,692	53,365
China	9,594,394	10,701,864	1,069,256
France	336,333	366,046	43,102
Germany	236,544	254,697	29,785
Hong Kong	2,290,792	2,810,167	346,020
India	175,896	188,456	26,931
Indonesia	412,779	483,573	77,724
Italy	162,769	179,607	13,691
Malaysia	501,592	583,178	76,573
Philippines	613,114	679,940	109,110
Russia	120,043	140,160	22,260
Singapore	492,252	549,200	55,273
South Korea	5,584,597	6,054,145	487,939
Spain	130,243	145,670	11,741
Taiwan	4,890,602	5,696,905	694,476
Thailand	1,318,977	1,426,212	219,830
The U.S.	1,723,861	1,853,869	219,307
U.K.	424,279	429,836	51,024
Vietnam	495,051	529,368	152,559
Others	1,380,898	1,493,982	212,354
Total	31,882,049	35,663,575	4,115,828

3.4.2. Decrease in travel consumption due to COVID-19

In 2019, over 31 million travelers came to Japan and consumed goods and services worth 5.1 trillion JPY (36.2 billion U.S.$) in total (Table 3-2), accounting for 1% of Japan's GDP in the same period. The linear trend model forecasts that 36 million foreign visitors could spend almost 6 trillion JPY in 2020 under the non-COVID scenario (Tables 3-1 and 3-2). However, the with-COVID scenario shows that there were only 4.1 million tourists and 675 billion JPY in travel consumption in 2020. These data suggest that almost 5 trillion JPY of the expected output from inbound markets was lost during the pandemic.

Table 0-2 Travel consumption by country in 2019 and 2020 in billion JPY.

2019		2020	
		Non-COVID-19 Scenario	With-COVID-19 Scenario
Australia	154	170	36
Canada	68	75	10
China	2,042	2,277	228
France	80	87	10
Germany	48	51	6
Hong Kong	357	438	54
India	28	30	4
Indonesia	54	63	10
Italy	32	36	3
Malaysia	67	78	10
Philippines	66	73	12
Russia	22	26	4
Singapore	85	95	10
South Korea	425	461	37
Spain	29	32	3
Taiwan	578	674	82
Thailand	173	187	29
The U.S.	327	351	42
U.K.	102	104	12
Vietnam	88	94	27
Others	306	331	47
Total	5,132	5,654	675

3.4.3. Economic impacts

Figure 3-1 shows the direct, indirect, and income-induced value-added effects under the with-COVID and non-COVID scenarios and the difference between the two scenarios, which quantifies the economic losses caused by the pandemic. The total inbound earnings under the with-COVID scenario were approximately 0.54 trillion JPY whereas inbound earnings under the non-COVID scenario were 3.98 trillion JPY; the economic loss calculated as the difference between the two scenarios was 3.44 trillion JPY. Thus, 87% of the expected inbound revenue in 2020 is lost.

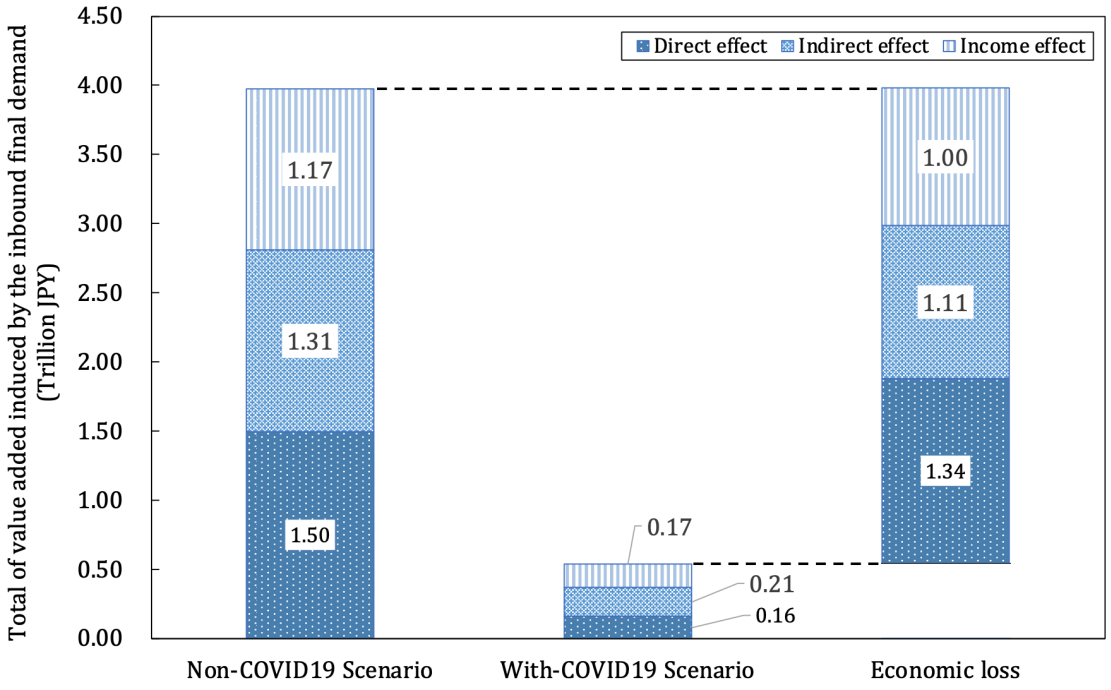


Figure 0-1. Direct, indirect, and income-induced economic effects under non-COVID19 and COVID scenarios and economic loss due to the pandemic.

Economic losses via both economic spillover effects (i.e., indirect and income effects) were larger than the amount spent in Japan by foreign visitors (i.e., direct

impact). Thus, the decrease in the number of visitors to Japan due to the pandemic has caused significant direct and indirect economic losses.

Figure 3-2 shows the top ten industrial sectors that accounted for the highest percentage of economic losses. The top three sectors were eating and drinking services (434 billion JPY), hotels (420 billion JPY), and wholesale trade (291 billion JPY). Focusing on the largest direct losses, the most damaged sectors were hotels (408 billion JPY), food and food services (357 billion JPY), and miscellaneous chemical products (167 billion JPY). The top three sectors that suffered indirect losses were wholesale trade (128 billion JPY), miscellaneous business services (76 billion JPY), and miscellaneous transport (75 billion JPY). The top three sectors that lost value induced by the income spillover effect were housing rent (275 billion JPY), retail trade (70 billion JPY), and wholesale trade (58 billion JPY). Sectors with large losses from indirect effects were closely related to hotels, and eating and drinking services, which also incurred large losses from direct effects. The large losses in the cosmetics, toilet preparation, and dentifrices sectors were mainly due to a sharp decline in the number of visitors from China and other travelers from Asia, who have a high per capita consumption of cosmetics (Figure 3-3).

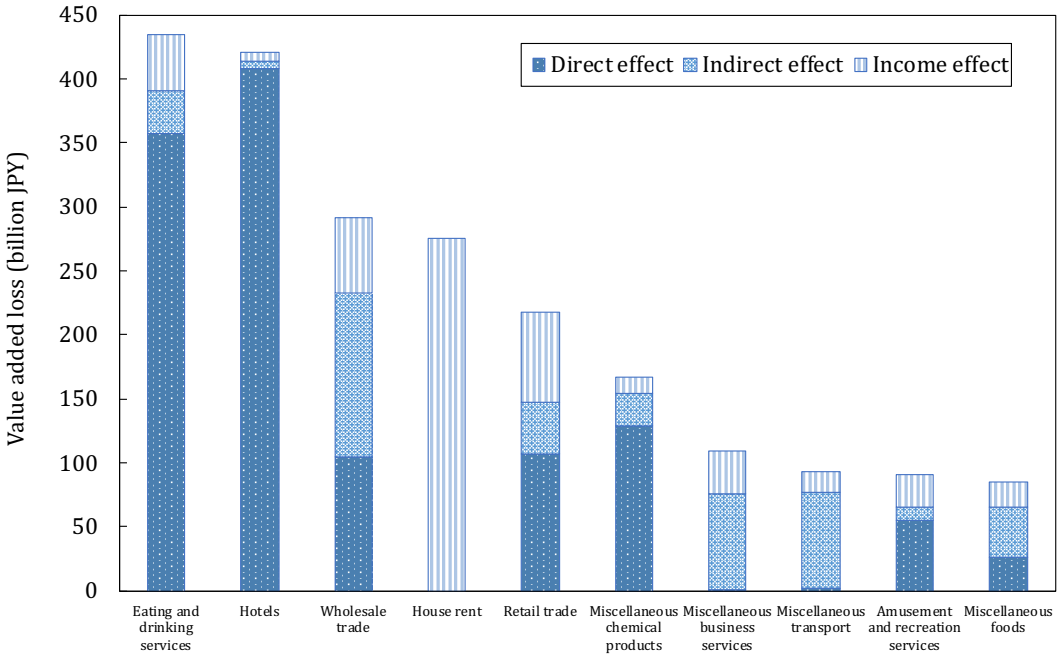


Figure 0-2 Top 10 industrial sectors with higher value-added losses.

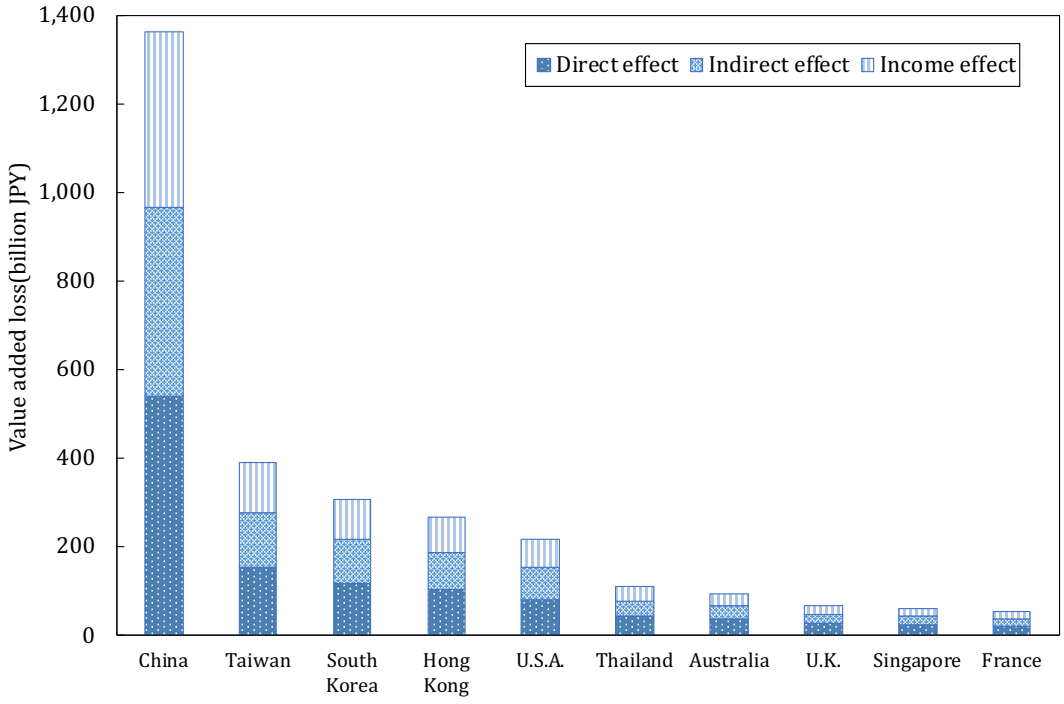


Figure 0-3. Top 10 nationalities with higher value-added losses by the nationality of visitors.

3.4.4. Social impacts

Figure 3-4 shows the three types of employment (direct, indirect, and income effects) in both scenarios and the differences between them, indicating the loss of employment opportunities caused by the pandemic. The number of employment opportunities in the with-COVID scenario was approximately 145,612 people whereas that in the non-COVID scenario it was 1,014,588 people. The social loss estimated from the difference between the two scenarios was 868,976 people. This result indicates that 86% of the employment opportunities expected in 2020 were lost. Compared with the economic impact, 46% of the social impact was occupied by direct effects and employment opportunities were less likely to spread to sectors other than those with an economic impact.

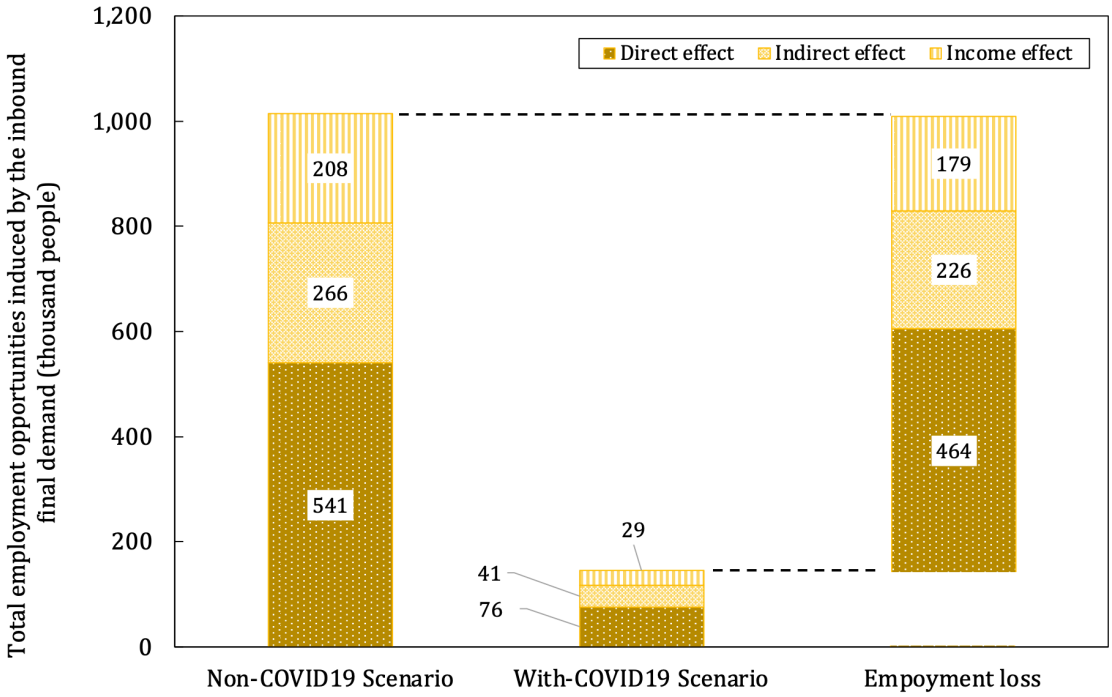


Figure 0-4. Direct, indirect, and income effects of employment opportunities in each scenario and estimated employment losses.

Figure 3-5 shows the top ten sectors that accounted for the highest percentages of employment losses. The top three sectors are eating and drinking services (233,317 jobs), hotels (139,885 jobs), and retail trade (117,738 jobs). Focusing on the largest direct losses, the sectors with the greatest damage were eating and drinking services (191,666), hotels (135,639), and retail trade (57,879). The top three sectors suffered indirect losses from miscellaneous business services (32,859 jobs), retail trade (22,072 jobs), and eating and drinking services (18,494 jobs). The top three sectors that lost employment opportunities due to the income spillover effect were retail trade (37,787 jobs), eating and drinking services (23,158 jobs), and miscellaneous business services (14,293 jobs). The losses in the eating and drinking services and hotel sectors were significantly greater than those in the other sectors, accounting for 43% of the total employment losses. These social losses were primarily caused by the rapid decline in inbound demand from Chinese visitors (Figure 3-6).

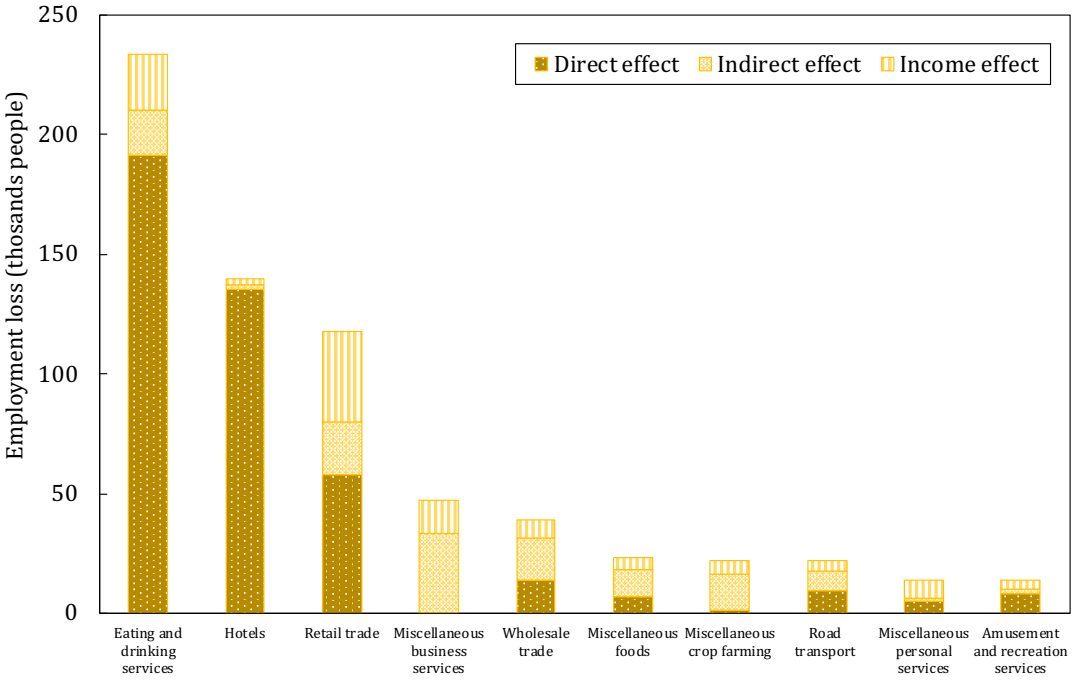


Figure 0-5. The top 10 sectors that accounted for the highest percentage of employment opportunities losses.

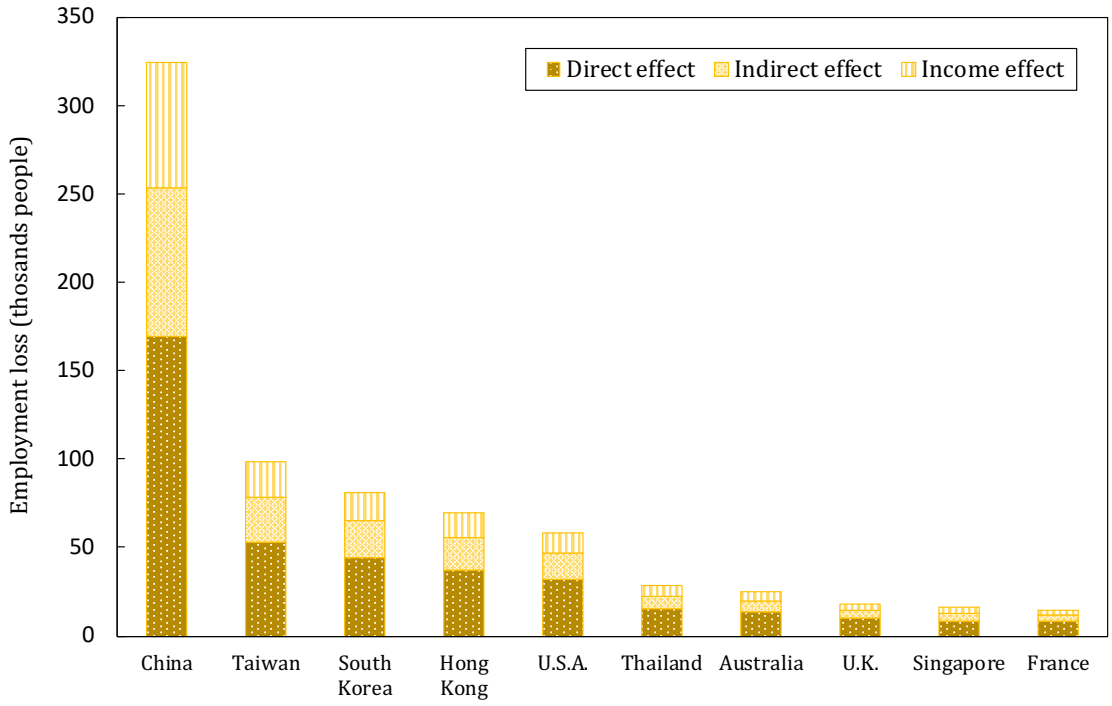


Figure 0-6. The top 10 nationalities of tourists that contributed to the employment losses.

3.4.5. Environmental impacts

Figure 3-7 shows the direct, indirect, and income effects of CO_2 emissions for each scenario, and their estimated environmental benefits. In the with-COVID scenario, it was estimated that 1.9 Mt-CO_2 of CO_2 was emitted whereas in the non-COVID scenario, 13.5 Mt-CO_2 emissions were estimated to have been emitted from the inbound market, resulting in a difference between of 11.6 Mt-CO_2. More than 82% of CO_2 emissions from inbound demand are due to indirect and income effects. Therefore, the impact of COVID-19 on the environment is mostly due to spillovers rather than direct effects.

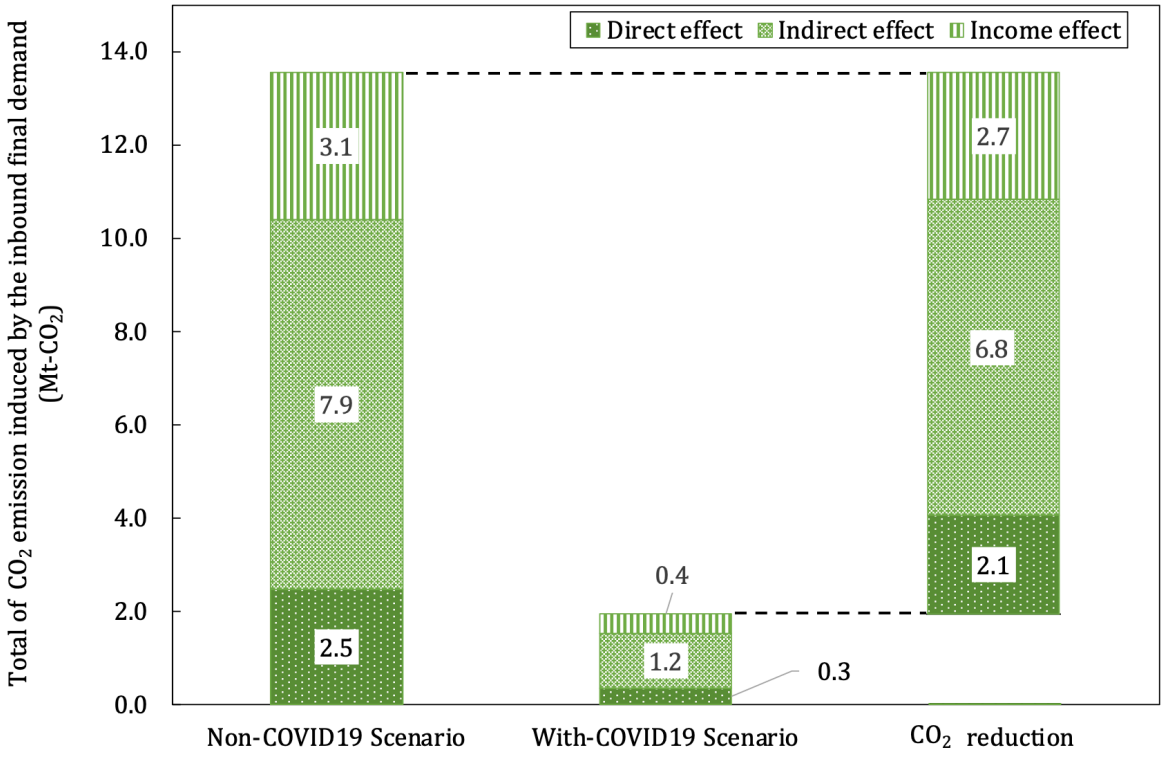


Figure 0-7. Direct, indirect, and income effects of CO_2 emissions in each scenario and estimated reductions in CO_2 emissions.

Figure 3-8 shows the top ten industries estimated by industry for the environmental benefits shown in Figure 3-3. The top three industries were electricity (5,571 kt-CO_2), road transport (1,195 kt-CO_2), and hotels (991 kt-CO_2). Among the top sectors, hotels (961 kt-CO_2), road transport (514 kt-CO_2), and eating and drinking services (263 kt-CO_2) were unique sectors that contributed to CO_2 reduction almost exclusively through direct effects.

Electricity, which contributed the most to the reduction in CO_2 emissions, accounted for 70.7% of the indirect effects and 29.3% of the income effects. Road transport, the second largest contributor to CO_2 reduction, accounted for 43.0% of the direct effect, 35.6% of the indirect effect, and 21.4% of the income effect. Hotels, as well as eating and drinking services, have directly contributed to CO_2 reduction. Waste management services, which indirectly contribute to the reduction in CO_2 emissions, are strongly influenced by the direct impacts of hotels and eating and drinking services.

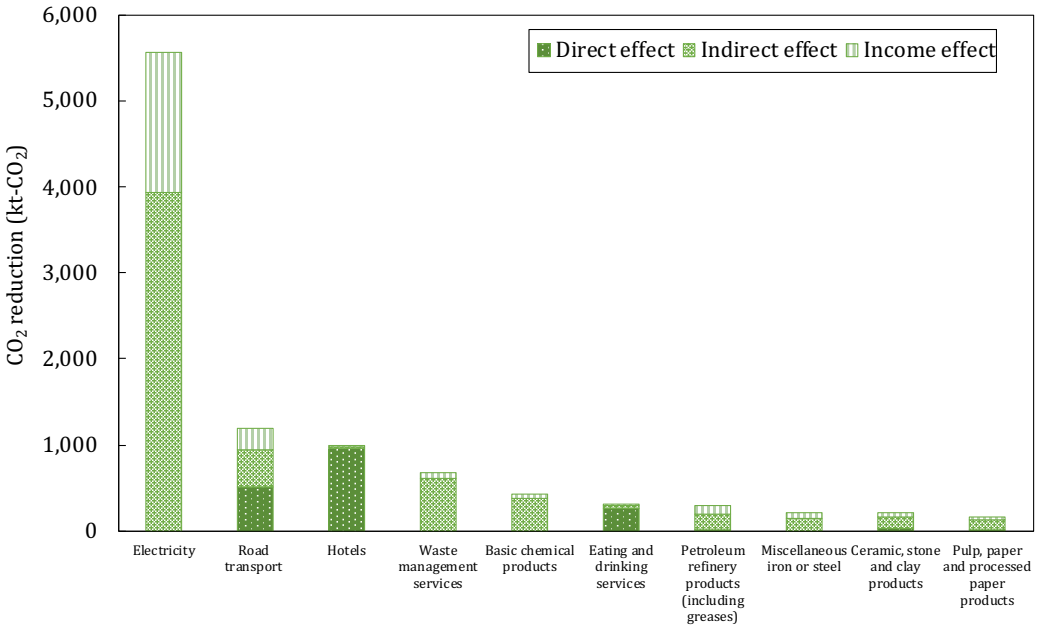


Figure 0-8. Top 10 sectors with CO_2 reduction by industry.

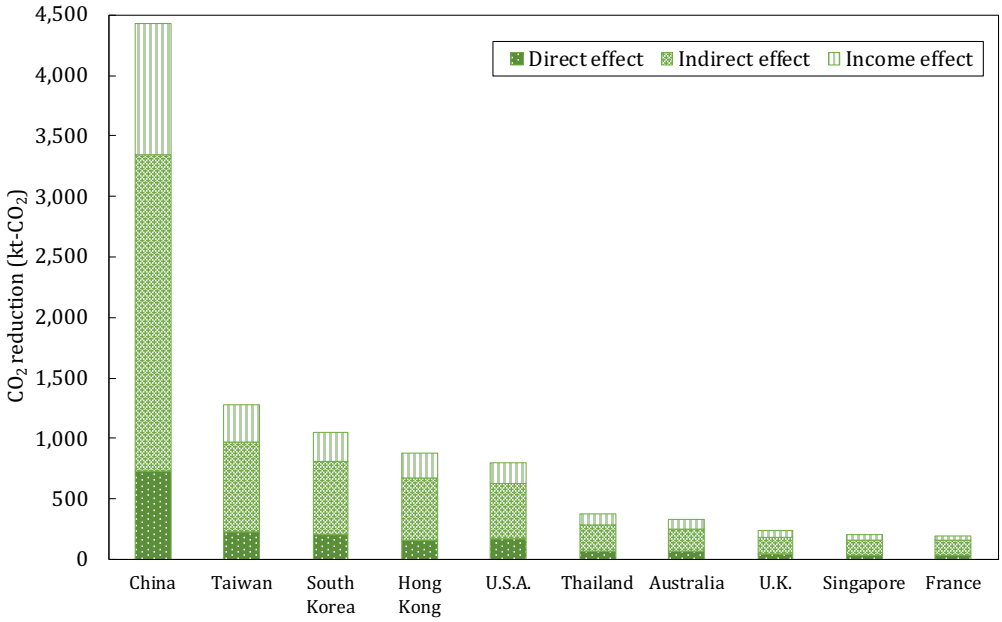


Figure 0-9. Top 10 categories of CO_2 reduction by nationality.

Table 3-3 shows the top five nationalities of tourists who contributed the most to all aspects (economy, society, and environment) and influenced the top ten

industrial sectors across the three aspects. All economic, social, and environmental impacts of COVID-19 through inbound markets relied on travelers from five nations (China, South Korea, Taiwan, Hong Kong, and the U.S.). The sectors with the largest direct effects among the three are shown in bold in Table 3-3. Thus, we can determine how the consumption patterns of travelers from different countries have different economic, social, and environmental impacts through industrial supply chains.

Table 0-3. Top five nationalities of visitors who influenced the top ten industries by three aspects.

		China	Hong Kong	South Korea	Taiwan	U.S.A.
Economic Impact	1	**Eating and drinking services**	**Eating and drinking services**	**Eating and drinking services**	**Eating and drinking services**	**Hotels**
	2	**Wholesale trade**	**Hotels**	**Hotels**	**Hotels**	**Eating and drinking services**
	3	**Hotels**	Wholesale trade	House rent	Wholesale trade	House rent
	4	**Miscellaneous chemical products**	House rent	Wholesale trade	House rent	Wholesale trade
	5	House rent	**Retail trade**	**Retail trade**	**Retail trade**	Retail trade
	6	**Retail trade**	Miscellaneous business services	Miscellaneous business services	**Miscellaneous chemical products**	**Miscellaneous transport**
	7	Miscellaneous business services	**Miscellaneous chemical products**	**Amusement and recreation services**	Miscellaneous business services	Miscellaneous business services
	8	**Amusement and recreation services**	**Goods rental and leasing (except real estate services)**	Miscellaneous foods	Miscellaneous foods	Road transport
	9	Miscellaneous transport	Miscellaneous transport	**Road transport**	**Goods rental and leasing (except real estate services)**	Electricity
	10	**Road transport**	Miscellaneous foods	Miscellaneous transport	Miscellaneous transport	Drinks
Social Impact	1	**Eating and drinking services**	**Eating and drinking services**	**Eating and drinking services**	**Eating and drinking services**	**Eating and drinking services**
	2	**Retail trade**	**Hotels**	**Hotels**	**Hotels**	**Hotels**
	3	**Hotels**	**Retail trade**	Retail trade	**Retail trade**	Retail trade
	4	Miscellaneous business services	Miscellaneous business services	Miscellaneous business services	Miscellaneous business services	Miscellaneous business services
	5	**Wholesale trade**	Wholesale trade	Wholesale trade	Wholesale trade	Wholesale trade
	6	**Miscellaneous foods**	**Miscellaneous crop farming**	Miscellaneous foods	Miscellaneous foods	Road transport
	7	Road transport	Miscellaneous foods	**Road transport**	Miscellaneous crop farming	**Miscellaneous crop farming**
	8	Miscellaneous crop farming	Road transport	Miscellaneous crop farming	Road transport	Miscellaneous foods
	9	**Miscellaneous chemical products**	**Miscellaneous personal services**	Miscellaneous personal services	**Miscellaneous personal services**	Miscellaneous personal services
	10	Miscellaneous personal services	Waste management services	**Amusement and recreation services**	Miscellaneous transport	**Waste management services**
Environmental Impact	1	Electricity	Electricity	Electricity	Electricity	Electricity
	2	**Road transport**	Road transport	**Road transport**	Road transport	**Hotels**
	3	**Hotels**	**Hotels**	**Hotels**	**Hotels**	**Road transport**
	4	Basic chemical products	Waste management services	Waste management services	Waste management services	Waste management services
	5	Waste management services	Basic chemical products	**Eating and drinking services**	Basic chemical products	**Eating and drinking services**
	6	Petroleum refinery products (including greases)	**Eating and drinking services**	Basic chemical products	**Eating and drinking services**	Petroleum refinery products (including greases)
	7	**Eating and drinking services**	Petroleum refinery products (including greases)	Petroleum refinery products (including greases)	Petroleum refinery products (including greases)	Ceramic, stone and clay products
	8	Miscellaneous iron or steel	Miscellaneous iron or steel	Miscellaneous iron or steel	Miscellaneous iron or steel	Basic chemical products
	9	**Miscellaneous chemical products**	Ceramic, stone and clay products	Ceramic, stone and clay products	Ceramic, stone and clay products	Miscellaneous iron or steel
	10	Ceramic, stone and clay products	Miscellaneous foods	Miscellaneous foods	Miscellaneous foods	**Pulp, paper and processed paper products**

3.4.6. Factors influencing the changes in the economic, social, and environmental multiplier effects in 2020 due to the COVID-19 pandemic

The 'counterfactual' structural decomposition analysis (SDA) based on two scenarios, with-COVID and non-COVID, developed in this study can assist policymakers in understanding the major factors influencing changes in economic, social, and environmental multiplier effects in 2020 due to the pandemic. Figure 3-10 presents the decomposition results of the economic multiplier effect. While the value-added coefficients ($\Delta V_{2020}^{va}, -0.31\%$), household disposable income ratio and labor income coefficients ($\Delta V_{2020}^{w}, 0.46\%$), and inbound final demand ($\Delta V_{2020}^{fd}, -100.00\%$) had a negative impact on the economic multiplier effect, input coefficients ($\Delta V_{2020}^{a}, 0.50\%$) and household expenditure coefficients ($\Delta V_{2020}^{h}, 0.08\%$) exerted a positive contribution. Inbound final demand was the largest factor contributing to economic losses owing to the pandemic. The top three nationalities (major contributors to economic loss) were China (-39.65%), Taiwan (-11.36%), and South Korea (-8.89%) (Figure 3-10).

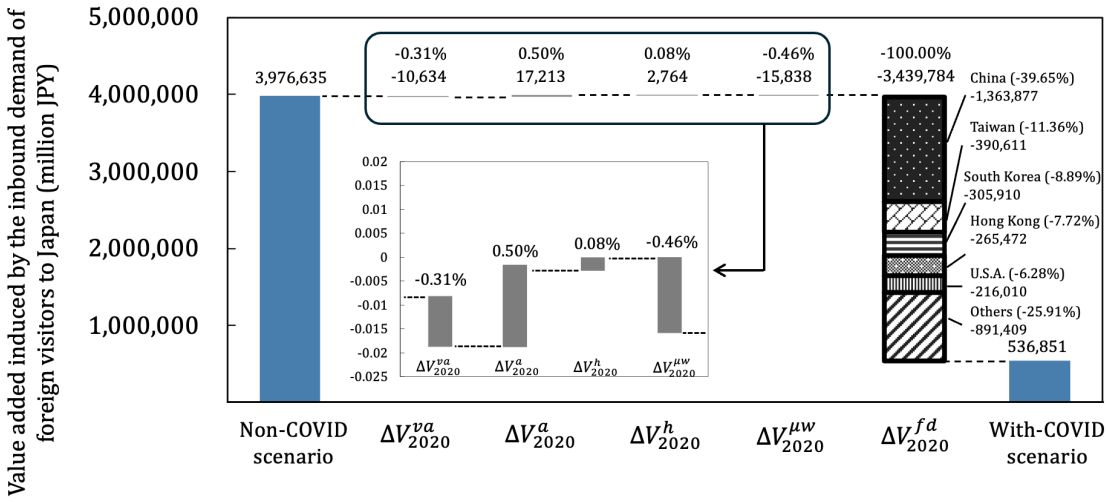


Figure 0-10. Factors influencing changes in the economic multiplier effects. Note that $\Delta \boldsymbol{V}_{\boldsymbol{2020}}^{\boldsymbol{va}}$ denotes the changes in the value-added coefficients of industries; $\Delta \boldsymbol{V}_{\boldsymbol{2020}}^{\boldsymbol{a}}$ denotes the changes in the input coefficients of industries; $\Delta \boldsymbol{V}_{\boldsymbol{2020}}^{\boldsymbol{h}}$ denotes the changes in the household expenditure coefficients; $\Delta \boldsymbol{V}_{\boldsymbol{2020}}^{\boldsymbol{w}}$ denotes the changes in the household disposable income ratio and the labor income coefficients of industries; $\Delta \boldsymbol{V}_{\boldsymbol{2020}}^{\boldsymbol{fd}}$ denotes the changes in the final demand of foreign visitors to Japan.

Figure 3-11 presents the decomposition results of the social multiplier effect. While the household disposable income ratio (ΔS_{2020}^{μ}), labor income coefficients (ΔS_{2020}^{w}), and inbound final demand (ΔS_{2020}^{fd}) had a negative impact, input coefficients (ΔS_{2020}^{a}) and household expenditure coefficients (ΔS_{2020}^{h}) had a positive contribution. Inbound final demand was the largest factor contributing to the loss of employment opportunities owing to the pandemic. The top three nationalities (i.e., the major contributors to the loss of employment opportunities) were China (-37.76%), Taiwan (-11.58%), and South Korea (-9.50%) (Figure 3-11). Similar decomposition results were observed for the environmental multiplier effect (Figure 3-6). Although household consumption and the disposable income ratio

declined by 6.6% and 5.9%, respectively, in 2020 due to the COVID-19 pandemic, the counterfactual SDA framework developed in this study estimates their marginal impacts at 0.08% and -0.46%, respectively. This suggests that most of the impact on the inbound tourism industry was primarily driven by a significant decrease in final demand from foreign tourists.

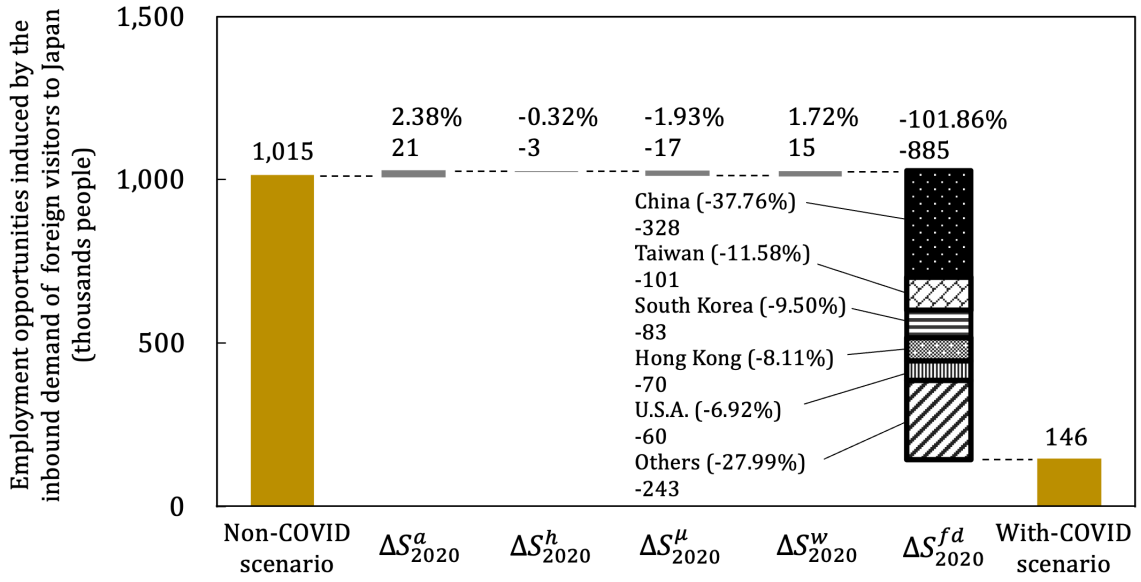


Figure 0-11. Factors influencing changes in the social multiplier effects.

Note that ΔS^{a}_{2020} denotes the changes in the input coefficients of industries; ΔS^{h}_{2020} denotes changes in the household expenditure coefficients; ΔS^{μ}_{2020} denotes change in the household disposable income ratio of the economy; ΔS^{k}_{2020} denotes changes in the labor income coefficients of industries; ΔS^{fd}_{2020} denotes changes in the final demand of foreign visitors to Japan.

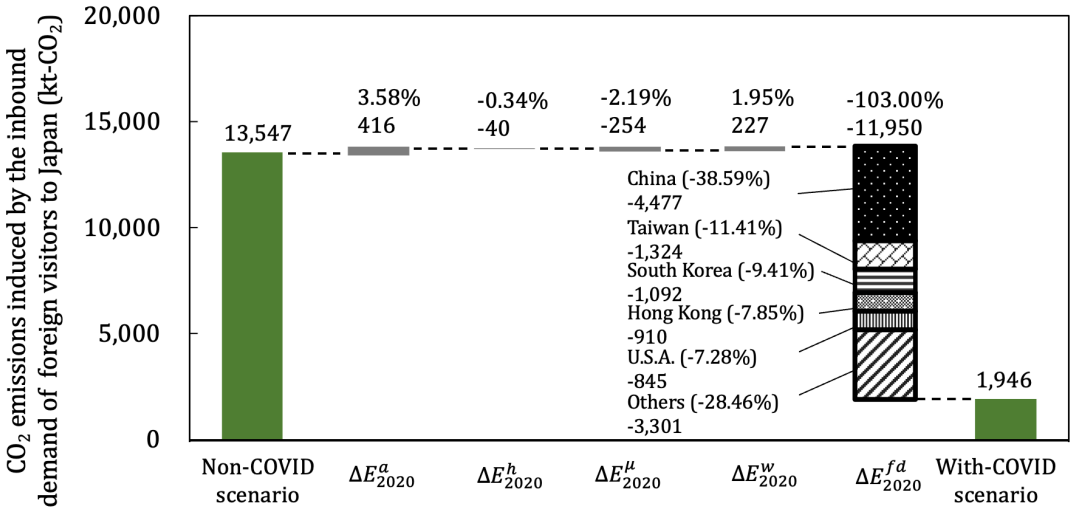


Figure 0-12. Factors influencing changes in the environmental multiplier effects. Note that ΔE_{2020}^{a} denotes the changes in the input coefficients of industries; ΔE_{2020}^{h} denotes changes in the household expenditure coefficients; ΔE_{2020}^{μ} denotes change in the household disposable income ratio of the economy; ΔE_{2020}^{w} denotes changes in the labor income coefficients of industries; ΔE_{2020}^{fd} denotes changes in the final demand of foreign visitors to Japan.

3.5. Limitations of this study

The novelty of this study lies in developing a "counterfactual" analysis based on limited information. A critical limitation was our inability to forecast the economic structure under the non-COVID scenario for 2020. Therefore, we used proxy economic structure data (i.e., the 2019 input–output table) to represent the non-COVID scenario. A key challenge remains in forecasting the 2020 input–output table for the non-COVID scenario with limited empirical data.

Additionally, the tourism satellite accounts of Japan used in this study provide data on commodity consumption by foreign visitors by country, including

expenditures on six transport services: (1) domestic aviation, (2) domestic railway transport, (3) domestic road transport, (4) goods rental and leasing (excluding real estate services, such as car rental), (5) domestic water transport, and (6) miscellaneous domestic transport. Therefore, this study focuses on domestic transport services consumed by foreign visitors and estimates the environmental impact of these domestic transport activities. However, owing to data limitations, the impact of international air travel could not be considered, potentially leading to an underestimation of the reduction in transport-related CO2 emissions presented in our results. According to Kitamura *et al*. (2020a), air transportation is the primary contributor to CO2 emissions from tourism in Japan. Therefore, future research should focus on both the international and domestic aviation sectors and develop sustainability policies targeting CO2 emissions from inbound tourism in Japan.

The triple bottom line analysis framework developed in this study does not account for the impact of changes in the imports of goods and services. While the framework focuses on analyzing the impacts within Japan, changes in the import structure due to the decline in inbound tourism demand caused by the COVID-19 pandemic may also have affected Japan's economy, society, and environment. Su *et al.* (2022) developed an SDA framework with two import factors: production technology and final demand (i.e., input imports and demand imports). Sun *et al*. (2023) applied this method to a case study in China, decomposing the impacts of input and demand imports on energy consumption from 2007 to 2020. Therefore, analyzing the impact of imports alongside inbound tourism in the context of disasters such as the COVID-19 pandemic could provide valuable insights into

Japan's disaster management policies related to tourism. However, a detailed import analysis is beyond the scope of this study and will be an important focus for follow-up research.

3.6. Discussion and Conclusions

This study revealed that in 2020, the pandemic resulted in a decrease in the number of foreign tourists and their travel consumption by 31 million people and 5.1 trillion JPY (36.2 billion U.S.$). These direct losses of final demand directly and indirectly induced 3.44 trillion JPY (24.4 billion U.S.$) of value-added loss (economic impact), loss of employment opportunities of 868,976 people (social impact), and 11.6 Mt-CO_2 of CO_2 emissions reduction (environmental impact).

These three aspects (economic, social, and environmental) are strongly affected by hotels, eating and drinking services, and rail passenger transport, accounting for a large proportion of tourist consumption. In particular, hotels and eating and drinking services induce huge electricity demands and indirectly contribute to a reduction in CO_2 emissions from the electric supply industry.

We propose a counterfactual SDA framework to identify the factors influencing changes in economic, social, and environmental multiplier effects arising from the 2020 pandemic. The decomposition results revealed that the primary cause of economic and social losses was the sharp decrease in the final demand by visitors to Japan. However, it is worth noting that a shift in the production structure due to the

pandemic also contributed to an increase in CO_2 emissions. Accordingly, we suggest two important factors for the development of the most sustainable and efficient countermeasures: (1) recovery of economic and social losses and (2) reduction of CO_2 emissions associated with inbound final demand.

3.6.1. Recovery of economic and social losses

We suggest that the government offer stipends to each sector depending on the magnitude of the loss, and that our data can be used to provide evaluation criteria for distribution. Policymakers should consider ways to restore the economy as identified by the amount of value-added loss. The results of our analysis not only cover the direct effect, which is easy to recognize without any calculations, but also the indirect and income effects, which are difficult to estimate and easily overlooked. Therefore, if policymakers aim to consider ways to reduce the unemployment risk due to the pandemic, they can use the results of the social impact in the same manner as the economic impact.

During the COVID-19 pandemic, the government provided cash payments to Japanese households (MIC, 2020a). However, the disposable income of households decreased by 6.6% between 2019 and 2020 (MIC, 2020b, 2021). Consequently, the economic and social losses from income-induced effects during the pandemic could not be fully mitigated by the financial aid provided to households. It would be desirable for the government to incorporate measures that promote household consumption into support policies.

3.6.2. Reduction of CO_2 emissions associated with inbound final demand

We recommend strategies for implementing an effective counter-COVID-19 policy that not only enhances the economic and social aspects of tourism, but also improves its environmental impact. As mentioned above, the primary source of CO_2 emissions in Japan's inbound-related supply chain is sectors that indirectly generate electricity to supply the hotel, food, and beverage service industries (Figure 3-8). Figure 3-8 further indicates that the road transport sector and waste management services had significant indirect CO_2 reduction effects during the study period. Ultimately, efforts must focus on reducing the CO_2 emissions associated with economic activities in these industries. Therefore, we recommend that the government incorporates counter-COVID-19 measures that incentivize the high-priority industries identified in this study to improve business conditions while simultaneously reducing their environmental impacts.

The reduction in CO_2 emissions resulting from the COVID-19 pandemic can be viewed as a 'temporary benefit' that may be lost as demand recovers after the pandemic. Therefore, we suggest that the government provide incentives for high-environmental-impact industries and inbound tourists to adopt more environmentally sustainable tourism practices during the recovery process. Specifically, during periods of business closure or the demand recovery process, the following three policies should be incorporated into the government strategy:

(1) Provide incentives for the hotel, food, and beverage service industries to transition to more environmentally sustainable operations during periods of business closure.
(2) Encourage a reduction in domestic travel distances for inbound tourists.
(3) Promote the reduction of waste generated by tourism.

The Japanese government has already implemented measures to distribute aid to businesses that were asked to shut down or operate within a few hours during the pandemic (Cabinet Office, 2022b). The main targets of this policy are lodgings and food and beverage service industries. However, instead of simply providing financial aid to stakeholders, it would be more effective to establish a system that allows companies to receive additional funding to support their efforts to reduce environmental impact during periods of reduced activity (Pablo-Romero *et al.*, 2017). For example, the amount of support can be determined based on the quantified environmental savings achieved by each company using energy-efficiency criteria (e.g., rate of LED lighting installation). Upgrading facilities, such as converting lighting into LED, is often difficult for companies that operate year-round. The closure periods during the pandemic provided opportunities for such updates. Thus, this policy could drive businesses in the lodging and food service sectors to adopt more eco-friendly business models, thereby significantly reducing indirect CO_2 emissions from the electricity sector.

To reduce domestic travel distance for inbound tourists, innovative tourism advertising should be developed to encourage visitors to enjoy and stay longer in a

single tourist region. Policies that promote increased spending by tourists within a single area would be effective in simultaneously recovering from economic and social losses and reducing indirect CO_2 emissions from road transportation (e.g., buses and taxis) used by foreign visitors.

Waste management services have also been crucial for reducing CO_2 emissions from inbound tourism. To minimize the waste generated during tourism activities, we recommend policies such as offering discounts to travelers who refrain from using hotel amenities and providing greater subsidies to companies that avoid excessive packaging. These policies could help reduce emissions from waste management (Juvan *et al.*, 2023).

Both the Sixth Energy Plan and Japan's COVID-19 policies include a post-COVID-19 perspective; however, there are no plans to decarbonize the tourism sector (Ministry of Economy, Trade, and Industry, 2021). Efforts to decarbonize tourism in Japan are essential because its environmental impact is increasing with rising tourism demands. This study provides important policy insights for stakeholders that should be considered in measures adopted by the Japanese government in the event of future COVID-19 waves, other pandemics, or various unforeseen disasters.

Chapter 4. Identifying critical supply chain paths affected by the decline in foreign tourist demand in Japan due to the COVID-19 pandemic: counterfactual structural path decomposition

4.1. Introduction

The COVID-19 pandemic, which severely disrupted Japan's inbound tourism demand, exposed the vulnerability of the tourism industry to various disasters—such as pandemics, earthquakes, and terrorism—and further highlighted the need for new disaster recovery policies that also take future sustainable development into account. Through proactive policies such as visa easing and the expansion of shipping routes, Japan rapidly expanded its tourism industry, particularly inbound tourism (Cabinet Secretariat, Government of Japan, 2016). Between 2012 and 2019, the number of inbound tourists to Japan increased by 281%, reaching 31.9 million in 2019 (JNTO, 2025a). During the same period, total travel expenditure grew by 436%, and amounted to 4.8 trillion JPY (30.6 billion USD) in 2019 (JTA, MLIT, 2025b). The Japanese government has set an ambitious target to increase the number of inbound foreign tourists to 60 million by 2030 and has long-term plans to further develop inbound tourism (Cabinet Secretariat, Government of Japan, 2016). However, the COVID-19 pandemic caused severe and unprecedented disruptions to Japan's tourism industry. Owing to lockdown measures, the country experienced an 87% decline in foreign tourists and an 84% reduction in tourism revenue in 2020 (JNTO, 2025a; JTA, MLTI, 2025b).

The World Travel and Tourism Council (WTTC) (2021b) reported that travel and tourism gross domestic product (GDP) declined by 5%, while jobs supported by travel and tourism decreased by 19% (equivalent to 62 million jobs). Lenzen *et al*. (2020) first estimated the global socio-economic losses and environmental impacts caused by COVID-19. Their study identified the tourism and transport industries as the most economically damaged sectors. Additionally, these industries significantly contributed to the reduction of greenhouse gas (GHG) emissions. According to a United Nations Environment Programme (UNEP) report, achieving the Paris Agreement target of 1.5℃ requires a 42% reduction in GHG emissions by 2030, which appears unrealistic given the current global situation in 2023 (UNEP, 2023a). Therefore, member nations of the Paris Agreement should not overlook the environmental benefits that accompanied socio-economic losses.

For the aforementioned reasons, the impacts of the COVID-19 pandemic on the economy (e.g., value added), society (e.g., employment opportunities), and the environment (e.g., CO_2 emissions) should be evaluated within a triple bottom line (TBL) framework. In Japan, two previous studies have evaluated the impacts of the COVID-19 pandemic on the country through tourism from a TBL perspective (Kitamura *et al.*, 2020b; Oga and Kagawa, 2025). Oga and Kagawa (2025) estimate the economic, social, and environmental impacts of the decline in Japan's inbound tourism demand using a counterfactual structural decomposition analysis. They reported a total loss of 3.4 trillion JPY in value added, 869 thousand jobs, and a reduction of 11.6 Mt-CO_2 emissions caused by the COVID-19 pandemic.

On May 5, 2023, the World Health Organization declared the end of the state of Public Health Emergency of International Concern (PHEIC) regarding the COVID-19 pandemic (WHO, 2023). Starting in 2022, the tourism industry in Japan began to recover in both domestic and inbound tourism. However, this does not mean that the threat of pandemics has entirely disappeared. Marani *et al*. (2021) compiled datasets of epidemics that occurred over the past 400 years and used statistical analysis to predict that the risk of a pandemic comparable to COVID-19 is 2.6% per year, with this likelihood expected to triple in the coming decades.

Additionally, the risks faced by the tourism industry are not limited to pandemics, but also include other disasters, such as terrorism and earthquakes. Several studies have explored the impacts of terrorism on the tourism industry (Baker, 2014; Sönmez and Graefe, 1998; Sönmez *et al*., 1999). Similarly, earthquakes are another type of disaster that significantly impacts the tourism industry. Japan is one of the countries with the highest number of earthquakes in the world (National Oceanic and Atmospheric Administration, 2024). In 2011, the Great East Japan Earthquake and resulting tsunami caused severe damage to the Tohoku region and led to a 50% reduction in foreign tourist arrivals to Japan (JNTO, 2012). Several studies have analyzed the impact of earthquakes on the tourism industry (Chan *et al.*, 2019; Huang and Min, 2002; Tsai and Chen, 2010).

Although inbound tourism is experiencing gradual recovery and is on a path of expansion once again after the pandemic, formulation of recovery policies is crucial to prepare for the recurrence of a new pandemic caused by an unknown virus

or the occurrence of other disasters. To provide concrete guidance for disaster recovery policies related to inbound tourism in Japan, this study develops an impact analysis framework for disasters in the inbound tourism using the COVID-19 pandemic as a case study.

This study combines structural path decomposition (SPD) with a counterfactual input-output approach to estimate the supply chain (SC) path-level impacts that, to the best of the author's knowledge, have not been considered in previous analyses.

Input–output analysis, which captures inter-industry ripple effects in markets (Leontief, 1953), has proven useful for analyzing the impacts of the COVID-19 pandemic on tourism (Lee *et al.*, 2024; Sun *et al.*, 2021). These previous studies applied a "consumption-exogenous" input-output model, which can estimate direct-indirect impact induced from final consumption expenditure. However, the impacts of COVID-19 have displayed notable spillover effects through the income–consumption linkage. Oga and Kagawa (2025) revealed that such effects accounted for approximately 29%, 21%, and 23% of the total economic, social, and environmental impacts, respectively. These income-induced effects cannot be captured via a "consumption-exogenous" input–output approach. Therefore, to analyze the impacts of COVID-19, a "consumption-endogenous" input–output model (Leontief–Miyazawa model) (Miyazawa, 1960; Miyazawa and Masegi, 1963) is more appropriate; thus, this study employs the Leontief–Miyazawa framework.

Furthermore, the SPD framework developed by Wood and Lenzen (2009) is useful in identifying the key industrial sectors affected and the main contributing factors. Structural Path Decomposition (SPD) is a method that integrates Structural Path Analysis (SPA) (see Defourny and Thorbecke, 1984; Lenzen, 2003), which quantitatively evaluates the ripple effects of each propagation order along SCs, with Structural Decomposition Analysis (SDA) (Dietzenbacher and Los, 1997, 1998, 2000; Hoekstra and van den Bergh, 2003), which decomposes the driving factors behind changes in economic, social, and environmental impacts. This approach enables a quantitative assessment of which industrial path contributed to the observed changes and which factors were responsible for those contributions. Oshita (2012) adopted the SPD framework to identify key sectors that contributed to CO_2 emissions in Japan between 1990 and 2000.

The novelty of the SPD framework employed in the current study lies in two aspects: first, it applies SPD, which has been used to decompose temporal changes, to the decomposition of differences between two scenarios, namely the actual case in 2020 and a counterfactual case in 2020 without the COVID-19 pandemic. Second, this study extends the application of SPD, which has primarily been used for carbon footprint assessment, to a comprehensive TBL evaluation encompassing economic, social, and environmental aspects.

The objective of this chapter is to identify SC hotspots and their driving factors in each aspect of the economic, social, and environmental consequences of the COVID-19 pandemic. Using this framework, this study evaluated the final demand by

foreign tourists during the pandemic compared to a counterfactual scenario without the pandemic. In addition, the direct and indirect economic losses, employment declines, and CO_2 reductions resulting from the decrease in the influx of foreign tourists to Japan due to the pandemic were quantified. Furthermore, this study identified key sectors and factors across three aspects (i.e., economic, social, and environmental) and proposed policy measures to support these sectors. The novelty of this study lies in providing a new counterfactual SPD framework based on a consumption-endogenous input-output analysis framework. This framework assumes that in the absence of the pandemic, the economic structure of 2020 can be approximated by that of the previous year (2019).

The remainder of this paper is structured as follows: Section 4.2 outlines the methodology employed, Section 4.3 describes the data utilized, Section 4.4 presents the empirical findings, and Section 4.5 provides concluding remarks.

4.2. Methodology

4.2.1. Setting up with- and non-COVID scenarios

Following the framework proposed by Oga and Kagawa (2025), this study constructs two scenarios: a with-COVID and a non-COVID scenario. The with-COVID scenario reflects the actual situation in 2020, whereas the non-COVID scenario represents a counterfactual case assuming that the pandemic had not occurred. The $(n \times 1)$ final demand column vectors ($\mathbf{f}^r_{with}$ and $\mathbf{f}^r_{non}$), which represent the

consumption by foreign tourists from region r under the with-COVID and non-COVID scenarios, respectively, are calculated as follows:

$$\mathbf{f}_{with}^{r} = c_{with}^{r}\mathbf{d}_{with}^{r} \quad (1)$$

$$\mathbf{f}_{non}^{r} = c_{non}^{r}\mathbf{d}_{non}^{r} \quad (2)$$

where c_{with}^{r} and c_{non}^{r} denote the actual and counterfactual numbers of foreign tourists, respectively, and $\mathbf{d}_{with}^{r}$ and $\mathbf{d}_{non}^{r}$ denote the corresponding column vectors of per-capita commodity consumption by foreign tourists from region r in each scenario. The value of c_{non}^{r} is estimated using a linear trend model based on the number of foreign tourists from the specific region between 2003 and 2019. To account for the structural change associated with Japan's inbound tourism promotion policy in 2012, extrapolation is applied using simple linear regression with two separate regression lines: one fitted to the period before the structural change $\left(c_t^r = \alpha_1^r + \beta_1^r t + e_{1,t}^r \ (t = 2003, 2004, \dots, \ b^r - 1)\right)$ and the other to the period after $\left(c_t^r = \alpha_2^r + \beta_2^r t + e_{2,t}^r \ (t = \ b^r, \ b^r + 1, \dots, 2019)\right)$. Here, α^r and β^r denote the intercept and slope of the linear trend model, respectively; e_t^r denotes independent and identically distributed error terms; and b^r denotes the year of the structural break for region r. The linear trend models were estimated using the ordinary least squares (OLS) method. $\mathbf{d}_{non}^{r}$ is derived using 2019 data on the per capita expenditure by nationality of inbound tourists to Japan, under the assumption that, if the COVID-19 pandemic had not occurred, their consumption patterns would

have remained largely unchanged from the previous year. Variables with the subscript "with" and "non" refer to the with- and non-COVID scenarios, respectively.

4.2.2. Consumption-endogenous input-output analysis

This study employs the Leontief-Miyazawa model developed by Miyazawa and Masegi (1963) to clarify the impact of the COVID-19 pandemic on domestic income and consumption behavior. This model endogenizes the process through which production generates income and, subsequently, household consumption. The vector of the actual domestic direct and indirect commodity outputs across n sectors denoted as $\mathbf{x}_{with}^{r}$ $(n \times 1)$, is calculated as follows. This vector is induced by the final demand of foreign tourists from a specific region r in 2020 under the with-COVID scenario, denoted as $\mathbf{x}_{with}^{r}$ $(n \times 1)$, which is induced by the final demand of foreign tourists from a specific region r in 2020 under the with-COVID scenario $(\mathbf{f}_{with}^{r})$, is calculated as follows:

$$\begin{aligned}\mathbf{x}_{with}^{r} &= \left(\mathbf{I} - \mathbf{A}_{with}^{d} - \mathbf{h}_{with}^{d}\mu_{with}\mathbf{w}_{with}\right)^{-\mathbf{1}}\mathbf{f}_{with}^{r} \\ &= \mathbf{L}_{with}\mathbf{f}_{with}^{r} \qquad (3)\end{aligned}$$

where $\mathbf{I}$ is an $(n \times n)$ identity matrix; $\mathbf{A}_{with}^{d}$ is an $(n \times n)$ input coefficient matrix defined as $\left(\mathbf{I} - \widehat{\mathbf{M}}_{with}\right)\mathbf{A}_{with}$; $\widehat{\mathbf{M}}_{with}$ is an $(n \times n)$ diagonal import coefficient matrix; $\mathbf{h}_{with}^{d}$ is an $(n \times 1)$ household expenditure coefficient column vector defined as $\left(\mathbf{I} - \widehat{\mathbf{M}}_{with}\right)\mathbf{h}_{with}$; μ_{with} is a disposable income ratio; $\mathbf{w}_{with}$ is

a $(1 \times n)$ row vector of labor income ratio in 2020; and $\mathbf{L}_{with} = \left(\mathbf{I} - \mathbf{A}^{d}_{with} - \mathbf{h}^{d}_{with}\mu_{with}\mathbf{w}_{with}\right)^{-1}$ is a non-competitive import-type, consumption-endogenous Leontief inverse matrix $(n \times n)$. Therefore, the direct-indirect output $\mathbf{x}^{r}_{with}$ includes income induced effects.

Let $\mathbf{v}_{with}$ denote a $(1 \times n)$ row vector whose elements represent the value-added coefficients; that is, the amount of value added directly generated by producing one unit of output in each industry i. Similarly, let $\mathbf{s}_{with}$ and $\mathbf{e}_{with}$ denote $(1 \times n)$ row vectors whose elements represent the amount of labor input and that of CO_2 emissions required to produce one unit of output in industry i, respectively. By multiplying Eq. (3) by $\mathbf{v}_{with}$, $\mathbf{s}_{with}$, and $\mathbf{e}_{with}$h, the economic, social, and environmental impacts, respectively, are obtained under the with-COVID scenario in 2020, as follows:

$$V_{with} = \sum_{r=1}^{R}(\mathbf{v}_{with}\mathbf{L}_{with}\mathbf{f}^{r}_{with}) \quad (4)$$

$$S_{with} = \sum_{r=1}^{R}(\mathbf{s}_{with}\mathbf{L}_{with}\mathbf{f}^{r}_{with}) \quad (5)$$

$$E_{with} = \sum_{r=1}^{R}(\mathbf{e}_{with}\mathbf{L}_{with}\mathbf{f}^{r}_{with}) \quad (6)$$

where R denotes the number of countries and regions.

Applying the same approach to the non-COVID scenario, unobservable economic (V_{non}), social (S_{non}), and environmental (E_{non}) impacts, respectively, are calculated.

4.2.3. Structural decomposition analysis (SDA)

The equation for calculating direct and indirect value added, including income-induced effects, is given as follows:

$$V = \mathbf{vLf} = \mathbf{v}(\mathbf{I} - \mathbf{A}^d - \mathbf{h}^d\mu\mathbf{w})^{-1}\mathbf{f}^r \tag{7}$$

Using the SDA framework developed by Dietzenbacher and Los (1997, 1998), Eq. (7) can be decomposed as:

$$\Delta V = \underbrace{\Delta\mathbf{vLf}^r}_{\Delta V_v} + \underbrace{\mathbf{v}\Delta\mathbf{Lf}^r}_{\Delta V_L} + \underbrace{\mathbf{vL}\Delta\mathbf{f}^r}_{\Delta V_f} \tag{8}$$

where ΔV_v, ΔV_L, and ΔV_f represent changes in the value-added coefficients, production structure, and final demand, respectively. Based on the extended decomposition method (see e.g., Kagawa and Inamura, 2001), ΔV_L can be further decomposed as follows:

$$\Delta V_L = \mathbf{v}\Delta\mathbf{Lf}^r$$
$$= \mathbf{v}\Delta(\mathbf{I} - \mathbf{A}^d - \mathbf{h}^d\mu\mathbf{w})^{-1}\mathbf{f}^r$$

$$= \mathbf{vL}(\Delta\mathbf{A}^d + \Delta\mathbf{h}^d\mu\mathbf{w} + \mathbf{h}^d\Delta\mu\mathbf{w} + \mathbf{h}^d\mu\Delta\mathbf{w})\mathbf{Lf}^r$$

$$= \mathbf{vL}\Delta\mathbf{A}^d\mathbf{Lf}^r + \mathbf{vL}\Delta\mathbf{h}^d\mu\mathbf{wLf}^r + \mathbf{vLh}^d\Delta\mu\mathbf{wLf}^r + \mathbf{vLh}^d\mu\Delta\mathbf{wLf}^r \quad (9)$$

By substituting Eq. (9) into Eq. (8), the change in value added can be decomposed as follows:

$$\Delta V = \underbrace{\Delta\mathbf{vLf}^r}_{\Delta V_v} + \underbrace{\mathbf{vL}\Delta\mathbf{A}^d\mathbf{Lf}^r + \mathbf{vL}\Delta\mathbf{h}^d\mu\mathbf{wLf}^r + \mathbf{vLh}^d\Delta\mu\mathbf{wLf}^r + \mathbf{vLh}^d\mu\Delta\mathbf{wLf}^r}_{\Delta V_L} + \underbrace{\mathbf{vL}\Delta\mathbf{f}^r}_{\Delta V_f} \quad (10)$$

The economic effects of the differences in each factor ($\Delta\mathbf{v}, \Delta\mathbf{A}^d, \Delta\mathbf{h}^d, \Delta\mu, \Delta\mathbf{w}$, and $\Delta\mathbf{f}^r$), which appear as six terms on the right-hand side of Eq. (10), are calculated using the additive Logarithmic Mean Divisia Index (LMDI) method (Ang and Lee, 1994; Ang *et al*., 2003; Wood and Lenzen, 2009).

4.2.4. Counterfactual structural path decomposition (SPD)

The Leontief–Miyazawa inverse matrix ($\mathbf{L}$) can be expanded using a Taylor series as follows:

$$\mathbf{L} = \left(\mathbf{I} - \mathbf{A}^d - \mathbf{h}^\mathbf{d}\mu\mathbf{w}\right)^{-1} = \mathbf{I} + \left(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w}\right) + \left(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w}\right)^2 + \left(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w}\right)^3 + \cdots \quad (11)$$

where the term $(\mathbf{A}^d + \mathbf{h}^d \mu \mathbf{w})$ captures the indirect effects arising from intermediate inputs and income-induced consumption, both of which are triggered per unit of final demand.

Applying Eq. (11) to Eq. (4), the direct and indirect economic impacts at each propagation order generated by foreign tourists from region r under the with-COVID scenario can be expressed as:

$$
\begin{aligned}
V_{with} = \sum_{r=1}^{R} \Big\{ & \mathbf{v}_{with} \mathbf{f}_{with}^{r} + \mathbf{v}_{with} \left(\mathbf{A}_{with}^{d} + \mathbf{h}_{with}^{d} \mu_{with} \mathbf{w}_{with} \right) \mathbf{f}_{with}^{r} \\
& + \mathbf{v}_{with} \left(\mathbf{A}_{with}^{d} + \mathbf{h}_{with}^{d} \mu_{with} \mathbf{w}_{with} \right)^{2} \mathbf{f}_{with}^{r} + \cdots \Big\} \\
= & \underbrace{\sum_{r=1}^{R} \mathbf{v}_{with} \mathbf{f}_{with}^{r}}_{\text{1st order effec}} + \underbrace{\mathbf{v}_{with} \left(\mathbf{A}_{with}^{d} + \mathbf{h}_{with}^{d} \mu_{with} \mathbf{w}_{with} \right) \mathbf{f}_{with}^{r}}_{\text{2nd order effec}} \\
& + \underbrace{\mathbf{v}_{with} \left(\mathbf{A}_{with}^{d} + \mathbf{h}_{with}^{d} \mu_{with} \mathbf{w}_{with} \right)^{2} \mathbf{f}_{with}^{r}}_{\text{3rd order effec}} + \cdots
\end{aligned}
\tag{12}
$$

The economic impact by foreign tourists from region r under the non-COVID scenario can be expanded in the same manner.

Based on this expansion, the differential in economic effects can be expressed using the following formula for each order of ripple effects through the industrial paths:

$$\Delta V = V_{with} - V_{non}$$

$$= \sum_{r=1}^{R} \left[\underbrace{\Delta(\mathbf{v}\mathbf{f}^r)}_{\text{1st order}} + \underbrace{\Delta\{\mathbf{v}(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w})\mathbf{f}^r\}}_{\text{2nd order}} + \underbrace{\Delta\{\mathbf{v}(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w})^2\mathbf{f}^r\}}_{\text{3rd order}} + \cdots \right] \quad (13)$$

The three terms in Eq. (13), which correspond to the first-, second-, and third-order effects, respectively, can be decomposed as follows:

1st order:

$$\sum_{r=1}^{R}\{\Delta(\mathbf{v}\mathbf{f}^r)\} = \sum_{r=1}^{R}(\Delta\mathbf{v}\mathbf{f}^r + \mathbf{v}\Delta\mathbf{f}^r) \quad (13a)$$

2nd order:

$$\sum_{r=1}^{R}[\Delta\{\mathbf{v}(\mathbf{A}^d + \mathbf{h}^d\mu\mathbf{w})\mathbf{f}^r\}]$$

$$= \sum_{r=1}^{R}\{\Delta(\mathbf{v}\mathbf{A}^d\mathbf{f}^r) + \Delta(\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r)\}$$

$$= \sum_{r=1}^{R}(\Delta\mathbf{v}\mathbf{A}^d\mathbf{f}^r + \mathbf{v}\Delta\mathbf{A}^d\mathbf{f}^r + \mathbf{v}\mathbf{A}^d\Delta\mathbf{f}^r + \Delta\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r + \mathbf{v}\Delta\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r + \mathbf{v}\mathbf{h}^d\Delta\mu\mathbf{w}\mathbf{f}^r$$
$$+ \mathbf{v}\mathbf{h}^d\mu\Delta\mathbf{w}\mathbf{f}^r + \mathbf{v}\mathbf{h}^d\mu\mathbf{w}\Delta\mathbf{f}^r) \quad (13b)$$

3rd order:

$$\sum_{r=1}^{R}[\Delta\{\mathbf{v}(\mathbf{A}^d+\mathbf{h}^d\mu\mathbf{w})^2\mathbf{f}^r\}]$$

$$=\sum_{r=1}^{R}\{\Delta(\mathbf{v}\mathbf{A}^d\mathbf{A}^d\mathbf{f}^r)+\Delta(\mathbf{v}\mathbf{A}^d\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r)+\Delta(\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{A}^d\mathbf{f}^r)+\Delta(\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r)\}$$

$$\begin{aligned}=\sum_{r=1}^{R}(&\Delta\mathbf{v}\mathbf{A}^d\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\Delta\mathbf{A}^d\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\mathbf{A}^d\Delta\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\mathbf{A}^d\mathbf{A}^d\Delta\mathbf{f}^r+\Delta\mathbf{v}\mathbf{A}^d\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\Delta\mathbf{A}^d\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{A}^d\Delta\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r\\&++\mathbf{v}\mathbf{A}^d\mathbf{h}^d\Delta\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{A}^d\mathbf{h}^d\mu\Delta\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{A}^d\mathbf{h}^d\mu\mathbf{w}\Delta\mathbf{f}^r+\Delta\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\Delta\mathbf{h}^d\mu\mathbf{w}\mathbf{A}^d\mathbf{f}^r\\&+\mathbf{v}\mathbf{h}^d\Delta\mu\mathbf{w}\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\Delta\mathbf{w}\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\Delta\mathbf{A}^d\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{A}^d\Delta\mathbf{f}^r+\Delta\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r\\&+\mathbf{v}\Delta\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\Delta\mu\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\Delta\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\Delta\mathbf{h}^d\mu\mathbf{w}\mathbf{f}^r\\&+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\Delta\mu\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\mu\Delta\mathbf{w}\mathbf{f}^r+\mathbf{v}\mathbf{h}^d\mu\mathbf{w}\mathbf{h}^d\mu\mathbf{w}\Delta\mathbf{f}^r)\end{aligned}$$

(13c)

The economic effects of the differences in each factor ($\Delta\mathbf{v}$, $\Delta\mathbf{A}^d$, $\Delta\mathbf{h}^d$, $\Delta\mu$, $\Delta\mathbf{w}$, and $\Delta\mathbf{f}^r$) at each order, as expressed in Eqs. (13a), (13b), and (13c), are calculated using the additive the LMDI method (Ang and Lee, 1994; Ang *et al*., 2003; Wood and Lenzen, 2009). The social and environmental impacts at each order can also be decomposed in the same way.

4.3. Data

The *observable* and *unobservable* numbers of foreign tourists to Japan from 21 countries and regions were obtained from the JNTO (2025a). The number of foreign tourists in each region in 2020 was used as the *observable* data for the with-COVID scenario, while data from 2003 to 2019 were used to estimate a linear trend model to predict the *unobservable* number of tourists under the non-COVID scenario.

The *observable* and *unobservable* per-capita commodity consumption data for foreign tourists were obtained from JTA (2025b). The per capita consumption data from each region for the with-COVID scenario in 2020 were obtained from the survey conducted in 2020 (JTA, MLIT, 2025b). On the other hand, the per capita consumption data from each region for the non-COVID scenario in 2020 were obtained from the survey conducted in 2019 (JTA, MLIT, 2025b). The detailed commercial and transportation margin table for 2015, published by the (MIC, 2019a), was used to convert the per capita commodity consumption of foreign visitors from purchaser prices to producer prices.

To estimate the economic, social, and environmental multiplier effects under the with- and non-COVID scenarios, this study employed the 2020 and 2019 input–output tables, respectively, each comprising 94 sectors, as published by the Cabinet Office of Japan (COJ, 2021; COJ, 2022). Furthermore, the disposable income ratios of the average working household in 2020 and 2019 were retrieved from the Household Survey Report by the MIC (MIC, 2020, 2021b), and were set as $\mu_{with} = 0.607$ and $\mu_{non} = 0.673$, respectively.

Because sector-specific employment and CO_2 emissions data for 2019 and 2020 were unavailable, this study used data from 2015. To assess the social impacts, labor input coefficients were calculated based on sectoral employment data from 2015 (MIC, 2019b), under the assumption that the labor input structure remained unchanged between the with- and non-COVID scenarios. For the environmental

impact evaluation, CO_2 emissions coefficients were derived from the 2015 version of the Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID) (Nansai, 2019; Nansai *et al.*, 2020). This study likewise assumed that sectoral emission intensities remained constant across both scenarios.

4.4. Results

4.4.1. Decomposition of pandemic-induced ripple effects by propagation order

The amount and share of economic (value added loss), social (employment loss), and environmental (CO_2 reduction) impacts attributable to each propagation order (1st to 3rd), based on the difference between the with- and non-COVID scenarios, as calculated using SPA formulated like Eq. (12) are presented in Table 4-1. Although the environmental share is slightly lower at 75%, the analysis results capture approximately 80% of the overall direct and indirect impacts resulting from the decline in inbound tourism demand caused by the COVID-19 pandemic. Higher-order effects beyond the 3rd order were excluded because of their relatively minor contributions to the total impact.

Table 0-1. Breakdown of economic, social, and environmental impacts by order of propagation and their shares of total impact.

	Value added loss (billion JPY)	Employment loss (thousand persons)	CO_2 reduction (kt-CO_2)
1st order	1,337	464	2,121
2nd order	928	182	4,321
3rd order	505	96	2,236
Share of the total	81%	86%	75%

Note: The economic impacts for each propagation order under the with-COVID scenario are estimated by $\sum_{r=1}^{R}\mathbf{v}_{with}\mathbf{f}_{with}^{r}$, $\sum_{r=1}^{R}\mathbf{v}_{with}\left(\mathbf{A}_{with}^{d}+\mathbf{h}_{with}^{d}\mu_{with}\mathbf{w}_{with}\right)\mathbf{f}_{with}^{r}$, and $\sum_{r=1}^{R}\mathbf{v}_{with}(\mathbf{A}_{with}^{d}+\mathbf{h}_{with}^{d}\mu_{with}\mathbf{w}_{with})^{2}\mathbf{f}_{with}^{r}$, respectively. Similarly, under the non-COVID scenario, they are estimated by $\sum_{r=1}^{R}\mathbf{v}_{non}\mathbf{f}_{non}^{r}$, $\sum_{r=1}^{R}\mathbf{v}_{non}(\mathbf{A}_{non}^{d}+\mathbf{h}_{non}^{d}\mu_{non}\mathbf{w}_{non})\mathbf{f}_{non}^{r}$, and $\sum_{r=1}^{R}\mathbf{v}_{non}(\mathbf{A}_{non}^{d}+\mathbf{h}_{non}^{d}\mu_{non}\mathbf{w}_{non})^{2}\mathbf{f}_{non}^{r}$, respectively. The differences in the economic impacts at each propagation order between the non-COVID and with-COVID scenarios are reported in the second column of Table 4-1. Similarly, the differences in the social and environmental impacts are presented in the third and fourth columns of Table 4-1, respectively.

4.4.2. LMDI-based SDA of economic, social, and environmental changes

The factor-wise changes identified through SDA using the LMDI method are presented in Table 4-2. Owing to data limitations, employment opportunity and CO_2 emissions coefficients were not included in the estimation. The decline in final demand by inbound tourists ($\Delta\mathbf{f}$) was the most significant contributing factor. In the case of economic impacts, the input coefficient ($\Delta\mathbf{A}$), consumption propensity ($\Delta\mathbf{h}$), and labor share ($\Delta\mathbf{w}$) contributed marginally in the increasing direction. For social and environmental impacts, the input coefficient ($\Delta\mathbf{A}$) and labor share ($\Delta\mathbf{w}$) also displayed slight positive contributions.

Table 0-2. SDA results based on LMDI.

	Changes in value added coefficients of industries	Changes in input coefficients of industries ($\Delta\mathbf{A}$)	Changes in household expenditure coefficients ($\Delta\mathbf{h}$)	Changes in household disposable income ratio ($\Delta\mu$)	Changes in labor income coefficients of industries ($\Delta\mathbf{w}$)	Changes in the final demand of foreign visitor to Japan ($\Delta\mathbf{f}$)
Economic impact (billion JPY)	-117	43	2	-30	38	-2,705
Social impact (thousand persons)	-	10	-1	-5	7	-753
Environmental impact (kt-$C0_2$)	-	258	-11	-59	80	-8,945

Note: Due to data limitations, employment opportunity and CO_2 emissions coefficients under the non-COVID scenario were unavailable for use in the SDA. Therefore, the social and environmental impacts associated with changes in these factor coefficients could not be estimated in this study.

4.4.3. Structural path decomposition in the economic impacts in 2020 due to the COVID-19 pandemic

The results of the SPD analysis of economic impacts caused by COVID-19 through Japan's inbound tourism are reported in 4-3. The 20 most affected industrial paths are listed, along with the contributing factors and nationalities of foreign tourists. The SC flows are represented in the order of Sector 1 → Sector 2 → Sector 3, with "Order" indicating the position along the path at which the change occurred. "Factor" refers to the category of variables that contributed to the change.

Among the top six SC paths with the largest economic losses, all were attributable to the decline in inbound tourism demand from China. These included five direct losses caused by decreases in final demand, specifically in eating and drinking services (-109.4 billion JPY), miscellaneous chemical products (-100.8 billion JPY), hotels (-77.0 billion JPY), wholesale (-65.6 billion JPY), and retail trade sectors (-61.7 billion JPY), as well as one direct loss in the hotels sector (-41.1 billion JPY) due to a decline in value-added coefficients. These findings indicate that the direct effects were more pronounced than the ripple effects. The decline in tourism demand from Taiwan, South Korea, Hong Kong, and the United States (U.S.) also resulted in direct economic losses, particularly in the accommodation and food services sectors.

Table 0-3. Result of SPD in economic impact due to the COVID-19 pandemic.

Rank	Nationalities of tourists	Factors	Sector (1st order)	Sector (2nd order)	Sector (3rd order)	Order	Billion JPY
1	China	Δf	Eating and drinking services			1	-109.4
2	China	Δf	Miscellaneous chemical products			1	-100.8
3	China	Δf	Hotels			1	-77. 0
4	China	Δf	Wholesale trade			1	-65.6
5	China	Δf	Retail trade			1	-61.7
6	Chaina	Δv	Hotels			1	-41.1
7	Taiwan	Δf	Eating and drinking services			1	-40.8
8	South Korea	Δf	Eating and drinking services			1	-37.8
9	Hong Kong	Δf	Eating and drinking services			1	-29.1
10	Taiwan	Δf	Hotels			1	-27.6
11	South Korea	Δf	Hotels			1	-26.6
12	The U.S.	Δf	Eating and drinking services			1	-25.2
13	The U.S.	Δf	Hotels			1	-25.1
14	Others	Δf	Eating and drinking services			1	-23.0
15	Hong Kong	Δf	Hotels			1	-20.9
16	Others	Δf	Hotels			1	-20.7
17	China	Δf	Amusement and recreation services			1	-18.4
18	Taiwan	Δv	Hotels			1	-17.3
19	Chaina	Δf	Hotels	Waste management services		2	-14.1
20	Taiwan	Δf	Miscellaneous chemical products			1	-13.4

The top 30 SC paths that experienced the most significant economic impacts are visualized in Fig. 4-1. The size of each bubble represents the value added of the corresponding industry. Among these 30 paths, 23 are attributed to the decline in inbound tourism demand from China. Notably, the three most affected paths are "hotels → waste management services (14.1 billion JPY)," "eating and drinking services → Wholesale trade (11.8 billion JPY)," and "hotels → miscellaneous transport (11.2 billion JPY)." These results indicate that the decrease in demand from Chinese tourists had a substantial ripple effect on the Japanese economy through SCs. The impacts originating from the hotels sector spread widely to industries such as waste management, house rent, miscellaneous transport, wholesale trade, and electricity. Similarly, the eating and drinking services sector triggered downstream effects on wholesale trade, drinks, retail trade, house rent, and miscellaneous foods. In addition, a reduction in the purchase of cosmetics and perfumes due to the decline in Chinese tourists resulted in a value-added loss of 7.3 billion JPY along the path miscellaneous chemical products → basic chemical products, which exceeded the economic loss observed in the hotels → waste management services path linked to the decrease in tourists from Taiwan. Note that several paths converged on the "house rent" sector. However, the decline in tourism demand during the COVID-19 pandemic is unlikely to have directly caused widespread rent defaults, which suggests that this result may not accurately reflect the real-world situation.

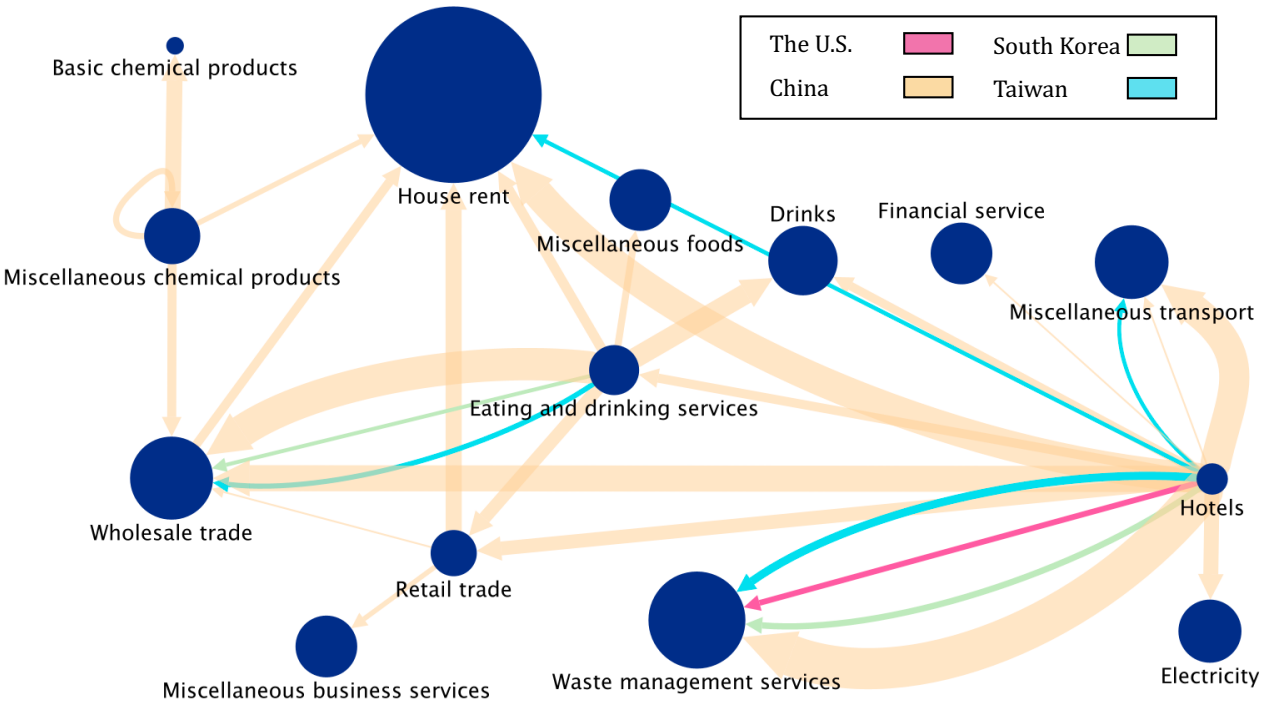


Figure 0-1. Network diagram of the top 30 industrial paths with the largest economic impacts from inbound tourism loss, identified through SPD.

4.4.4. Structural path decomposition in the social impacts in 2020 due to the COVID-19 pandemic

The top 20 paths of social impacts resulting from the decline in Japan's inbound tourism demand due to COVID-19, as identified through SPD analysis, are presented in Table 4-4. The decrease in tourist demand from China, Taiwan, South Korea, Hong Kong, the U.S., Thailand, and Australia had strong direct effects on the hotels and eating and drinking services sectors. Notably, the direct loss in the latter sector associated with the decline in Chinese tourists ranked first and was approximately 1.5 times greater than the loss in hotels, which ranked second.

Table 0-4. Result of SPD in social impact due to the COVID-19 pandemic.

Rank	Nationalities of tourists	Factors	Sector (1st order)	Sector (2nd order)	Sector (3rd order)	Order	People
1	China	Δf	Eating and drinking services			1	-60,645
2	China	Δf	Hotels			1	-39,307
3	China	Δf	Retail trade			1	-33,402
4	Taiwan	Δf	Eating and drinking services			1	-22,600
5	South Korea	Δf	Eating and drinking services			1	-20,931
6	Hong Kong	Δf	Eating and drinking services			1	-16,113
7	Taiwan	Δf	Hotels			1	-14,362
8	The U.S.	Δf	Eating and drinking services			1	-13,970
9	South Korea	Δf	Hotels			1	-13,212
10	Others	Δf	Eating and drinking services			1	-12,766
11	The U.S.	Δf	Hotels			1	-12,739
12	Hong Kong	Δf	Hotels			1	-10,641
13	Others	Δf	Hotels			1	-10,525
14	China	Δf	Wholesale trade			1	-8,557
15	Taiwan	Δf	Retail trade			1	-6,688
16	Thailand	Δf	Eating and drinking services			1	-6,614
17	Australia	Δf	Eating and drinking services			1	-6,122
18	Australia	Δf	Hotels			1	-5,192
19	China	Δf	Miscellaneous chemical products			1	-5,001
20	Hong Kong	Δf	Retail trade			1	-4,564

The top 30 SC paths that experienced the most significant social impacts are visualized in Fig. 4-2. The size of each bubble represents the employment coefficient of the corresponding industry. The impacts were particularly pronounced for inbound tourism demand declines from China, Taiwan, South Korea, the U.S., and Hong Kong. Among the affected sectors, hotels and eating and drinking services appeared as the largest bubbles, thereby indicating their substantial role in generating spillover effects on other industries. In particular, three paths, "hotels → retail trade," "eating and drinking services → retail trade," and "hotels → eating and drinking services," were identified as having incurred especially large employment losses.

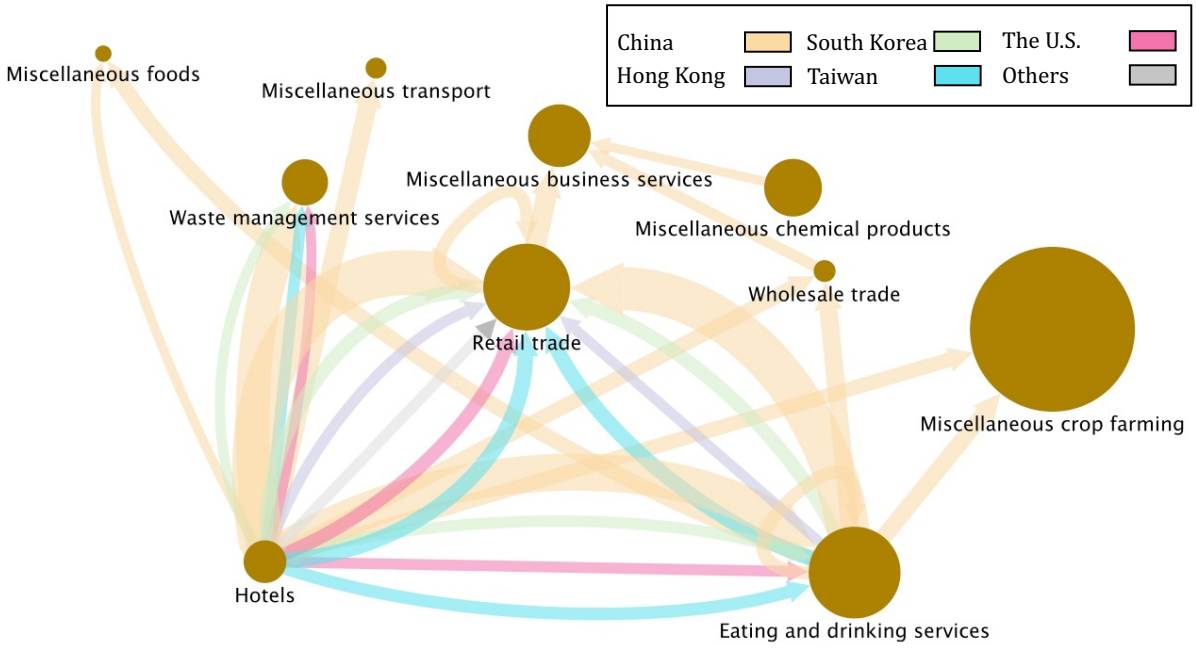


Figure 0-2. Network diagram of the top 30 industrial paths with the largest social impacts from inbound tourism loss, identified through SPD.

4.4.5. Structural path decomposition in the environmental impacts in 2020 due to the COVID-19 pandemic

The top 20 structural paths of environmental impacts resulting from the decline in Japan's inbound tourism demand due to COVID-19, as identified through SPD analysis are presented in Table 4-5. Significant emissions reductions were observed along the "hotel → electricity" paths associated with the decline in tourist demand from China, Taiwan, South Korea, the U.S., and Hong Kong. These reductions are largely attributable to indirect CO_2 savings in the electricity sector, which centrally supplies the energy required for tourism-related consumption. Although the hotel sector itself is not typically associated with high CO_2 emissions intensity,

the reduction in emissions along the path associated with Chinese tourists ranks second. In addition, the decline in purchases of cosmetics and perfumes by Chinese tourists resulted in significant emissions reductions along the paths “miscellaneous chemical products → electricity” (-104 kt-CO_2) and “miscellaneous chemical products → basic chemical products” (-84 kt-CO_2). When combined, these reductions exceed those observed in the fourth-largest path, “hotel → electricity,” which is associated with the decline in tourist demand from Taiwan.

Table 0-5. Result of SPD in environmental impact due to the COVID-19 pandemic.

Rank	Nationalities of tourists	Factors	Sector (1st order)	Sector (2nd order)	Sector (3rd order)	Order	kt-CO_2
1	China	Δf	Hotels	Electricity		2	-434
2	China	Δf	Hotels			1	-278
3	China	Δf	Road transport			1	-185
4	Taiwan	Δf	Hotels	Electricity		2	-159
5	China	Δf	Eating and drinking services	Electricity		2	-155
6	China	Δf	Retail trade	Electricity		2	-151
7	China	Δf	Hotels	Waste management services		2	-146
8	South Korea	Δf	Hotels	Electricity		2	-145
9	The U.S.	Δf	Hotels	Electricity		2	-140
10	Hong Kong	Δf	Hotels	Electricity		2	-117
11	Others	Δf	Hotels	Electricity		2	-116
12	China	Δf	Miscellaneous chemical products	Basic chemical products		2	-104
13	Taiwan	Δf	Hotels			1	-102
14	South Korea	Δf	Hotels			1	-94
15	The U.S.	Δf	Hotels			1	-90
16	China	Δf	Miscellaneous chemical products	Electricity		2	-84
17	China	Δf	Eating and drinking services			1	-83
18	Hong Kong	Δf	Hotels			1	-75
19	Others	Δf	Hotels			1	-75
20	China	Δf	Miscellaneous chemical products			1	-74

The top 30 SC paths that experienced the most significant environmental impacts are visualized in Fig. 4-3. The size of each bubble represents the CO_2 emissions coefficient of the corresponding industry. The decline in inbound tourism demand from ten countries and regions—Australia, China, England, France, Hong Kong, Singapore, South Korea, Taiwan, Thailand, and the United States—contributed to the reduction in CO_2 emissions. This reduction was largely driven by indirect decreases in electricity demand caused by five specific sectors: hotels, eating and drinking services, retail trade, miscellaneous chemical products, and waste management services.

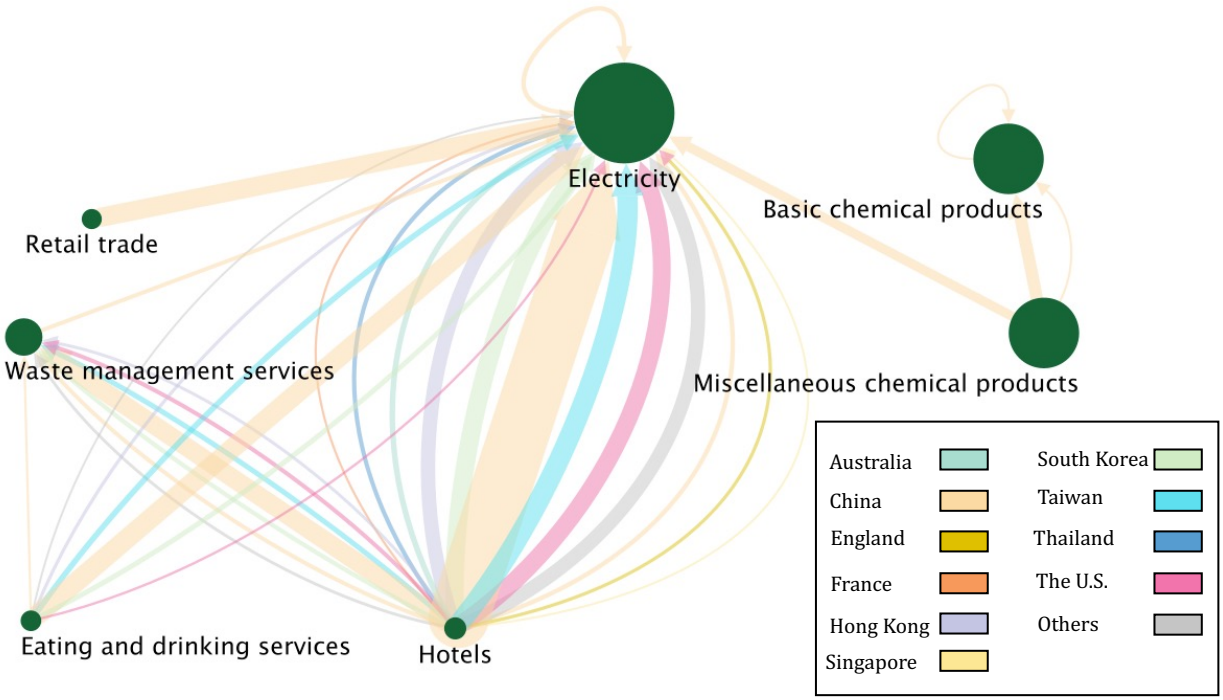


Figure 0-3. Network diagram of the top 30 industrial paths with the largest environmental impacts from inbound tourism loss, identified through SPD.

4.5. Discussion and Conclusions

4.5.1. Decomposition results of the inbound tourism shock

This study employed a consumption-endogenous input-output analysis to quantify the counterfactual difference between the with- and non-COVID scenarios. SPD was applied to this difference to identify the SCs most affected by the decline in inbound tourism demand caused by the COVID-19 pandemic. The analysis was conducted across economic, social, and environmental aspects disaggregated by the 21 nationalities of inbound tourists and six decomposition factors.

The coverage of the estimated impacts captured by the SPD accounted for 81%, 86%, and 75% of total economic (value added), social (employment opportunities), and environmental (CO_2 emissions) impacts, respectively, which indicates that the method successfully explained the majority of the observed changes. The most significantly impacted SC path in the economic impact was "hotels → waste management services," which resulted from the decline in final demand by inbound tourists from China, with a value-added loss of -14 billion JPY. In the social impact, the greatest damage was observed in the "hotels → retail trade" path, which was also associated with Chinese tourists, consequently resulting in an employment loss of -3,655 persons. In the environmental impact, the path "hotels → electricity" displayed the largest CO_2 reduction at -434 kt-CO_2.

The SPD framework employed in this study is based on an income-endogenous

input-output model, which allowed for the incorporation of income-related spillover structures into the analysis. Specifically, the decomposition included changes in household expenditure coefficients, household disposable income ratios, and labor income coefficients. However, the contribution of these income-related factors was found to be minimal. The substantial decline in final demand by inbound tourists was the overwhelmingly dominant factor driving the observed impacts.

Regarding the economic aspect, the results revealed that the decline in inbound tourism demand from China had a significant ripple effect throughout the SC. In particular, the consumption propensity of Chinese tourists played a major role in determining the scale of economic losses. This can be attributed to the structural reliance of Japan's inbound tourism market on the active consumption behavior of Chinese visitors, which has supported a substantial portion of value added. Regarding the social impacts, the ripple effects were relatively limited compared to those in the economic and environmental domains. Notably, service industry connections that rely on in-person interactions were especially fragile and faced significant disruption. In terms of environmental impacts, the stagnation of five energy-intensive industries contributed significantly to CO_2 emissions reductions. These included sectors affected by declines in tourism demand regardless of nationality, namely hotels, eating and drinking services, and waste management, as well as those strongly influenced by the sharp decrease in Chinese tourism demand, such as miscellaneous chemical products and wholesale trade.

Overall, the findings suggest that Japan's inbound tourism market is supported

by an SC centered around the hotel and eating and drinking services sectors. The decline in final demand resulted in varying types of impacts across the economic, social, and environmental dimensions, with each exhibiting distinct characteristics.

4.5.2. Implications for tourism recovery and risk management

Based on the findings, this study proposes policy directions for formulating balanced recovery strategies across the economic, social, and environmental dimensions in the context of inbound tourism under disaster conditions.

First, in terms of economic recovery, when formulating economic support measures for damaged industries, for the government to recognize that the damage occurred because of a trade-off between economic loss and environmental benefits is important. The "hotels → waste management services," which is the most damaged SC path economically, also contributed to the reduction in CO_2 emissions. Although waste management services contribute significantly to value-added generation from inbound tourism, they also produce high level of CO_2 emissions. Economic support for such industries should be conditional on the commitment of supported firms and businesses to pursue decarbonization efforts. Furthermore, the analysis revealed that economic impacts were strongly influenced by the consumption propensity of tourists from China, which suggests that reducing Japan's heavy reliance on the Chinese inbound market could function as an effective risk hedge in times of future crises.

For social losses, support for labor transitions from stagnating industries to those that experienced growth during the pandemic is necessary. The retail trade sector was indirectly affected by the decline in the final demand for hotels and eating and drinking services, which exposed it to a high risk of unemployment. In addition, service-sector linkages that rely heavily on face-to-face interaction were particularly vulnerable and suffered substantial damage. Industries that benefited from the pandemic were those well-suited to the shift toward remote operations, such as IT-related sectors and e-commerce. By contrast, workers in face-to-face service industries are likely to face difficulties in transitioning to these sectors. This study recommends that the government support the workforce in these sectors by facilitating transitions to alternative industries that are less vulnerable to pandemic-related disruptions through job training and employment programs.

Regarding environmental impacts, this study highlights that the stagnation of five energy-intensive sectors indirectly contributed to CO_2 emissions reductions by decreasing electricity demand. Therefore, embedding incentives to lower the energy intensity of these sectors into recovery support schemes would be effective in enhancing the sustainability of inbound tourism in the post-pandemic period.

4.5.3. Toward disaster-resilient inbound tourism

The finding that final demand had the greatest influence on outcomes suggests that this analytical framework is not only applicable to pandemics, but also broadly adaptable to various disasters that may trigger sudden drops in demand, such as

large-scale earthquakes. As of 2025, Japan's inbound tourism industry has surpassed pre-pandemic levels of growth, and the government is actively considering further expansion strategies (JNTO, 2025b). However, the inbound tourism market's structural vulnerability to disasters, whether pandemics or natural hazards, remains unchanged. Therefore, policymakers should adopt counterfactual SPD-based analysis for proactive risk assessment at the SC level and for the careful development of SC-based disaster recovery strategies tailored to the inbound tourism industry.

Chapter 5. Conclusions

This Ph.D. dissertation develops a comprehensive, fine-grained analytical framework to assess the impacts of depressed tourism demand under disaster conditions, and applies it empirically to Japan's inbound tourism during the COVID-19 pandemic.

In Chapter 3, using a consumption-endogenous, environmentally extended input–output (EEIO) model for Japan, I quantify the triple-bottom-line impacts of the pandemic-induced collapse of inbound tourism—economic (value added loss), social (employment loss), and environmental (CO_2 reduction). It applies SDA to attribute the observed changes to their driving factors and evaluates counterfactual scenarios that posit a 2020 without COVID-19 in order to isolate the demand-shock effect. The results highlight hotels, eating and drinking services, air transport, and retail as key conduits of economic and employment losses, while electricity supply and waste-management services emerge as major upstream contributors to CO_2 reduction. The chapter concludes with policy-relevant implications for a balanced recovery strategy that couples sectoral support with decarbonization commitments in upstream services.

Chapter 4 combines a consumption-endogenous input–output model with with- and non-COVID scenarios and an SPD that resolves changes along explicit supply-chain paths. The chapter shows that shocks were dominated by the collapse in final demand from Chinese visitors, maps where effects propagate upstream

(electricity, wholesale, waste), and draws policy implications: target support to path-level hotspots, condition aid on decarbonization in energy-intensive upstream services, and facilitate labor transitions away from face-to-face services most exposed to demand shocks. The framework generalizes to other disasters that trigger sudden demand drops, offering a path-resolved, policy-ready lens for risk assessment and recovery design.

This Ph.D. dissertation establishes a decision-ready evidence base for disaster-era shocks to tourism by linking demand collapses to their economy–society–environment consequences along concrete supply chains. Rather than stopping at aggregate effects, it traces which supplier–consumer routes amplify losses or deliver environmental gains, and by how much, making visible the asymmetry that the same shock can hit different industries on the economic and social sides while easing pressures upstream on the environmental side. The analysis highlights actionable hotspots—for example, accommodation → electricity and accommodation → waste linkages—and shows how targeted support can be coupled with upstream decarbonization to avoid rebound during recovery. By integrating counterfactual comparison with a transparent attribution of drivers and a path-resolved reading of results, the dissertation provides a practical, reproducible lens for crises in which final demand and production technology move.

Acknowledgements

In completing this dissertation for the Ph.D. in Economics, I have been sustained by the guidance and encouragement of many people. I am especially indebted to my supervisor, Prof. Shigemi Kagawa (Kyushu University), for his deep knowledge, incisive advice, and unwavering support—from my undergraduate days through this work. He taught me to find genuine enjoyment and curiosity in research, and he opened doors to opportunities and experiences that have shaped my academic path. I am certain that this dissertation would not have been completed without his dedicated mentorship. I also thank the faculty and staff of the Graduate School of Economics at Kyushu University, my lab colleagues and friends for their helpful comments and everyday support, and my family for their patience and constant encouragement.

I have been continually inspired by the students, lab mates, and senior researchers at Kyushu University, as well as by colleagues in the Student Communication Network at The Institute of Life Cycle Assessment, Japan. They have been friendly competitors and true companions, pushing me to aim higher while sharing ideas generously. Our habit of cheering each other on made study sessions productive and the everyday rhythm of graduate school genuinely enjoyable. To my lab members in particular: you turned these past six years into a community where we could strive seriously and celebrate wholeheartedly. Thank you for the energy, camaraderie, and countless moments that made my time in the lab unforgettable.

Finally—and above all—I owe my deepest thanks to my family for their unwavering support and patience. I can never fully repay your encouragement. Without you, this long and demanding Ph.D. journey would not have been possible. I gratefully dedicate this dissertation to you.

This research was supported in part by JSPS KAKENHI Grant Number JP24KJ1790.

October 2025



Appendix

Table S1. Estimated parameters of the linear trend model (after the structural break).

Country and region c	$\tilde{\alpha}_2^c$	t value for $\tilde{\alpha}_2^c$	$\tilde{\beta}_2^c$	t value for $\tilde{\beta}_2^c$	R^2	Sample period	Structural break b^c	F value in statistical tests for a structural break
Australia	-125.577	-47.723	0.063	47.888	0.998	2013~2019	2013	105.753
Canada	-74.411	-28.858	0.037	28.960	0.994	2013~2019	2013	56.909
China	-2253.290	-29.954	1.121	30.052	0.997	2015~2019	2015	327.275
France	-61.053	-29.345	0.030	29.463	0.994	2013~2019	2013	26.551
Germany	-37.800	-38.673	0.019	38.857	0.997	2013~2019	2013	28.028
Hong Kong	-567.527	-7.193	0.282	7.214	0.912	2013~2019	2013	43.248
India	-33.417	-27.393	0.017	27.493	0.993	2013~2019	2013	116.925
Indonesia	-104.226	-13.397	0.052	13.432	0.973	2013~2019	2013	122.472
Italy	-32.165	-21.732	0.016	21.810	0.990	2013~2019	2013	41.024
Malaysia	-111.021	-12.695	0.055	12.737	0.970	2013~2019	2013	106.988
Philippines	-165.941	-44.653	0.082	44.748	0.998	2013~2019	2013	430.233
Russia	-43.080	-9.637	0.021	9.658	0.989	2017~2019	2017	19.585
Singapore	-102.103	-19.744	0.051	19.810	0.987	2013~2019	2013	39.291
South Korea	-637.306	-5.482	0.318	5.509	0.669	2003~2019	-	10.594
Spain	-28.473	-29.045	0.014	29.136	0.994	2013~2019	2013	32.643
Taiwan	-916.375	-8.137	0.456	8.171	0.930	2013~2019	2013	52.239
Thailand	-268.075	-18.898	0.133	18.961	0.986	2013~2019	2013	197.502
U.S.A.	-314.487	-26.414	0.157	26.517	0.993	2013~2019	2013	74.655
UK	-70.075	-9.671	0.035	9.711	0.950	2013~2019	2013	57.303
Vietnam	-135.440	-14.743	0.067	14.771	0.978	2013~2019	2013	192.287
Others	-264.702	-31.273	0.132	31.387	0.995	2013~2019	2013	103.897

Note: The estimated linear trend model is $\tilde{n}_t^c = \tilde{\alpha}_2^c + \tilde{\beta}_2^c t$ where $\tilde{n}_t^c$ represents the number of foreign visitors in million persons and $\tilde{\alpha}^c$ and $\tilde{\beta}^c$ represent the estimated two parameters.

Table S2. Estimated parameters of the linear trend model (before the structural break).

Country and region c	$\tilde{\alpha}_1^c$	t value for $\tilde{\alpha}_1^c$	$\tilde{\beta}_1^c$	t value for $\tilde{\beta}_1^c$	R^2
Australia	-2.882	-0.519	0.002	0.556	0.037
Canada	2.545	0.547	-0.001	-0.516	0.032
China	-250.540	-5.614	0.125	5.638	0.761
France	-8.213	-1.741	0.004	1.767	0.281
Germany	0.403	0.117	0.000	-0.085	0.001
Hong Kong	-47.109	-2.957	0.024	2.982	0.526
India	-3.190	-2.726	0.002	2.778	0.491
Indonesia	-6.013	-2.544	0.003	2.573	0.453
Italy	-2.870	-1.365	0.001	1.388	0.194
Malaysia	-10.188	-3.361	0.005	3.391	0.590
Philippines	18.396	4.745	-0.009	-4.719	0.736
Russia	0.276	0.217	0.000	-0.174	0.003
Singapore	-15.389	-2.509	0.008	2.530	0.445
South Korea	-637.306	-5.482	0.318	5.509	0.669
Spain	-4.177	-2.142	0.002	2.157	0.368
Taiwan	-55.205	-1.181	0.028	1.207	0.154
Thailand	-30.981	-4.713	0.016	4.737	0.737
U.S.A.	21.187	1.207	-0.010	-1.165	0.145
UK	13.288	3.261	-0.007	-3.213	0.563
Vietnam	-7.557	-11.116	0.004	11.163	0.940
Others	-19.215	-1.757	0.010	1.796	0.287

Note: The estimated linear trend model is $\tilde{n}_t^c = \tilde{\alpha}_1^c + \tilde{\beta}_1^c t$ where $\tilde{n}_t^c$ represents the number of foreign visitors in million persons and $\tilde{\alpha}_1^c$ and $\tilde{\beta}_1^c$ represent the estimated two parameters.

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