

Development of New Database of Embodied CO₂ Emission Intensities and Its Application to the LCA of Residential Buildings

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**Development of New Database of Embodied CO₂ Emission Intensities and Its
Application to the LCA of Residential Buildings**

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

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Chapter 1: Introduction

1.1. The current state of global warming

According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), greenhouse gas (GHG) emissions from human activities, particularly CO₂, are increasing, accelerating global warming. The rise in surface temperatures caused by global warming has led to various adverse impacts, including flooding, reduced water availability, the spread of infectious diseases, and extreme heat (IPCC, 2022). In 2015, the Paris Agreement, which succeeded the 1997 Kyoto Protocol, was adopted globally. The Paris Agreement primarily set goals to limit the global average temperature increase to 1.5°C above pre-industrial levels and to achieve net-zero greenhouse gas emissions by the latter half of the 21st century. Furthermore, according to the Sixth IPCC Report, achieving the 1.5°C target requires a 99% reduction in CO₂ emissions by 2050 compared to 2019 levels.

In response, Japan has set a CO₂ reduction target to achieve carbon neutrality by 2050. Additionally, emission targets for fiscal year 2030 have been established across five sectors: industry, commercial, residential, transportation, and energy transformation and own use. Among these, the residential sector, which is closely linked to activities such as housing construction, energy use in homes, and consumption, has been assigned the most ambitious reduction target compared to other sectors. It aims to reduce emissions by 66% by fiscal year 2030 relative to fiscal year 2013 levels (Ministry of the Environment, 2021). However, as shown in Figure 1-1, as of 2022, the residential sector's reduction rate stands at -24.5% compared to fiscal year 2013, falling short of even half the target (Ministry of

the Environment, 2024). Without effective measures, achieving this goal will be impossible. Moreover, in Japan, detached residential buildings account for 81% of owner-occupied homes (Ministry of Internal Affairs and Communications, 2024), underscoring the importance of implementing targeted measures for these buildings.

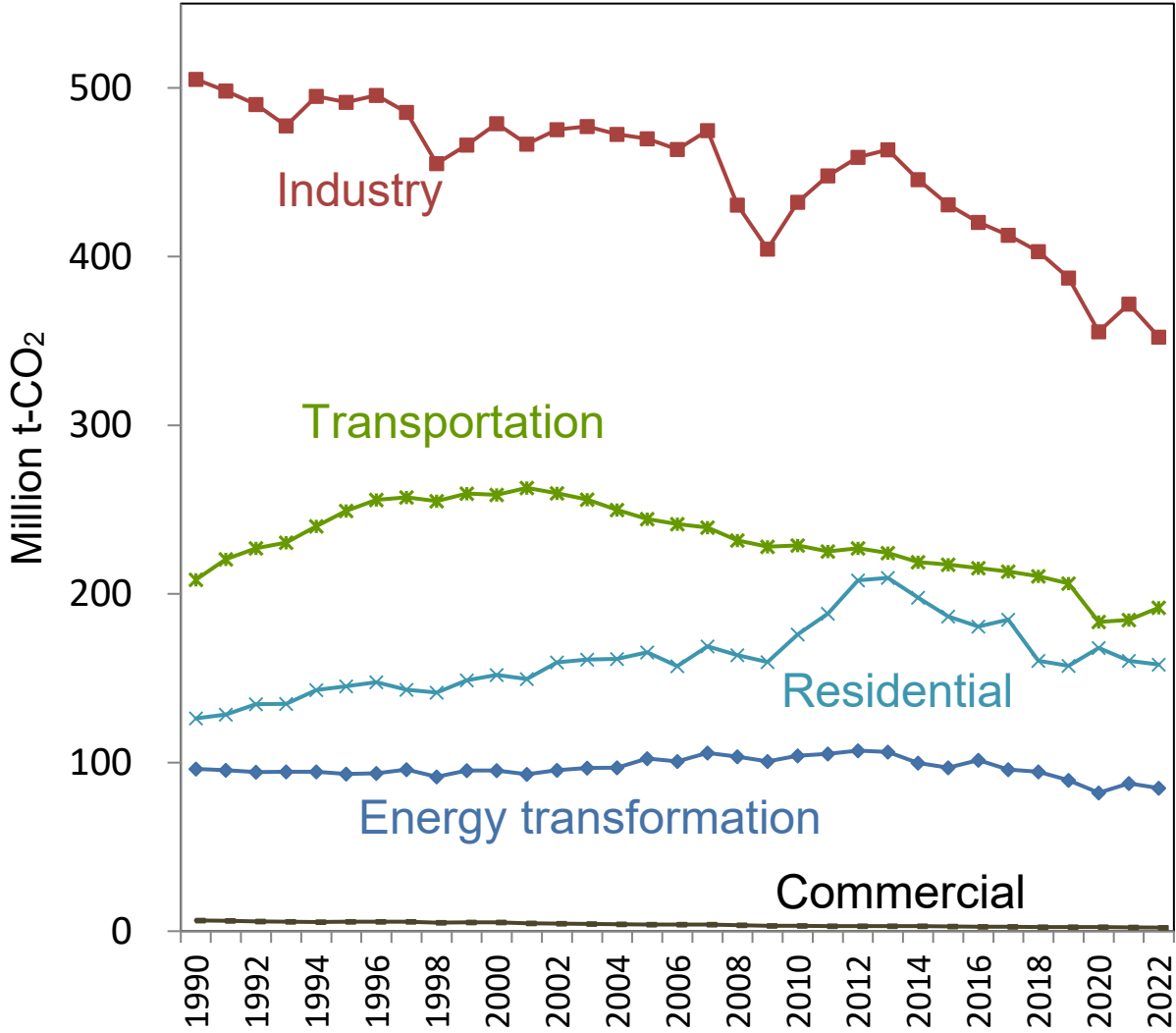


Figure 1-1. Trends in GHG emissions by sector in Japan (Source: Ministry of the Environment (2024))

1.2. The significance of GHG emission estimation data in reduction policies

GHG emissions estimation data plays a crucial role in reduction policies (IPCC, 2022). Specifically, this data forms the foundation for understanding the current state of GHG emissions, setting reduction targets, and evaluating progress. By accurately estimating GHG emissions, policymakers can implement effective measures and identify which sectors or areas have the greatest potential for emission reductions.

Additionally, GHG emissions estimation data serves as a guide for companies and local governments in advancing their own efforts to reduce emissions, promoting the adoption of appropriate emission reduction measures and technologies. For example, accurately tracking data related to Scope 1 (direct emissions), Scope 2 (indirect emissions from energy use), and Scope 3 (emissions related to the supply chain) is essential for companies to identify their emission sources and prioritize areas for reduction (Matthews et al., 2008).

In 2023, the International Sustainability Standards Board (ISSB) made a decision to mandate the disclosure of corporate greenhouse gas (GHG) emissions (IFRS Foundation, 2023). This decision marks a significant step forward in enhancing the visibility and transparency of emissions across entire corporate supply chains, particularly with the requirement to disclose Scope 3 emissions beginning in 2027. The measurement and reporting of Scope 3 emissions will be conducted in accordance with the globally recognized GHG Protocol standards. The GHG Protocol, jointly established in 1998 by the World Business Council for Sustainable Development (WBCSD) and the World Resources Institute (WRI), serves as a valuable framework offering reliability and

standardization in the calculation and reporting of GHG emissions (GHG Protocol, 2011).

In Japan, the 3EID (Environmental Extended Input-Output Database) is featured on the GHG Protocol website as one of the representative environmental extended input-output (EEIO) databases, playing a vital role in the field of GHG emissions evaluation (GHG Protocol, 2024). With the acceleration of efforts to evaluate and report GHG emissions among Japanese companies, the utilization of 3EID, a key tool for emissions calculation, is expected to expand further. This expansion will enable Japanese companies to comply with international standards while strengthening their initiatives toward achieving sustainability goals.

However, the current international situation presents new challenges to the GHG emissions calculation process. Specifically, the surge in crude oil prices triggered by Russia's invasion of Ukraine (Bank of Japan, 2023) has led to significant increases in energy prices and accompanying inflation. These economic fluctuations may be reflected in the accounting data underlying environmental impact estimation databases, such as 3EID, which are based on input-output table, potentially resulting in an overestimation of GHG emissions calculations. Such discrepancies pose serious challenges to ensuring international reliability and comparability. Against this backdrop, the development of tools and guidelines to enable companies to measure Scope 3 emissions more accurately is an urgent priority.

1.2. Structure of this thesis

This Ph.D. thesis comprises 5 chapters (Figure 1-2). Chapter 2 provides a comprehensive literature review on life cycle assessment (LCA), environmentally extended input-output analysis, and LCA in the building sector. It also covers related extended input-output models, structural decomposition analysis, and stock-flow estimation of products. Additionally, the objectives of this study and the significance of addressing them are detailed in this chapter.

Chapter 3 compares two non-survey methods: the double-deflation method (DD method) and a combined method (CD method) that integrates the DD method with the generalized RAS method to deflate an input–output table (IOT). These methods were applied to estimate new datasets of embodied CO₂ emission intensity for Japan, using IOTs for 2005, 2011, and 2015 at constant 2015 prices. Additionally, the estimated data for 367 commodity sectors for specific years (2005 and 2011) were compared. Finally, based on the results, this chapter provides policy implications for governments and life-cycle assessment practitioners regarding the estimation of CO₂ emissions data and its use when analyzing changes in the carbon footprint of products.

In Chapter 4, the embodied CO₂ emission intensity datasets developed in Chapter 3 are incorporated into the analysis framework for residential LCA through time series analysis. This chapter investigates the impact of the economic lifetime of detached wooden residential buildings in Japan on CO₂ emissions during the manufacturing and use phases. Specifically, it estimates the economic lifetime of detached wooden

residential buildings based on real estate transaction data and assesses the effects of changes in CO₂ emissions during the manufacturing and use phases by altering the average lifetime. Based on these findings, this chapter provides evidence and key insights for environmental policy regarding the economic lifetime of buildings.

Chapter 5 summarizes the results from Chapters 3 and 4 and presents the conclusions of this dissertation.

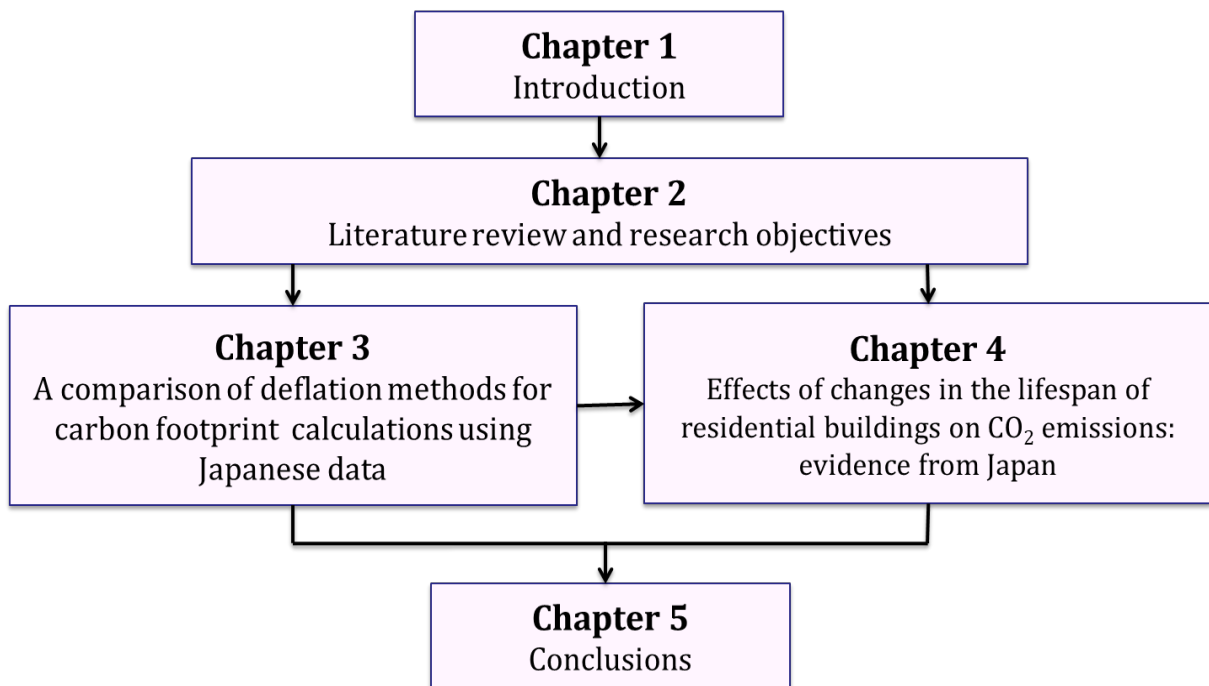


Figure 1-2. Structure of this thesis

The contents of Chapters 3 and 4 in this dissertation have been published in the following peer-reviewed journals as follows.

Chapter 3:

Matsushima, S., Kagawa, S., Nansai, K., Xue, J. (2024) ‘A Comparison of Deflation Methods for Carbon Footprint Calculations using Japanese Data’ *Economic Systems Research*, 36, 337-352.

Chapter 4:

Matsushima, S. (2024) ‘Effects of Changes in the Economic Lifespan of Residential Buildings on CO₂ Emissions: Evidence from Japan’, *Journal of Industrial Ecology*, Revise & Resubmit. [Published in open access on Research Square: <https://doi.org/10.21203/rs.3.rs-5216695/v1>]

Chapter 2: Literature Review

2.1. Life-cycle assessment (LCA)

To address problems such as climate change, it is necessary to incorporate environmental considerations into the decision-making processes of businesses, individuals, governments, and policymakers (Nilsson and Eckerberg, 2007). LCA began to be developed in the 1960s as a tool for assessing environmental impacts, particularly due to growing concerns about environmental degradation and resource limitations (e.g., Finnveden and Moberg, 2005; Bjørn et al., 2017). LCA is an environmental assessment method that evaluates the 'life cycle' of products and services, from the procurement of materials to waste disposal (ISO, 2006a; ISO, 2006b). The International Organization for Standardization (ISO) standardized LCA as part of the ISO 14000 series, an international environmental management standard, in 1997 (Klüppel, 1999). There is general agreement that LCA is an effective tool for assessing environmental performance (Finnveden et al., 2009). LCA is increasingly being used as a decision-making tool for process selection, design, and optimization in the fields of research, industry, and policy (Del Borghi et al., 2007; McManus and Taylor, 2015).

There are three main approaches in LCA. The first is the process model, which aggregates the environmental impacts at each stage of a product's life cycle—resource procurement, manufacturing, use, and disposal—commonly referred to as the 'cradle-to-grave' approach (Gäbel et al., 2004; Eriksson et al., 2007; Luo et al., 2019). This approach allows for detailed analysis of specific products and is particularly useful for companies aiming to achieve lower environmental impacts in manufacturing (Heijungs, 1994; Reich,

2005). For instance, Luo et al. (2019) used a process model LCA to compare station-based bicycle-sharing systems (with return ports) and dockless systems (without return ports), evaluating the environmental impacts of these services based on differences in their operational systems. However, the process model has a limitation: analysts can arbitrarily set system boundaries, which may lead to underestimation of life-cycle CO₂ emissions if indirect emissions from suppliers are not fully accounted for (Lenzen, 2000; Suh et al., 2004). Moreover, Raynolds et al. (2000) highlighted that it is impossible to determine a complete footprint using this approach.

The second is an input-output (IO) model that is based on input-output analysis (Lave et al., 1995; Hendrickson et al., 1997; Hawkins et al., 2007). The estimation using the IO model enables the identification of footprints across the entire supply chain, allows for analysis without the need for creating company-specific inventory data, and can be conducted in a short time (Lenzen, 2000). For example, Lave et al. (1995) used input-output analysis and pollution emission data to evaluate the footprints generated by automobiles, refrigerators, computers, as well as paper cups and plastic cups. However, the IO model, being based on input-output tables, aggregates industries and products broadly on a monetary basis. As a result, the analysis relies on the average technological levels and input-output structures of industries, leading to low resolution in the analytical results (Hertwich, 2005; Peters, 2008). Additionally, the IO model can only assess emissions up to the upstream stage of production in the product's lifecycle, so it cannot account for the environmental impacts during the use phase, recycling, or disposal (Lave et al., 1995).

The third is a hybrid model that combines the IO model and the process model. The hybrid model is recommended in the literature as a means to reduce the bias of process models or to improve the accuracy of input-output analysis (Suh, 2004; Chen, 2009; Crawford and Stephan, 2013; Ward et al., 2018). For example, Chen (2009) conducted an analysis that includes both the wastewater generation stage and the treatment stage, using a case study on automobile wastewater treatment by combining process-based environmental inventory data with input-output tables. However, Yang et al. (2017) pointed out that while the hybrid model approach addresses the bias caused by supplier selection in process-based LCA, it also incorporates estimation bias due to the sectoral aggregation in input-output tables. Additionally, Perkins and Suh (2019) emphasized that regardless of whether the data comes from an IO model database or a process model database, priority should be given to high-quality data that takes both precision and accuracy into account. To summarize this subsection, environmental assessment using LCA continues to attract significant attention in many fields today. Additionally, it has been shown that both process models and IO models complement each other's characteristics; however, the issue of estimation bias due to integration remains a concern even in hybrid models.

Additionally, IPCC WGI (2014) points out that our lifestyles have a significant impact on the environment. In particular, Nishijima (2017) emphasizes that the lifecycle of durable goods is one of the major contributors to global warming, given their widespread presence in our daily lives. Researchers have discussed the trade-off between the lifespan of durable goods and their replacement cycles using stock-flow analysis. This has been incorporated into LCA of durable goods such as automobiles (Kakudate et al.,

2002; Van Schaik and Reuter, 2004; Spitzley et al., 2005; Kagawa et al., 2006, 2008, 2009, 2011, 2013, 2015; Brand et al., 2013; Stahel and Clift, 2016; Nakamoto et al., 2018, 2019, 2022), air conditioners (De Kleine et al., 2011; Nishijima, 2017), smartphones (Suckling and Lee, 2015), vacuum cleaners (Bobba et al., 2016), aircraft (Kito, 2021), and ships (Shimotsuura, 2024). Most of these existing studies estimate product lifetime functions and stock quantities by using data related to the physical lifespan of products, from production to disposal. Among them, Nakamoto and Kagawa (2018) is one of the few studies that quantified economic stock and flow by estimating the economic lifetime function of cars using used car transaction data.

2.2. Environmentally extended Input–Output analysis (EEIOA)

In the 1960s, when pollution issues were prominent, environmentally extended input-output analysis (EEIOA) began to be applied, integrating external factors associated with production and consumption into the input-output tables developed by Wassily Leontief (1936). EEIOA has been used for quantitative estimation of issues that are now major concerns due to the adverse effects of global warming, such as greenhouse gas emissions (Feng et al., 2015; Hoekstra et al., 2016; Nansai et al., 2020), water usage (Emmerson et al., 1995; Zhang et al., 2012; Roson and Sartori, 2015), air pollution (Lange, 1998; Guan et al., 2014; Meng et al., 2015; Nagashima et al., 2017; Nansai et al., 2021), biodiversity loss (Lenzen et al., 2012; Moran and Kanemoto, 2017; Marquardt et al., 2019), deforestation (Hoang and Kanemoto, 2021; Sun et al., 2023), and land use (Lenzen and Murray, 2001). For example, Nansai et al. (2020) estimated the CO₂ emissions from Japan's healthcare services between 2011 and 2015. They suggested that, in addition to

implementing technological improvements in the healthcare service supply chain, it is necessary to provide the public with additional options to simultaneously promote health and mitigate greenhouse gas emissions to protect the planet's well-being.

EEIOA is now widely applied not only to estimate environmental impacts but also to assess resource use (Wood and Garnett, 2009; Weinzettel and Kovanda, 2011; Galli et al., 2012; Wiedmann et al., 2015; Plank et al., 2018; Watari et al., 2020), energy demand and footprints (Liao et al., 2007; Sun, 1998; Weber, 2009; Zhang and Lahr, 2014), and waste generation (Nakamura and Kondo, 2006; Beylot, 2015; Liao et al., 2015). For example, Zhang and Lahr (2014) estimated the regional differences in energy consumption across China from 1987 to 2007 using structural decomposition analysis (SDA). They identified the key factors driving regional disparities and highlighted that the sharp increase in China's energy consumption between 2002 and 2007 was largely attributed to the production of more energy-intensive goods for investment and export during this period. Here, environmentally extended structural decomposition analysis (SDA) helps policymakers quantitatively understand the key factors behind changes in environmental impacts and is used for policy assessment and formulation (Su and Ang, 2012a, 2012b). However, Dietzenbacher and Temurshoev (2012) compared the results of a time series analysis using current price input-output tables and constant price input-output tables, and discovered that deflation bias occurs at the sectoral level. Based on this, SDA is applied to study the physical factors contributing to changes in emissions (such as emission intensities, energy intensity, production technologies, etc.) (Nagashima, 2018), and therefore, time series input-output data should be properly deflated.

2.3. LCA of buildings

At the launch of a construction project, property developers, architects, and urban planners use LCA to identify major impacts or critical processes across the building life cycle (Bribián et al., 2009; Vilches et al., 2017). In the field of building sector LCA, analysis has been conducted using three approaches: process models, IO models, and hybrid models (Vilches et al., 2017). Researchers can analyze the environmental impact of specific construction technologies on energy consumption and CO₂ emissions using the process model (Zhang et al., 2019). Numerous LCA studies on residential buildings have utilized the process model approach (Adalberth, 1997; Peuportier, 2001; Thormark, 2002; Erlandsson and Borg, 2003; Mithraratne and Vale, 2004; Asif et al., 2007; Citherlet and Defaux, 2007; Utama and Gheewala, 2008; Bribián et al., 2009; Blengini and Carlo, 2010; Ortiz-Rodríguez et al., 2010; Morrissey and Horne, 2011; Cuéllar-Franca and Azapagic, 2012; Rossi et al., 2012; Monteiro and Freire, 2012; Bastos et al., 2014; Grant et al., 2014; Morsi et al., 2022). For instance, Monteiro and Freire (2012) analyzed the life cycle energy demand of a residential building in Portugal, assuming a lifespan of 50 years, using European life cycle inventory data. Bastos et al. (2014) studied the life cycle energy and GHG emissions of three types of residential buildings in Lisbon, assuming a lifespan of 75 years and found that the use phase was a critical stage for energy requirements and GHG emissions. However, these studies assumed a uniform lifespan for houses and did not statistically analyze the lifespan as a function of specific house types. Current studies using the process model have primarily focused on individual buildings or specific construction technologies, with few studies providing nationwide insights into energy consumption and emissions throughout the building life cycle.

Chang et al. (2014) developed an IO model that divided the construction sector into 14 subsectors to calculate the energy consumption of the supply chain for buildings in China. They found that aggregating subsectors led to an overestimation of the embodied energy consumption of buildings. In 2015, Imada et al. (2024) developed an environmentally extended input-output framework that considered the functional units of residential buildings and identified the carbon footprint and hotspots within the supply chain structure of Japanese residential buildings. However, these studies focused on emissions from the manufacturing phase and upstream processes without accounting for the environmental impact during the use phase of buildings.

There are also several studies that have conducted building sector LCA using hybrid models (Fay et al., 2000; Lenzen and Treloar, 2002; Bontinck et al., 2017; Chikada, 2017; Säynäjoki et al., 2017; Tonooka, 2017). Lenzen and Treloar (2002) combined a “tiered” hybrid LCA with an environmentally extended input-output framework to analyze the energy inputs in the production of building materials used in wooden residential buildings through structural path analysis. However, this study was limited to the assessment of the manufacturing phase within a building’s life cycle. Bontinck et al. (2017) demonstrated a framework for automating GHG emissions analysis using a hybrid LCA, focusing on structural insulated panels (SIPs) used in housing materials, and evaluated their potential for broader applications. However, this study focused primarily on specific construction technologies, without providing a nationwide understanding of energy consumption or emissions from residential buildings. In a hybrid LCA, evaluation options largely depend on the system boundary set between the process data and IO data, often involving

subjective choices by the LCA practitioner (Säynäjoki et al., 2017).

In summary, existing residential LCA studies have yet to conduct comprehensive nationwide research based on statistically reliable building lifespans. Kayo and Tonosaki (2022) conducted the first study to identify the lifespan functions and half-lives of all wooden and nonwooden buildings in Japan from 1964 to 2020, contributing to the forecasting of building stocks. However, this study only considered the “physical” lifespan, namely from construction to demolition. It is important to note that there are approximately nine million vacant houses in Japan (13.8% of all residential buildings), and this number is increasing (Ministry of Internal Affairs and Communications, 2024). To conduct a nationwide LCA of residential buildings that includes the use phase, it is crucial to estimate the “economic” lifespan of buildings and exclude the environmental impact of vacant houses that are no longer used by residents. Cai et al. (2015) conducted the only nationwide study, to our knowledge, exploring the reduction of emissions during the “manufacturing” phase by extending the lifespan of buildings in China, but it did not integrate the “use” phase into its analysis. This study also only considered the “physical” lifespan from construction to demolition and could not account for the “economic” lifespan of buildings. According to Wuyts et al. (2019), the “economic obsolescence” of residential buildings, influenced by external factors such as legal regulations, may affect building lifespans.

Additionally, in Japan, the energy-saving standards for residential buildings have been updated, leading to improved insulation performance and stricter installation requirements for new residential buildings (Ministry of the Environment, 2021).

Consequently, an increase in the proportion of new buildings in Japan's residential stock was expected to reduce CO₂ emissions during the nationwide use phase. Previous studies have shown that improved insulation performance in residential buildings reduces the energy consumption and CO₂ emissions during use (Radhi, 2009; Ballarini et al., 2014). However, extensive research has been conducted on direct and embodied material requirements based on the stock-flow analysis of residential buildings in Japan (Komatsu et al., 1992; Tanikawa and Hashimoto, 2009; Miatto et al., 2017; Wuyts et al., 2019; Kayo and Tonosaki, 2022). To our knowledge, no previous study has yet to assess how a combination of the end-of-use phase for old residential buildings and the introduction of new ones affects the life cycle environmental impact of residential buildings.

2.4. Summary and contribution of the thesis

Previous studies have advanced the development of three LCA approaches: the process model, the IO model, and the hybrid model, and have quantitatively analyzed the environmental impacts of products. However, there has been limited analysis in LCA studies using low-cost, high-resolution, and comprehensive data.

Moreover, previous studies employing EEIOA have quantitatively clarified the CO₂ emission structure across the entire supply chain associated with final demand. These studies have also utilized structural decomposition analysis to identify technological factors contributing to changes in emissions over time. However, in the analysis of temporal changes in emissions, the effects of deflation should be considered. Despite this need, no time-series data reflecting deflation in embodied environmental load intensity

has been developed.

Additionally, while previous studies have used the three LCA approaches to estimate GHG emissions and carbon footprints from the production of building materials and energy use in residential buildings, they have not incorporated lifespan functions into the LCA. Furthermore, they lack dynamic analyses that account for the stock-flow of residential buildings or the economic lifespan while excluding the influence of vacant houses.

Therefore, in Chapter 3, this paper utilizes Japan's 2005, 2011, and 2015 input-output tables, applying a new non-survey method to deflate the 2005 and 2011 tables to 2015 prices. This approach enables the estimation of embodied CO₂ emission intensities for 367 sectors. The resulting data supports the development of high-resolution, environmentally extended IO datasets and their application to time-series LCA analysis.

In Chapter 4, this paper identifies the economic lifespan of residential buildings in Japan and combines the embodied CO₂ emission intensities developed in Chapter 3 with a stock-flow model to estimate the life cycle CO₂ emissions of residential buildings nationwide. This chapter further analyzes the impact of changes in the economic lifespan of residential buildings on the life cycle CO₂ emissions of the national housing stock and discusses effective environmental policies for the building sector from the perspective of extending building longevity.

Chapter 3: A comparison of deflation methods for carbon footprint calculations using Japanese data

3.1. Introduction

Since Wassily Leontief (1970) developed environmentally extended input–output (hereafter referred to as EIO) tables for the U.S. economy and analyzed air pollutants from U.S. industries, EIO tables have been widely used as one of the main estimation methods to assess environmental burdens from the industrial sector of the country in question. As a seminal contribution, a special issue on the topic of carbon footprint and input–output analysis was published in this journal, and the role of the input–output tables in the practice of greenhouse gas accounting was argued at various levels in the special issue (Wiedmann, 2009).

In Japan, the National Institute for Environmental Studies estimated greenhouse gas emissions from commodity production activities and publicly provided the database entitled “Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables” (hereafter referred to as 3EID) (Nansai et al., 2003). The 3EID database has not only been used in many product life-cycle assessments (LCAs), but has also been employed to build the Eora of global multiregional input-output databases (Lenzen et al., 2013).

The 3EID database for a specific year (e.g., 2015) is estimated by using a “nominal” input-output table (IOT) evaluated in “current” commodity prices (e.g., commodity prices in 2015) published by the Ministry of Internal Affairs and Communications (MIC) every

five years (MIC, 2020a). Therefore, even if we simply compared the multi-year embodied CO₂ emission intensities of a specific sector provided in the 3EID, it could not be interpreted that the change in sectoral-embodied CO₂ emission intensities was due to “physical” technological changes over time. The change in the sectoral-embodied CO₂ emission intensity may have been due to price inflation or deflation in the economy.

It is important for LCA researchers and practitioners to evaluate the embodied CO₂ emission intensity of a specific commodity with a focus on the physical reality. In estimating the embodied CO₂ emission intensities of sectors with a focus on the physical production technologies in the economy, LCA researchers can use linked IOTs (e.g., linked IOTs of 2005, 2011, and 2015) evaluated in “constant” commodity prices for a specific year (e.g., commodity prices in 2015) published by the MIC (MIC, 2020b). In principle, we can see that the linked IOTs at constant prices are not influenced by price inflation or price deflation, but by both physical production technologies and physical final demand.

Environmentally extended structural decomposition analysis (SDA) can quantitatively assist policymakers in understanding the significant contributors to changes in environmental burden. The results of this decomposition have been used for policy assessment and formulation (e.g., Su and Ang, 2012a, 2012b). For instance, SDA has been applied to study the factors contributing to changes in embodied emission intensities, including emission factor, energy mix, energy intensity, and Leontief structure effects. In doing so, the “environmental” decomposition results should reflect both physical production technologies and final physical demand. Therefore, the time-series

input-output datasets should be appropriately deflated.

However, an important problem is the estimation of exact IOTs at constant prices. In Japan, the IOTs at constant prices were estimated by the double-deflation method (hereinafter referred to as the DD method) of a simple non-survey method (MIC, 2020b). The DD method assumes sectoral price homogeneity in the sense that intermediate and final purchases of products supplied by a specific sector is deflated by a “single” composite price index of the products (MIC, 2020b).

For the sectoral price homogeneity assumption, Dietzenbacher and Hoen (1999, P1695) pointed out the following: *“For example, intermediate deliveries from sector i to sector j typically cover a basket of goods, the composition of which will differ from that of a basket delivered from sector i to another sector k . Therefore, the price of each basket delivered by sector i will be different because of its different compositions. Using a single price index for each basket affects the results.”* The above quote from Dietzenbacher and Hoen (1999, P1695) captures the crucial problem with using the DD method. Dietzenbacher and Hoen (1998) recommended using the RAS method as a non-survey method to deflate an IOT.

It is important to note that the RAS method does not impact “real” value added, and it is equivalent to the DD method from the perspective of the core purpose of estimating real value added. Therefore, the DD method has been favored as the conceptually preferred approach for calculating “real” value added owing to its fewer assumptions (Bureau of Economic Analysis, U.S.A., 2023). However, as Dietzenbacher

and Hoen (1999) highlighted, the DD method is unsuitable for accurately estimating “real” intermediate inputs.

It is important to clarify why the RAS method is more suitable than the DD method. The DD method can be represented as $\hat{\mathbf{R}}\mathbf{Z}$, where $\mathbf{Z} = (z_{ij})$, representing an interindustry transaction matrix, and $\hat{\mathbf{R}}$ denotes a diagonal matrix with its diagonal elements denoted as r_i , which are the price indices of products supplied by a specific sector i . In this matrix calculation, the intermediate purchases of products supplied by specific sector i are deflated to $r_i z_{ij}$. Meanwhile, based on the RAS method, we can estimate the deflated interindustry transaction matrix as $\hat{\mathbf{R}}\mathbf{Z}\hat{\mathbf{S}} = (r_i z_{ij} s_j)$, where $\hat{\mathbf{S}}$ denotes a diagonal matrix with its diagonal elements denoted as s_j , which can be interpreted as the price indices of products purchased by a specific sector j . Consequently, the RAS method ultimately provides a cell-specific price index for the (i, j) interindustry transaction as $p_{ij} = r_i s_j$. The DD method can be formulated as $\hat{\mathbf{R}}\mathbf{Z}\mathbf{I}$, where $\mathbf{I}$ represents the identity matrix. Therefore, the DD method can be interpreted as a special case of the RAS method (i.e., the biproportional method) in which $\hat{\mathbf{S}}$ coincides with $\mathbf{I}$.

The RAS method can estimate an *unknown* input coefficient matrix and an *unknown* intermediate delivery matrix to satisfy the constraints of the given row sum vector and column sum vector of the matrix (see Miller and Blair, 2009; Dietzenbacher and Miller, 2009). Junius and Oosterhaven (2003) further developed the generalized RAS (GRAS) method, which allows the application of the RAS method to a more general matrix that includes both positive and negative entries. Lenzen et al. (2007) modified the GRAS method proposed by Junius and Oosterhaven (2003).

Time-series datasets of the embodied energy and emission intensity data should be estimated based on reliable IOTs at constant prices and should provide information to the public. In doing so, LCA practitioners can easily access an open database and analyze changes in the carbon footprint of products over time.

The novelty of this study is as follows. First, to the best of our knowledge, this study is the first attempt to estimate datasets of high-resolution embodied CO₂ emission intensity data in Japan using Japan's IOTs for 2005, 2011, and 2015 at constant prices in 2015. In this study, two datasets of linked IOTs at constant prices were estimated using two non-survey methods: A basic method and a combined method (CD method). The basic method refers to the DD method, whereas the CD method is an elaborated approach based on the DD and GRAS methods. The CD method was applied to an intermediate consumption matrix for which the row and column constraints were calculated using double deflation. Second, we compared two datasets of the embodied CO₂ emission intensities for 367 commodity sectors in a specific year (2005 or 2011), estimated using an IOT deflated by both the basic and CD methods. Su et al. (2010) investigated the impact of sector aggregation when estimating CO₂ emissions embodied in an economy's exports using the input-output analysis framework. Lenzen (2011) showed that when dealing with different classifications of environmental and input-output data, it is preferable to disaggregate input-output data rather than aggregate environmental data, even when environmentally sensitive sectors are occasionally merged within the economic input-output database. Third, we aggregated the embodied CO₂ emission intensity data of 367 sectors into those of 39 sectors and evaluate which aggregated

sectors include higher uncertainty caused by an extreme price homogeneity assumption for the DD method.

The remainder of this paper is organized as follows. Section 2 describes the methodology of the study. Section 3 describes the data used in this study. Section 4 presents the empirical results. Section 5 discusses the major findings and concludes the paper.

3.2. Methodology

3.2.1. Embodied CO₂ emission intensity

When we use two input-output datasets, estimated using the two non-survey methods of the DD method (Miller and Blair, 2009; MIC, 2020b) and the CD method based on the GRAS approach¹ (Junius and Oosterhaven, 2003; Lenzen et al, 2007), the embodied CO₂ emission intensities of sectors in year t can be estimated as follows:

¹ When defining the economic transaction matrix, which includes intermediate and final commodity deliveries to producers and final consumers at current prices as $\mathbf{Z}^{curr} = (Z_{ij}^{curr})$, the economic transaction matrix at constant prices can be easily obtained as $\mathbf{Z}^{DD} = (\tau_i Z_{ij}^{curr}) = (Z_{ij}^{DD})$, where τ_i denotes the price deflator for commodity i . The GRAS elaboration method, i.e., the CD method, aims to determine the optimal bi-proportional coefficients r_i and s_j in the matrix elements $Z_{ij}^{GRAS} = r_i s_j Z_{ij}^{curr}$ under the two constraints of $\sum_j Z_{ij}^{GRAS} = \sum_j \tau_j Z_{ij}^{curr}$ and $\sum_j Z_{ij}^{GRAS} = \sum_i \tau_i Z_{ij}^{curr}$ (see Lenzen et al. (2007) for detailed mathematics).

$$\mathbf{e}_{DD}^t = \mathbf{d}^t(\mathbf{I} - \mathbf{A}_{DD}^t)^{-1} = \mathbf{d}^t \mathbf{L}_{DD}^t \quad (3.1)$$

and

$$\mathbf{e}_{CD}^t = \mathbf{d}^t(\mathbf{I} - \mathbf{A}_{CD}^t)^{-1} = \mathbf{d}^t \mathbf{L}_{CD}^t \quad (3.2)$$

where $\mathbf{e}_{DD}^t = (e_{DD,j}^t)$ and $\mathbf{e}_{CD}^t = (e_{CD,j}^t)$ represent the embodied CO₂ emission intensity row vectors, $\mathbf{d}^t = (d_j^t)$ is the direct CO₂ emission coefficient row vector whose element shows CO₂ emissions directly generated per unit of production of a specific sector j , $\mathbf{I}$ is the identity matrix, and $\mathbf{A}_{DD}^t$ and $\mathbf{A}_{CD}^t$ are the intermediate input coefficient matrices calculated using intermediate input matrices obtained from the two input-output datasets at constant prices.² $\mathbf{L}_{DD}^t = (\mathbf{I} - \mathbf{A}_{DD}^t)^{-1}$ and $\mathbf{L}_{CD}^t = (\mathbf{I} - \mathbf{A}_{CD}^t)^{-1}$ represent the Leontief inverse matrices from the two input-output datasets. It is noteworthy that the intermediate input coefficient matrices in Eqs. (3.1) and (3.2) include not only a portion of domestically produced intermediate goods, but also a portion of imported intermediate goods.

² From the input-output dataset estimated by the DD method, the intermediate input coefficient matrix, $\mathbf{A}_{DD}^t = (a_{DD,ij}^t)$, can be calculated by the equation: $a_{DD,ij}^t = Z_{DD,ij}^t / x_{DD,j}^t$, where $Z_{DD,ij}^t$ represents the intermediate input of commodity i required per unit of output of commodity j , and $x_{DD,j}^t$ represents the gross output of commodity j . In the same way, we can calculate the intermediate input coefficient matrix, $\mathbf{A}_{CD}^t$, from the input-output dataset estimated by the CD method.

In Eqs. (3.1) and (3.2), we assume that all imported intermediate goods (e.g., steel products imported from China to Japan) are produced using domestic production technologies (e.g., steel manufacturing in Japan). Therefore, Eqs. (3.1) and (3.2) provide only “competitive-import-type” embodied CO₂ emission intensity data.³ Su and Ang (2013) demonstrated that the implications regarding the results of CO₂ emissions embodied in trade, derived from two imports assumptions, namely the “competitive-import type” and the “non-competitive-import type,” are not the same. Additionally, Su et al. (2022) showed that the effects of import data treatment on the input-output analysis of embodied emissions are significant at the sector level. Therefore, we estimated the embodied emission intensities based on the IOTs using both import assumptions. In this article, since we empirically investigated how the two price deflation methods affect embodied CO₂ emission intensities via physical production technologies expressed by both imported and domestic intermediate commodities, we focused on the “competitive-import type” embodied CO₂ emission intensities. Both the results of “competitive-import type” embodied CO₂ emission intensities and “non-competitive-import type” embodied

³ From the input-output datasets, the “non-competitive-import type” embodied CO₂ emission intensities of sectors can be estimated by the equations: $\bar{\mathbf{e}}_{DD}^t = \mathbf{d}^t \{ \mathbf{I} - (\mathbf{I} - \hat{\mathbf{M}}_{DD}^t) \mathbf{A}_{DD}^t \}^{-1} = \mathbf{d}^t \bar{\mathbf{L}}_{DD}^t$ and $\bar{\mathbf{e}}_{CD}^t = \mathbf{d}^t \{ \mathbf{I} - (\mathbf{I} - \hat{\mathbf{M}}_{CD}^t) \mathbf{A}_{CD}^t \}^{-1} = \mathbf{d}^t \bar{\mathbf{L}}_{CD}^t$, where $\hat{\mathbf{M}}_{DD}^t$ and $\hat{\mathbf{M}}_{CD}^t$ are the import coefficient matrices whose i^{th} diagonal element shows a percentage of “imported” commodity i in the domestic demand of the commodity i ; otherwise it is zero. It should be noted that if a country imports nothing at all, $\hat{\mathbf{M}}_{DD}^t$ or $\hat{\mathbf{M}}_{CD}^t$ coincides with the zero matrix. In this case, we have $\bar{\mathbf{e}}_{DD}^t = \mathbf{e}_{DD}^t$ and $\bar{\mathbf{e}}_{CD}^t = \mathbf{e}_{CD}^t$, and the “non-competitive-import type” embodied CO₂ emission intensities are exactly the same as the “competitive-import type” embodied CO₂ emission intensities.

CO₂ emission intensities are provided in Supplementary Material S.3.3 (Tables S3-7, S3-8, S3-9, and S3-10).

3.2.2. Comparison of CO₂ emission intensity data obtained by input-output datasets estimated by the two non-survey methods

The relative difference in CO₂ emission intensity between the two non-survey methods estimated in Section 2.1 is identified by the following equation:

$$\alpha_{j_l}^t = \frac{e_{CD,j_l}^t - e_{DD,j_l}^t}{e_{DD,j_l}^t} \quad (j_l \in l) \quad (3.3)$$

where $\alpha_{j_l}^t$ represents the relative difference in the embodied CO₂ emission intensity of sector j_l belonging to aggregated sector l . If the embodied CO₂ emission intensity under the CD method, e_{CD,j_l}^t , is exactly the same as that under the DD method, e_{DD,j_l}^t , the difference function is $\alpha_{j_l}^t = 0(\%)$. The estimated values $\alpha_{j_l}^t$ are provided in Table S3-11 of Supplementary Material S.3.3.

Eq. (3.3) provides a statistical distribution of the difference in the embodied CO₂ emission intensities of sectors belonging to a specific aggregate sector, l . The mean and standard deviation (S.D.) for the difference in the aggregated sector l can be easily calculated as

$$\mu_l^t = \frac{\sum_{j_l \in l} \alpha_{j_l}^t}{N_l} \quad (3.4)$$

$$\sigma_l^t = \sqrt{\frac{\sum_{j_l \in l} (\alpha_{j_l}^t - \mu_l^t)^2}{N_l}} \quad (3.5)$$

where N_l denotes the number of sectors belonging to the aggregated sector l .

3.3. Data

This study used the officially available IOTs for 2005, 2011, and 2015 in constant prices in 2015 in Japan, which were estimated by the DD method (MIC, 2020). The IOTs illustrate intermediate purchases from 496 commodity sectors to 376 commodity sectors, as well as final purchases from 496 commodity sectors to 25 final demand sectors (MIC, 2020a) (see Table S3-5 in Supplementary Material S.3.2). Therefore, intermediate and final purchases are represented as a rectangular matrix (MIC, 2020a; 496 rows $\times$ 401 columns). Intermediate and final purchases for a specific commodity in the available IOTs are deflated by a single price deflator (MIC, 2020a). However, Dietzenbacher and Hoen (1999) pointed out that the sectoral price homogeneity assumption does not reflect the real economy.

We set the rectangular matrix for the intermediate and final purchases of 2005 (2011), estimated using the DD method, as the initial target matrix to be estimated using the GRAS method (Junius and Oosterhaven, 2003; Lenzen et al., 2007). The available IOTs for 2005, 2011, and 2015 in the 2015 constant prices, estimated using the DD method, are provided in Tables S3-1, S3-2, and S3-3 in Supplementary Material S.3.2,

respectively. The IOTs for 2005, 2011, and 2015 in the 2015 constant prices, estimated using the CD method, are provided in Tables S3-4, S3-5, and S3-6 in Supplementary Material S.3.2, respectively. The MATLAB code for GRAS used in this study is provided in Supplementary Material S.3.1.

The National Institute for Environmental Studies released direct and embodied CO₂ emissions intensity data consistent with Japan's IOTs of 2005, 2011, and 2015 in “current” prices that cover 367 commodity sectors (Nansai, 2019; Nansai *et al.*, 2020). Therefore, we aggregated the (496 commodity sectors $\times$ (376 commodity sectors + 25 final demand sectors)) rectangular matrix for intermediate and final purchases in the estimated IOTs at constant prices into the (367 commodity sectors $\times$ (367 commodity sectors + 25 final demand sectors)) rectangular matrix for intermediate and final purchases. Consequently, the size of the intermediate input coefficient matrix and Leontief inverse matrix in Eqs. (3.1) and (3.2) is (367 $\times$ 367), and the size of the direct CO₂ emission coefficient row vector in Eqs. (3.1) and (3.2) is (1 $\times$ 367).

This study further aggregated the 367 commodity sectors into a large-sector classification of 39 commodity sectors to identify the larger gap in sector-embodied CO₂ emission intensities between the two non-survey methods. It should be noted that any sector $j_l = 1, 2, \dots, 367$ belongs to the aggregated sector $l = 1, 2, \dots, 39$ (see Table 3-1).

Table 3-1. Sector classification in this study

Code	Aggregated sector name	Basic classification code
c1	Agriculture, Forestry, And Fishing	bc1 - bc25
c2	Mining	bc26 - bc29
c3	Beverages and Foods	bc30 - bc60
c4	Textile products	bc61 - bc73
c5	Pulp, Paper and Wood products	bc74 - bc90
c6	Miscellaneous manufacturing products (1/3)	bc91
c7	Chemical products	bc92 - bc118
c8	Petroleum and Coal products	bc119 - bc121
c9	Plastic products and rubber products	bc122 - bc124
c10	Miscellaneous manufacturing products (2/3)	bc125 - bc126
c11	Ceramic, Stone and Clay products	bc127 - bc138
c12	Iron and Steel	bc139 - bc151
c13	Non-ferrous metals	bc152 - bc162
c14	Metal products	bc163 - bc169
c15	General-purpose machinery	bc170 - bc177
c16	Production machinery	bc178 - bc189
c17	Business oriented machinery	bc190 - bc196
c18	Electronic components	bc197 - bc201
c19	Electrical machinery	bc202 - bc215
c20	Information and Communication electronics equipment	bc216 - bc224
c21	Transportation equipment	bc225 - bc239
c22	Miscellaneous manufacturing products (3/3)	bc240 - bc248
c23	Construction	bc249 - bc260
c24	Electricity, Gas and Heat supply	bc261 - bc264
c25	Water supply	bc265 - bc267
c26	Waste management service	bc268 - bc269
c27	Commerce	bc270 - bc271
c28	Finance and Insurance	bc272 - bc274
c29	Real estate	bc275 - bc278
c30	Transport and postal services	bc279 - bc299
c31	Information and communications	bc300 - bc309
c32	Public administration	bc310 - bc311
c33	Education and research	bc312 - bc326
c34	Medical, health care and welfare	bc327 - bc335
c35	Membership-based associations, n.e.c.	bc336 - bc337
c36	Business services	bc338 - bc347
c37	Personal services	bc348 - bc365
c38	Office supplies	bc366
c39	Activities not elsewhere classified	bc367

Note: Detailed sector classifications are presented in Table S3-1 of Supplementary Material S.3.2.

3.4. Results

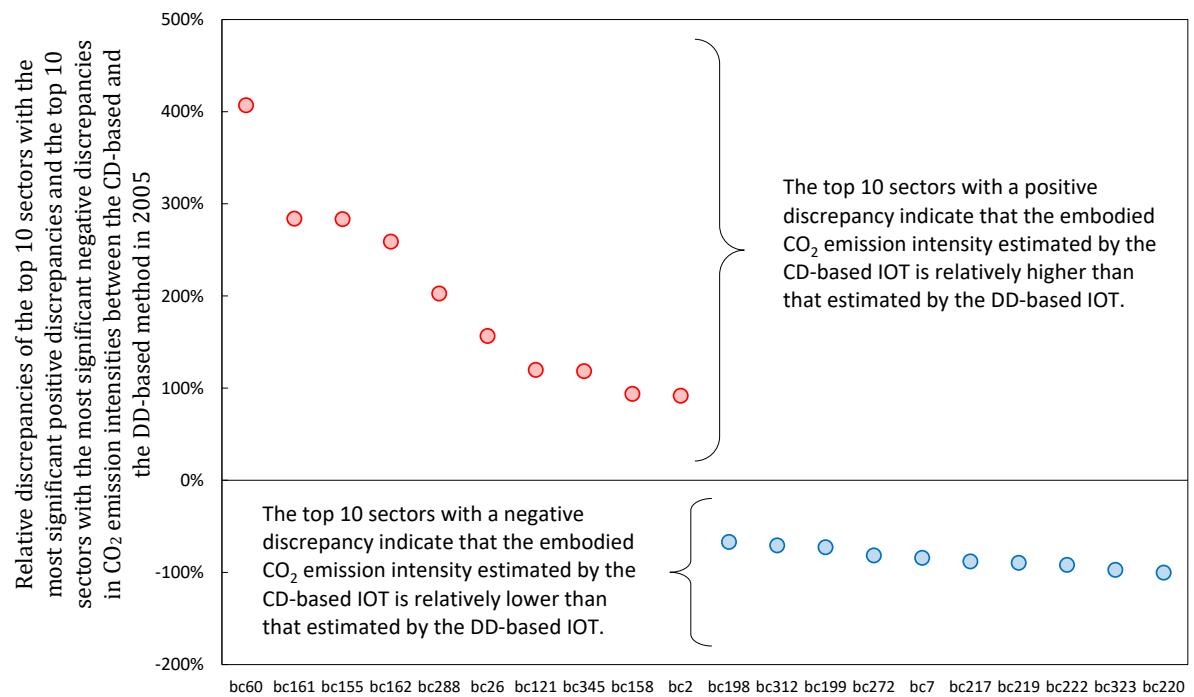
3.4.1. Embodied CO₂ emission intensity from the IOT in constant prices based on the two different non-survey methods

Figures 3-1(a) and 3-1(b) show plots of the relative discrepancies of the top 10 sectors with the most significant positive discrepancies and the top 10 sectors with the most significant negative discrepancies in the embodied CO₂ emission intensities of the 367 sectors of Japan between the CD-based and DD-based IOTs of 2005 and 2011, respectively. The relative difference on the vertical axis was calculated using Eq. (3.3). In 2005 and 2011, the respective embodied CO₂ emission intensities were approximately along the $\alpha=0(\%)$ (Table S7-11 of Supplementary Material S.3.3). This means that for each sector, the embodied CO₂ emission intensities estimated by the DD-based and CD-based IOTs are roughly the same.

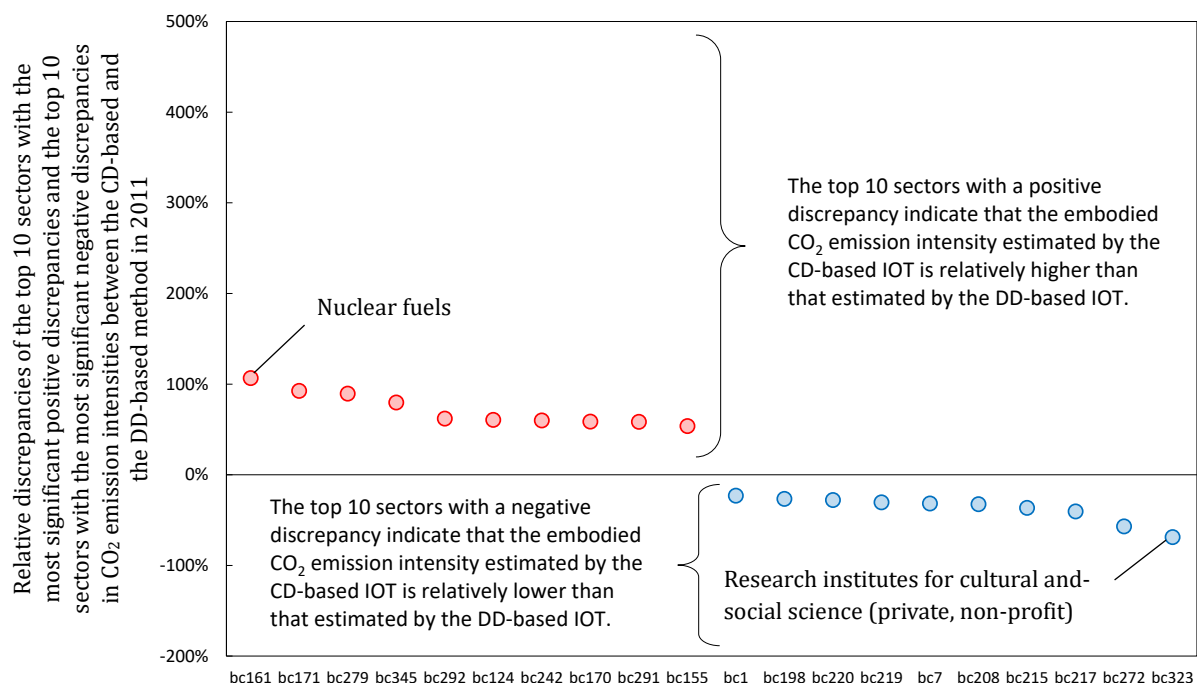
Meanwhile, Figures 3-1(a) and 3-1(b) show that some sectors deviate considerably from the $\alpha=0(\%)$ line. For example, in Figure 3-1(a), the embodied CO₂ emissions intensity of the tobacco sector (bc60) estimated by the CD-based IOT for 2005 was 407% larger than that estimated by the DD-based IOT for 2005 (Figure 3-1(a)). This implies that if LCA practitioners used the embodied CO₂ emission intensity of the tobacco sector (bc60), estimated by the officially available DD-based IOT of 2005, the life-cycle product emissions would be considerably underestimated. Thus, the straightforward DD method may conceal the CO₂ increase in this sector through the incorrect use of price deflators. Conversely, considering that the embodied CO₂ emission intensity of the research institutes for cultural and social science (non-profit institutions) sector (bc323), estimated

by the CD-based IOT for 2011, was 69% smaller than that estimated by the DD-based IOT for 2011 (Figure 3-1(b)), the DD method may further conceal the CO₂ mitigation effort in this sector.

It is important to note that Figures 3-1(a) and 3-1(b) were made from the embodied CO₂ emission intensities of sectors obtained by using the “competitive-import type” IOTs of 2005 and 2011 in 2015 constant prices, respectively. The “competitive-import type” IOTs implicitly assume that imported products (e.g., iron and steel that was produced in China and imported to Japan) were produced using domestic production technologies (e.g., Japan’s steel manufacturing technology). The LCA practitioners may wonder how the domestic production technology assumption affects the embodied CO₂ emission intensities of the sectors. As in the second footnote, we excluded imports from intermediate and final purchases in IOTs at constant prices and, subsequently, estimated the embodied CO₂ emission intensities of the 367 sectors as $\bar{e}_{DD}^t$ and $\bar{e}_{CD}^t$. In summary, for each sector, the “non-competitive-import type” embodied CO₂ emission intensity estimated by the DD-based and CD-based IOTs are *roughly* the same in 2005 and 2011 (Table S3-11 of Supplementary Material S.3.3); however, some sectors, such as the tobacco sector (bc60) and railway transport sector (passengers) (bc279), show a large difference between the embodied emission intensities of the DD-based and CD-based IOTs (Figures S3-1).



(a) The plots of 2005.



(b) The plots of 2011.

Figure 3-1. The plots of relative discrepancies of the top 10 sectors with the most significant positive discrepancies and the top 10 sectors with the most significant negative discrepancies in embodied CO₂ emission intensities of 367 sectors of Japan between the CD-based the DD-based IOTs of 2005 and 2011 in 2015 constant prices.

3.4.2. Difference in the embodied CO₂ emission intensities of sectors belonging to a specific aggregated sector estimated by the DD-based and CD-based IOTs

Figures 3-2(a) and 3-2(b) show the box-and-whisker diagram for the difference in the embodied CO₂ emission intensities of sectors belonging to a specific aggregated sector that were estimated by the “competitive-import type” DD-based IOT and “competitive-import type” CD-based IOT, respectively. The difference on the vertical axis was calculated using Eqs. (3.3), and the numbers (1, 2, ..., 39) on the horizontal axis correspond to the numbers in the large classification code (c1, c2, ..., c39). A difference value far from $\alpha = 0(\%)$ indicates that the embodied CO₂ emission intensity of a specific sector estimated by the CD-based IOT is significantly different from that estimated by the DD-based IOT.

There was a large variation in the difference in embodied CO₂ emission intensities of the five sector groups in 2005 of non-ferrous metals (c13) (S.D. =115%); finance and insurance (c28) (S.D. =77%); beverages and foods (c3) (S.D. =73%); mining (c2) (S.D. =66%); and petroleum and coal products (c8) (S.D. =51%) (Figure 3-2(a) for the box-and-whisker diagram). We also find large variations in the differences between the aforementioned sector groups in 2011 (Figure 3-2(b)).

A detailed look at Figure 3-2(a) also shows that the average value of the differences for the sectors belonging to the non-ferrous metals group (c13) was approximately unity in 2005, implying that in this sector group (c13), the embodied emission intensities based on the CD-based IOT were approximately 87% larger than those based on the DD-based IOT on the sector average (see $\times$ mark #13 in Figure 3-2(a)). Specifically, in the non-

ferrous metals group (c13), the sector average of the embodied CO₂ emission intensities based on the 2005 DD-based IOT in 2015 constant prices was 3.18 t-CO₂ per million JPY, while the sector average of the embodied CO₂ emission intensities based on the 2015 IOT in 2015 current prices was 4.23 t-CO₂ per million JPY. This result reveals that the embodied CO₂ intensity of the non-ferrous metals group increased 33.02% between 2005 and 2015. However, in this sector group (c13), noting that the sector average of the embodied CO₂ emission intensities based on the 2005 CD-based IOT in 2015 constant prices was 5.19 t-CO₂ per million JPY, the CO₂ emission rate during the decade is quite different: For one, 33%, and for the other, -18.5%. Thus, the life-cycle emission reduction effort of a sector group might not be correctly evaluated because of the problem of deflating the IOTs.

In this context, the average differences in the embodied CO₂ emission intensities of the “non-competitive import type” for sectors within the information and communication electronics equipment group (c20) were remarkable in 2005 (65 %) and 2011 (24 %). Su et al. (2022) highlighted the substantial impact of import data processing on various sectors, including the manufacturing of communication equipment, computers, and other electronic equipment.

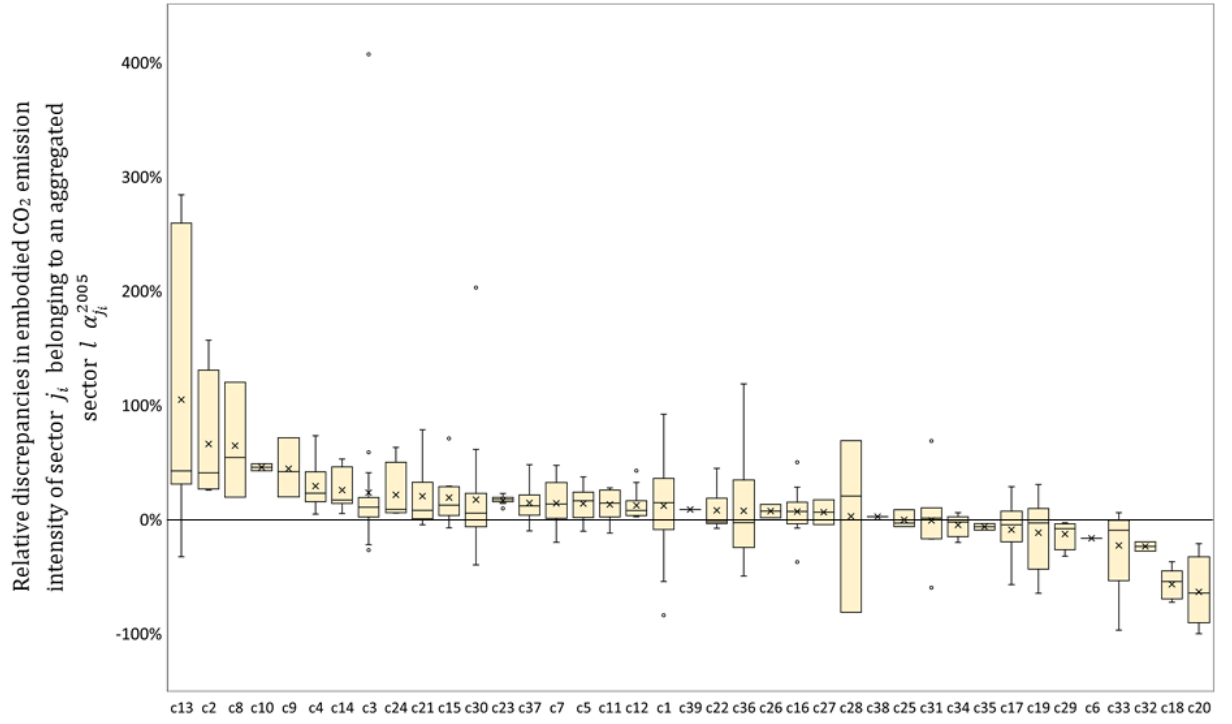
Figures 3-3(a) and 3-3(b) display box-and-whisker diagrams illustrating the discrepancies in the carbon footprints of the sectors within a specific aggregated sector. These discrepancies were estimated using the “competitive-import type” DD-based IOT and “competitive-import type” CD-based IOT, respectively. The difference along the vertical axis was calculated using the equation: $\beta_{jl}^t = \frac{e_{CD,jl}^t f_{CD,jl}^t - e_{DD,jl}^t f_{DD,jl}^t}{e_{DD,jl}^t f_{DD,jl}^t}$, where β_{jl}^t

represents the discrepancy in the carbon footprint of sector j_l within the aggregated sector l . The DD- and CD-based carbon footprints of sector j_l were calculated by multiplying the embodied emission intensities of sectors e_{DD,j_l}^t and e_{GRAS,j_l}^t , by the final demand of sectors j_l , f_{DD,j_l}^t and f_{CD,j_l}^t , respectively.

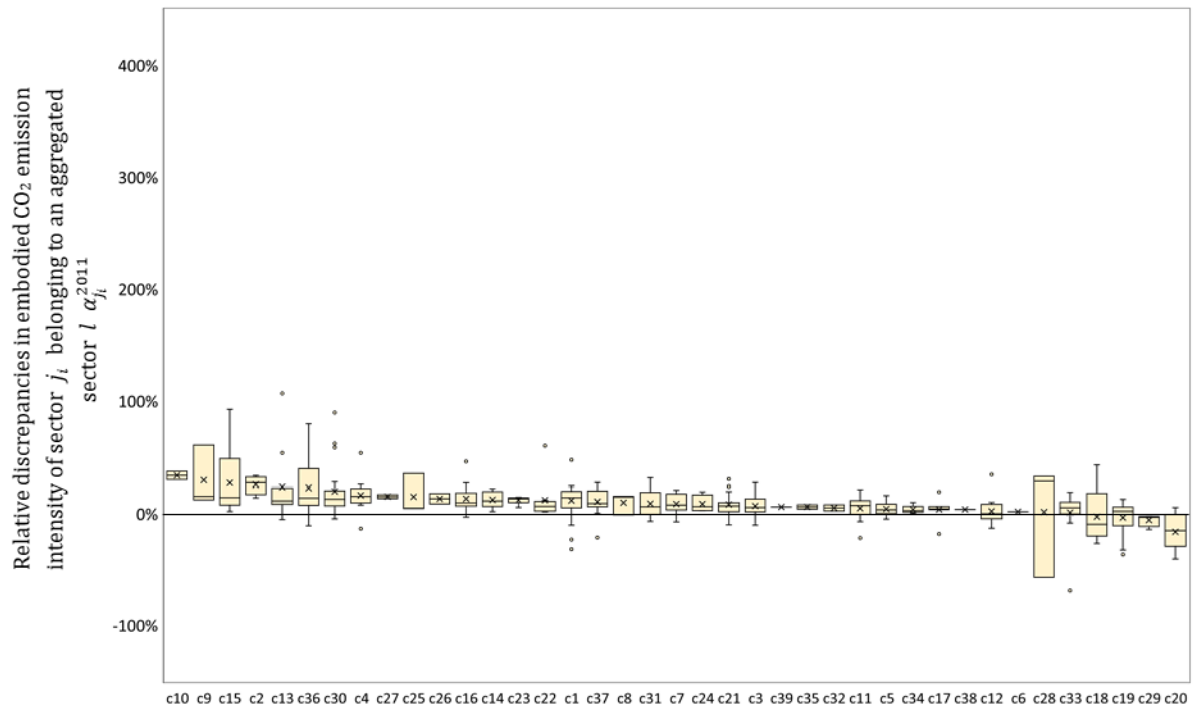
In 2005, significant variations were observed in the differences in carbon footprints among the sector groups: Mining (c12) (S.D. = 1504%), textile products (c4) (S.D. = 437%), and chemical products (c7) (S.D. = 394%) (see Figure 3-3(a) for the box-and-whisker diagram). Similarly, in 2011, substantial variations were found in the differences among sector groups: Ceramic, stone, and clay products (c11) (S.D. = 1255%); business services (c36) (S.D. = 1203%); miscellaneous manufacturing products (3/3) (c22) (S.D. = 585%), which includes sectors like "tatami" (straw matting), straw products, jewelry, and adornments (refer to Figure 3-3(b)).

A detailed analysis of Figure 3-3(a) reveals that the average difference between sectors within the mining group (c2) was 776% in 2005. This implies that within this sector group (c2), the carbon footprint based on the CD-based IOT was 776% larger than that based on the DD-based IOT, on average, for the sector. Specifically, in the mining group (c2), a comparison between the sector's average carbon footprint based on the 2015 IOT and 2005 DD-based IOT at 2015 constant prices showed a 44% reduction in the sector's average carbon footprint during this decade. Conversely, a comparison between the sector's average carbon footprint based on the 2015 IOT and 2005 CD-based IOT at 2015 constant prices shows a 33% increase in the sector's average carbon footprint during this decade. Thus, the evaluation of emission reduction efforts throughout the supply

chain of the mining group (c2) might not be accurate because of issues in deflating the IOTs.

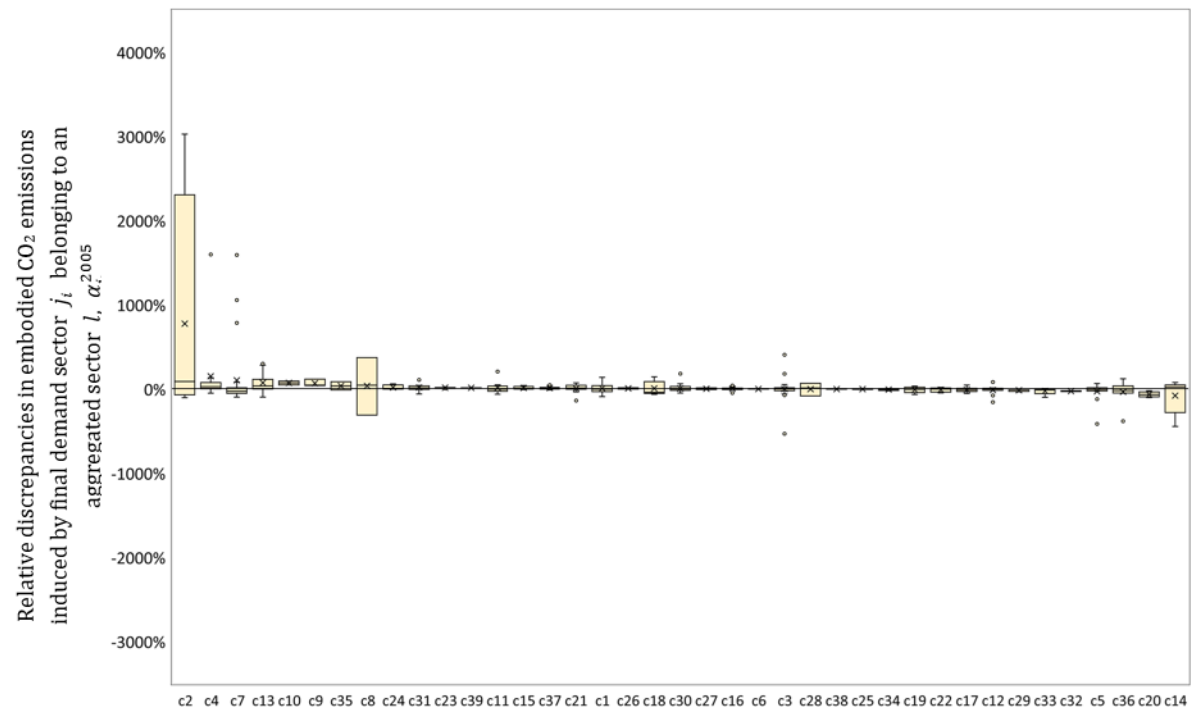


(a) Box-and-whisker diagram of 2005.

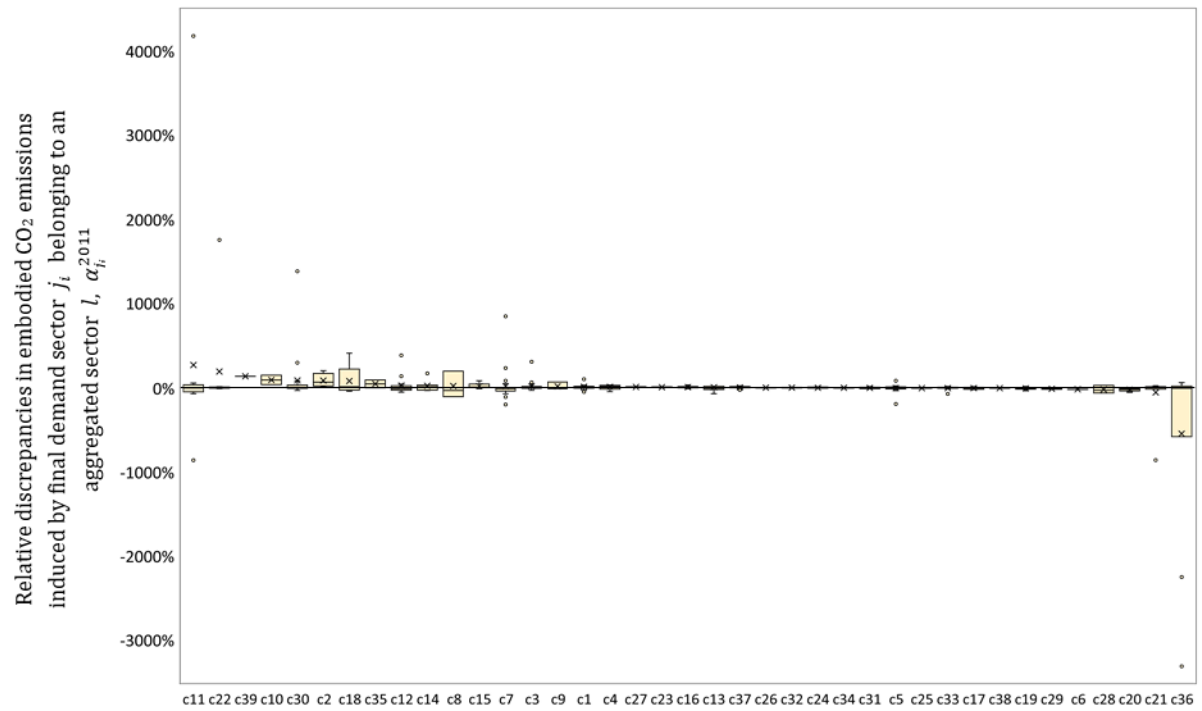


(b) Box-and-whisker diagram of 2011.

Figure 3-2. Box-and-whisker diagram for the relative discrepancies in the embodied CO₂ emission intensities of sectors belonging to a specific aggregated sector that were estimated by the DD-based and CD-based IOTs in 2005 and 2011.



(a) Box-and-whisker diagram of 2005.



(b) Box-and-whisker diagram of 2011.

Figure 3-3. Box-and-whisker diagram for the relative discrepancies in the embodied CO₂ emissions induced by final demand sectors belonging to a specific aggregated sector that were estimated by the DD-based and CD-based IOTs in 2005 and 2011.

3.4.3. Discrepancy in the embodied CO₂ emission intensities of aggregated sectors based on the DD-based and CD-based IOTs

Based on the available IOT data of 2005, which comprises 367 sectors at current prices, LCA practitioners can initially aggregate these 367 sectors into 39 sectors at current prices. Subsequently, they can convert the aggregated IOT data in current prices into constant prices of 2015 using the DD method. The DD-based aggregated IOT data for the 39 sectors at constant prices readily provides the embodied CO₂ emission intensities for these aggregated sectors in 2005. We refer to this set of estimated emission intensities derived from the DD-based aggregated input-output system as Type I emission intensity data.

Alternatively, using the available IOT data from 2005, which comprises 367 sectors at current prices, LCA practitioners can use the aggregated IOT of 39 sectors at current prices and, subsequently, convert the aggregated IOT data in current prices into constant prices of 2015 using the CD method. Similarly, we refer to this set of estimated emission intensities derived from the CD-based aggregated input-output system as Type II emission intensity data. It is important to note that the Type I and Type II emission intensity datasets can be seen as two approximate datasets of the “true” aggregated emission intensity data derived from the disaggregated input-output system of 367 sectors at “constant” prices. This “true” aggregated emission intensity data is referred to as Type III emission intensity data.

Based on the 2005 IOT data, we conducted an empirical analysis to determine whether the alternative yields results closer to reality, examining which of Type I and II are closer to Type III. Figure 3-4 shows a bar graph illustrating the discrepancies between Type III

and Types I and II. It should be noted that the discrepancy was calculated by subtracting the Type I (or Type II) emission intensity of a specific sector from the Type III emission intensity of the same sector. The blue bars represent discrepancies between Type III and Type I, whereas the red bars represent discrepancies between Type III and Type II. Based on the results, we found that the average discrepancy in the blue bars was -1.00 (t-CO₂), and in the red bars, it was 0.17. Furthermore, discrepancies ranged from -1.61 (t-CO₂) to 0.73 (t-CO₂) in the blue bars and from -2.22 (t-CO₂) to 1.57 (t-CO₂) in the red bars, with percentages relative to the results in Type III ranging from -89% to 19% for the blue bars and from -195% to 41% for the red bars, indicating significant disparities. In other words, when LCA researchers and/or practitioners aggregate sectoral-embodied CO₂ emission intensities at constant prices, it is strongly recommended to use a CD-based IOT with a higher sector resolution of 367 sectors at constant prices, as estimated in this study. We emphasize that the DD-based IOT with a higher sector resolution of 367 sectors at constant prices does not yield reliable aggregated sector-embodied CO₂ emission intensities at constant prices.

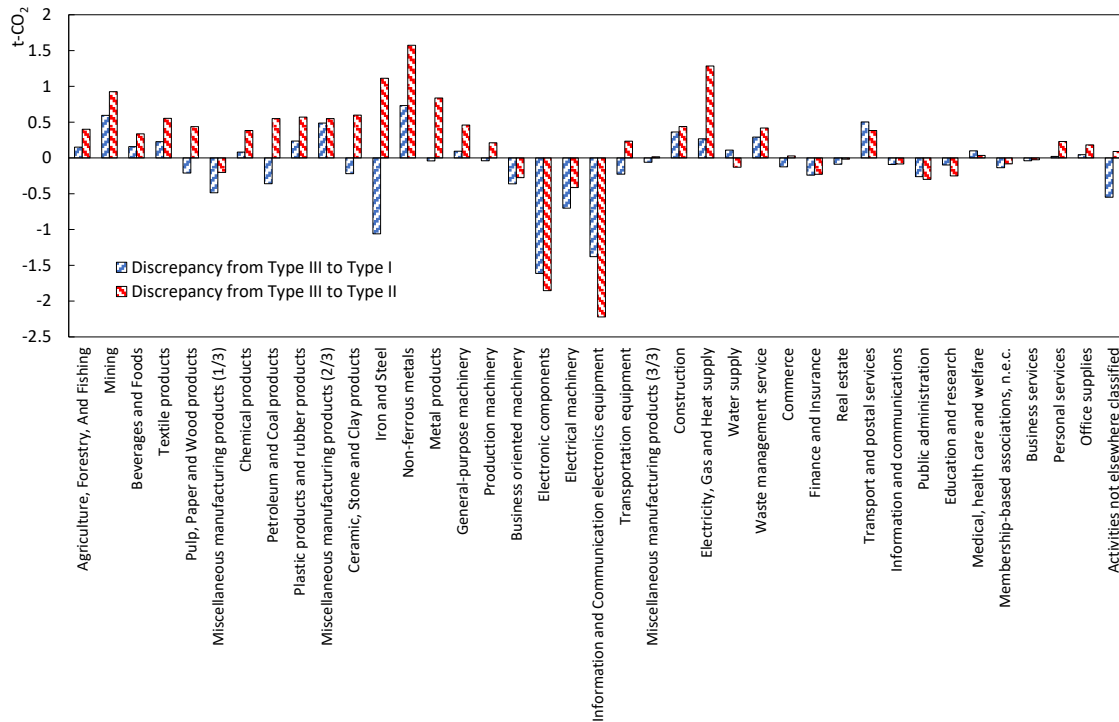


Figure 3-4. Bar graphs depicting discrepancies between Type III and either Type I or Type II in the embodied CO₂ emission intensities of 2005. Note: The Type I embodied CO₂ emission intensity data of 2005 was estimated using the DD-based aggregated IOT data for the 39 sectors at constant prices of 2015. The Type II embodied CO₂ emission intensity data of 2005 was estimated using the aggregated IOT of 39 sectors in current prices of 2005 and, subsequently, converting the aggregated IOT data in current prices into constant prices of 2015 using the CD method. The Type III embodied CO₂ emission intensity data of 2005 was estimated using the CD-based aggregated IOT data for the 39 sectors at constant prices of 2015.

3.5. Discussion and Conclusions

It is well known that IOTs are secondary statistics that describe all intermediate and final purchases in a year in a country. The Japanese government conducts a survey on a wide variety of enterprises every five years and collects information on the intermediate commodities necessary for producing a specific commodity in a year (MIC, 2020). Based on the survey data, intermediate purchases in the Japanese IOT are described as a commodity-by-commodity table in “monetary” terms. It is important to note that, at least in Japan, it is very difficult to collect information on the detailed prices of intermediate goods in a commodity basket delivered from sector i to sector j owing to time and budget constraints. Therefore, we cannot calculate a price deflator of the specific intermediate delivery from sector i to sector j based on the survey data, and it is difficult to estimate the IOT in “constant” prices due to the lack of detailed price deflators of the intermediate deliveries.

Researchers have so far estimated the changes in the embodied CO₂ emissions of the economy over time and investigated the sources of the changes in the embodied CO₂ emissions (e.g., Nansai et al., 2009). Researchers can also use a publicly available database of embodied CO₂ emission intensities (Nansai, 2019) to compare the embodied CO₂ emission intensity of a specific commodity during the study period. Since the embodied CO₂ emission intensities of commodity sectors were estimated using the IOTs in “current” prices, the above-mentioned comparison analysis includes the effects of price changes and, thus, does not reflect the physical reality of the economy.

To highlight the physical reality of the economy, researchers can estimate the embodied CO₂ emission intensities of commodity sectors based on the IOTs in “constant” prices, estimated using the DD method, as in Nansai et al. (2009). However, this study demonstrates that in some sectors, such as the tobacco sector, the embodied CO₂ emission intensities estimated by DD-based IOTs are considerably higher than those estimated by CD-based IOTs, which implicitly consider the price deflators of intermediate deliveries.

The results also show that in some aggregated sector groups, such as non-ferrous metals, finance and insurance, beverages and foods, mining, and petroleum and coal products, larger uncertainties exist in the embodied CO₂ emission intensities based on IOTs at constant prices, as shown in Figures 3-2(a) and 3-2(b). The price index has been shown to vary across transactions due to factors such as large-scale transactions, geographical conditions, and transaction timing. In particular, the non-ferrous metals group, which includes materials and products such as copper, zinc, and aluminum, is primarily traded in large quantities for use in major industries like construction, automotive manufacturing, and aerospace. As a result, the significant variation in price indices across transactions is considered to have a substantial impact on CO₂ emission intensity.

Su et al. (2010) conducted an empirical investigation of the effects of sector aggregation on CO₂ emissions embodied in Chinese exports. Their study revealed significant aggregation biases in the total CO₂ emissions embodied in these exports. It is noteworthy that Su et al. (2010) used the 2002 Chinese IOTs at “current” 2002 prices. They emphasized the importance of carefully selecting the sector aggregation level when

estimating CO₂ emissions embodied in Chinese exports. Building on the crucial insights provided by Su et al. (2010), this study sheds light on the research topic of appropriately deflating a country's IOTs. It highlights that IOTs in “constant” prices, deflated using various methods, can yield wide variations in embodied CO₂ emission intensities and embodied CO₂ emissions at different aggregation levels. Based on these results, we recommend not using the simple DD method to estimate embodied CO₂ emissions from the IOTs at constant prices. Instead, we suggest using the embodied CO₂ emissions database from IOTs with higher sector resolution estimated through an elaboration method that combines both the DD and GRAS methods. The LCA practitioners can use Japan's embodied CO₂ emissions database on this journal's website. When conducting LCAs for large-scale products in sectors such as construction, it is strongly recommended to use the database provided in this study.

Chapter 4: Effects of changes in the lifespan of residential buildings on CO₂ emissions: evidence from Japan

4.1. Introduction

In Japan, residential buildings have relatively short lifespans (Wuyts et al., 2019). The government has established a statutory useful life of 22 years for wooden houses (National Tax Agency, 2017); which accounts for approximately 90% of detached residential buildings. The statutory useful life refers to the number of years during which a depreciable asset can be expected to provide the usual benefits for its intended purpose, assuming normal maintenance and repair. This period is defined by the ‘Ordinance on the Useful Life of Depreciable Assets’ (Ministry of Finance, 1965). Residential buildings that exceed their statutory useful lives have little value and are difficult to resell in the real estate market (Fukumoto, 2012). Thus, residential buildings older than 22 years that are not in active use do not typically find a place in the second-hand market, diverting housing demand toward new residential buildings.

This situation has economic merits. The construction sector is a significant industry in both developed and developing countries (Ortiz et al., 2009), and the demand for new construction is expected to create employment opportunities and the corresponding ripple economic effects. However, this has also raised environmental concerns. A large amount of CO₂ is emitted during the construction of new residential buildings (Huang et al., 2018; Onat and Kucukvar, 2020; Imada et al., 2024), which may meet the requirements for decarbonization. Recently, energy-efficient housing, such as zero-energy houses (ZEH), has been attracting attention owing to environmental considerations (Ministry of the

Environment, 2020). Progressing toward replacing Japan's residential building stock with housing based on newer energy efficiency standards could help mitigate the amount of energy consumed and CO₂ emitted by older houses. In other words, the lifespan of residential buildings may involve a trade-off, where increased CO₂ emissions occur during the manufacturing phase, driven by the rising demand for new residential buildings, in contrast to decreased CO₂ emissions during the use phase due to a higher proportion of new buildings within the overall residential building stock. Therefore, the environmental impact assessment of residential buildings does not need to include an assessment of the manufacturing and use phases independently, but rather a life cycle assessment (LCA), which assesses material extraction, manufacturing, and use until the end of life (Udo de Haes et al., 2004). In this study, the impact of the lifespan of detached wooden residential buildings in Japan on CO₂ emissions throughout their life cycle was examined.

More specifically, this study analyzed the trade-off between increased CO₂ emissions during the manufacturing phase of new residential buildings and decreased CO₂ emissions during the use phase, owing to a higher proportion of new buildings in the stock. The novelty of this study is as follows: First, it represents the first attempt to investigate the impact of changes in the lifespan of detached houses on CO₂ emissions during the manufacturing and use phases at the national level. This study combines an environmentally extended input-output model with a stock-flow model to conduct a nationwide LCA of detached wooden residential buildings in Japan, considering the material extraction, manufacturing, use, and end-of-use phases. Second, this study estimates the "economic" lifespan of detached wooden residential buildings. Using real estate transaction data, this study statistically estimates the period until houses are no

longer used by residents and excludes the impact of vacant houses from the LCA. Additionally, by analyzing the effect of economic lifespan on national emissions, this study provides valuable insights for policymaking. By discussing how regulations, such as the statutory useful life of buildings, impact the environmental burden of the residential sector, this study offers insights that can serve as guidelines for future policies aimed at reducing overall carbon emissions from the residential sector.

4.2. Methodology and data

4.2.1 Estimation of the economic lifespan of residential buildings and stock dynamics

To estimate the probability density function of the economic lifespan of such buildings in Japan, this study collected data from the period from construction up to the point when 234 detached wooden residential buildings were no longer in use by homeowners. Specifically, this study utilizes a real estate database that contains information on residential buildings constructed over various years and later traded as worthless land attachments (Ministry of Land, Infrastructure, Transport and Tourism, 2023). In this study, the economic lifespan of a residential building was defined as the period from its construction to its transaction as a worthless land attachment. These old residential buildings include properties ranging from those that have become old without ever being on the second-hand market since their construction to those that have been used by multiple households across the second-hand market and aged naturally.

Figure 4-1 illustrates the economic lifetimes of residential buildings, representing the lifetime of residential buildings used by a single household (Case 1) and that of residential

buildings used by multiple households (Case 2). Residential buildings that are no longer used before reaching the statutory useful life still hold value, being transferred to subsequent households through the second-hand market. However, those that are not used after reaching their statutory useful life lose their value. In other words, the data indicate the period during which residential buildings are actively in use, regardless of the number of households using them, and do not include periods during which buildings are vacant or demolished. Based on these data, the economic probability density function of the residential buildings was estimated.

This study examines the four lifetime distribution functions considered most plausible in the context of durable goods (normal, Weibull, gamma, and Rayleigh distributions) (Bayus, 1988; Islam and Meade, 2000; Oguchi and Fuse, 2015; Kito, 2021), as well as the preferred log-normal distribution in the context of Japanese housing studies (Tsutsumi and Komatsu, 2004; Hashimoto et al., 2007; Tanikawa et al., 2015; Miatto et al., 2017; Kayo and Tonosaki, 2022). The maximum likelihood estimation was utilized for lifetime distribution functions. The most appropriate probability density function for the database was identified by applying the Akaike information criterion (AIC). After estimating the parameters of the optimal lifetime distribution function, the cumulative survival probability distribution function $F(t)$ (i.e., the probability that a housing unit manufactured in year 0 is still in use as a residence after t years) was derived. The cumulative survival probability $\varphi(t)$ in year t for a housing unit manufactured in year 0 can be defined as $\varphi(t) = 1 - F(t)$.

The stock of detached wooden residential buildings in Japan was estimated based on

the identified $F(t)$ values. This study assumed that all detached residential buildings follow the same distribution function. The economic residential stock in year t of newly manufactured buildings in year i was estimated as follows:

$$\begin{cases} S(1) = B(1) \\ S(2) = B(2) + \varphi(1)B(1) \\ S(3) = B(3) + \varphi(2)B(1) + \varphi(1)B(2) \\ \vdots \\ S(t) = B(t) + \sum_{i=1}^{t-1} \varphi(t-i)B(i) \end{cases} \quad (4.1)$$

where $S(t)$ represents the stock of detached wooden residential buildings in use in year t and $B(t)$ represents the number of detached wooden residential buildings newly constructed in year t . According to the Ministry of Land, Infrastructure, Transport, and Tourism (2024b), newly constructed detached wooden residential buildings will account for approximately 90% of all newly constructed detached residential buildings each year from 1988 to 2023. Therefore, this study assumed that the proportion of newly constructed detached wooden residential buildings was 90% of all the newly constructed detached residential buildings for each year from 1950 to 2020. Consequently, for the number of newly constructed detached wooden residential buildings, this study utilized the time series data of buildings starting in 2023 (Ministry of Land, Infrastructure, Transport, and Tourism, 2024b), multiplied by 90%. $\varphi(t-i)$ represents the survival probability of residential buildings manufactured in year i at year t . The number of construction years, denoted as t , ranged from 1950 to 2020.

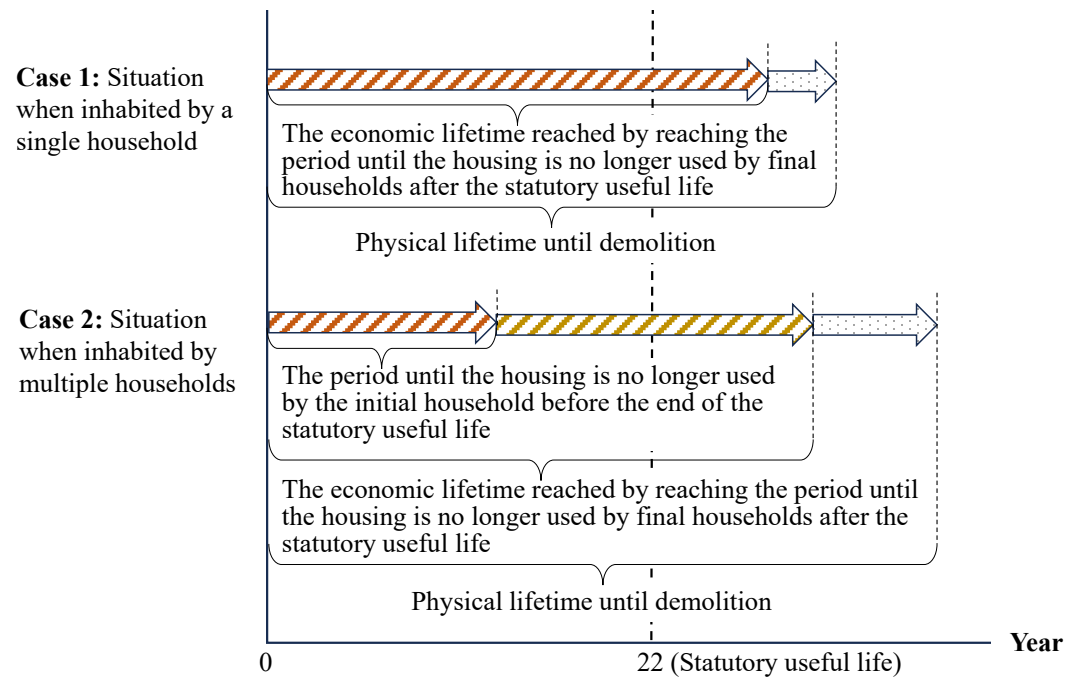


Figure 4-1. Economic and physical lifetimes of residential buildings used by single and multiple households

4.2.2 CO₂ emissions from residential buildings during the manufacturing phase

To estimate the CO₂ emissions induced by the construction of new residential buildings and the manufacturing of essential materials, this study adopted an extended environmental input-output model (Miller and Blair, 2009). This model addresses emissions throughout the supply chain associated with the construction of new residential buildings and manufacture of materials. The production vector $\mathbf{x} = (x_i)(i = 1, \dots, n)$ in an input-output table with n industries is described as follows:

$$\begin{aligned}\mathbf{x} &= \mathbf{Z}\mathbf{i} + \mathbf{f} \\ &= \mathbf{A}\mathbf{x} + \mathbf{f}\end{aligned}\tag{4.2}$$

where $\mathbf{Z} = (z_{ij})$ is the intermediate input matrix consisting of 367 commodity sectors and z_{ij} indicates the intermediate input from sector i to sector j . For the data for $\mathbf{Z}$, this study utilized the intermediate consumption matrix of input-output tables for 2005, 2011, and 2015 at 2015 constant prices in Japan (Matsushima et al., 2024) to estimate the time-series CO₂ emissions for 2005, 2011, and 2015. The available IOTs for 2005, 2011, and 2015 are provided in Table S3-4, S3-5, and S3-6, respectively, in the Supplementary Material S.3.2. Here, $\mathbf{f}$ denotes the final demand vector, with its element in the wooden residential building sector having a value of and all other elements being zero. This study calculates the average demand per wooden residential building by dividing the production value of wooden residential construction in the 2015 input-output tables from the Ministry of Internal Affairs and Communications (2019) by the number of newly constructed detached residential buildings in 2015, obtained from the Building Starts data in 2023.

Specifically, the production value of wooden residential construction in 2015 was 8,821.83 million JPY, and there were 406,990 newly constructed detached wooden residential buildings in 2015. Therefore, the average demand per wooden residential building was calculated as 21.7 million JPY per unit ($8,821,830 \text{ thousand JPY} \div 406,990 \text{ units}$). The average demand for wooden residential buildings includes wooden residences of various sizes, such as apartment buildings or detached houses. In this study, the average demand was assumed equivalent to the average demand for detached wooden residential buildings. For the residential building sector in the final demand vector, $\mathbf{f}$, the value obtained by converting the number of newly constructed units to a monetary value using the average demand per residential building was substituted.

By defining an input coefficient matrix $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1} = (z_{ij}/x_j) = (a_{ij})$, which expresses the intermediate input for sector i necessary for the production of sector j , the following equation was obtained:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f} \quad (4.3)$$

where $\mathbf{I}$ represents the identity matrix and $\mathbf{L} = (l_{ij})$ represents the Leontief inverse matrix. The elements l_{ij} represent the intermediate input for sector i required to satisfy one unit of final demand for sector j . Using Eq. (4.4), the embodied CO₂ emissions from the construction of new residential buildings were estimated as follows:

$$q^c(t) = \mathbf{d}^c(t)\mathbf{L}(t)\mathbf{f}(t) \quad (4.4)$$

where $q^c(t)$ represents the direct and indirect CO₂ emissions associated with the construction of residential buildings in year t and $\mathbf{d}^c(t)$ denotes the direct CO₂ emission coefficient vector associated with the manufacturing of residential buildings in year t . For $\mathbf{d}^c(t)$, this study utilized direct CO₂ emission coefficients from the Embodied Energy and Emission Intensity Data (3EID) for Japan, using the input-output tables released by The National Institute for Environmental Studies (Nansai, 2019; Nansai et al., 2020). The 3EID database estimates greenhouse gas emissions from commodity production activities and provides data that fully correspond to the 367 sectors of input-output tables in Japan.

4.2.3 CO₂ emissions from residential buildings during the use phase

In this study, the CO₂ emissions resulting from the use of each residential building in year t , denoted as $q^u(t)$, were calculated using the stock-flow model presented in section 3.1:

$$q^u(t) = d_v^u(t)S_v(t) \quad (4.5)$$

Here, $q^u(t)$ indicates the CO₂ emissions resulting from the use of residential buildings constructed in year t . d_v^u represents the intensity of CO₂ emissions from the use of residential buildings constructed during period v . Ishikawa et al. (2017) estimated the energy consumption intensity by construction period for detached residential buildings using the primary energy consumption calculation program provided by the Building Research Institute under the Ministry of Land, Infrastructure, Transport, and Tourism (Building Research Institute, 2017). This study utilized the graph from Ishikawa

et al. (2017) titled “Trends in Energy Consumption per Household by Region, Construction Method, and Year of Construction—Detached Houses,” and the regional average energy consumption intensity by construction period as the energy consumption intensity per construction period for residential use. The energy consumption intensity (GJ per unit per year) used for the estimation is presented in Table 4-1.

Furthermore, this study assumes that all energy consumed during residential use is electricity. Using the energy consumption and CO₂ emission data for the electricity sector from 3EID for 2005, 2011, and 2015, this study calculated the CO₂ emissions per unit of energy consumption and CO₂ emission intensity from residential use and adopted them as $d_v^u(t)$ in Eq. (4.5). The construction period of the residential buildings, denoted by v , was classified into six intervals: before 1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2020.

Table 4-1. Energy consumption intensity per unit per year from residential usage, categorized by the construction period per unit, as derived from Ishikawa et al. (2017)

(GJ per unit per year)						
Energy consumption intensities (GJ per unit per year)	Construction period					
	–1970	1971–1980	1981–1990	1991–2000	2001–2010	2011–2020
	142.0	137.3	130.9	122.1	112.0	103.5

Note: Intensity numbers have been rounded off to the second decimal place.

4.2.4 Scenario analysis changing the economic life of residential buildings

Research on the life cycle analysis of residential buildings has shown that CO₂ emissions during the disposal and repair phases are marginal throughout the entire life cycle (Tonooka, 2017). This section explains how this study compares the CO₂ emissions during the manufacturing and use phases in 2015, estimated under various average lifespan scenarios, with those estimated under the 2015 manufacturing and usage CO₂ emissions. To introduce variations in the average lifespan scenarios, the survival probability was adjusted based on the lifetime distribution function (section 3.1) and the average lifespan. Specifically, 76 scenarios, denoted by $k = 1, 2, \dots, 76$, were constructed, including lifespan extensions of 1–50 years, a baseline scenario with no changes, and lifespan reductions of 1–25 years (Table S4-1 in Supplementary). Additionally, this scenario analysis assumed that the total stock of residential buildings remained constant from 1950 to 2020 and that all residential buildings followed the modified average lifetime. The number of buildings $B_k(t)$ in year t in scenario k was expressed as follows:

$$\begin{aligned}
 B_k(1) &= S(1) \\
 B_k(2) &= S(2) + \varphi_k(1)B_k(1) \\
 B_k(3) &= S(3) + \varphi_k(2)B_k(1) + \varphi_k(1)B_k(2) \\
 &\vdots \\
 B_k(t) &= S(t) + \sum_{i=1}^{t-1} \varphi_k(t-i)B_k(i)
 \end{aligned} \tag{4.6}$$

Let the cumulative probability density function at this time be $F_k(t)$, and let $\varphi_k(t) = 1 - F_k(t)$. CO₂ emissions $q_k^c(t)$ during the manufacturing phase and $q_k^u(t)$ during

the use phase in year t under scenario k are represented by equations (7) and (8), respectively:

$$q_k^c(t) = \mathbf{d}^c(t)\mathbf{L}(t)\mathbf{f}_k(t) \quad (4.7)$$

$$q_k^u(t) = \sum_{v=1}^6 d_v^u(t)S_{k,v}(t) \quad (4.8)$$

where $\mathbf{f}_k(t)$ represents the final demand vector for residential buildings newly constructed in year t under lifespan scenario k . $S_{k,v}(t)$ indicates the stock built during the “predetermined” period v in year t under scenario k . The study period is divided into six periods: before 1970 ($v = 1$), 1971–1980 ($v = 2$), 1981–1990 ($v = 3$), 1991–2000 ($v = 4$), 2001–2010 ($v = 5$), and 2011–2020 ($v = 6$). The intensity of the CO₂ emissions during the use phase, represented by $d_v^u(t)$, was assumed to remain constant within each of these subperiods.

4.3. Results and Discussion

4.3.1 Economic lifespan of residential buildings

Table 4-2 presents the estimated distribution function parameters for the economic lifespan of detached residential buildings in Japan. The distribution curve is shown in Figure S4-1. The AIC section in Table 4-2 shows that the smallest value is in the normal distribution (AIC=1880.86) with parameters of $\sigma=13.35$ and $\mu=34.99$. The economic lifetime distribution function obtained from the maximum likelihood estimation was statistically significant at the 1% level. Thus, the probability density function for the economic lifetime of detached residential buildings best fit the normal distribution. Therefore, in this study, the cumulative survival probability $\varphi(t)$ can be illustrated as $\varphi(t) = 1 - F(t) = 1 - \frac{1}{2} \left\{ 1 + \operatorname{erf} \left(\frac{t-34.99}{\sqrt{2 \times 13.35^2}} \right) \right\}$ with the cumulative distribution function $F(t)$ of the normal distribution.⁴

The estimated lifetimes of Japanese residential buildings have been previously reported to follow a log-normal distribution (Tanikawa et al., 2015; Miatto et al., 2017; Kayo and Tonosaki, 2022), inconsistent with the results of the present study. However, this difference is explained by the use of real estate data to measure the economic lifetime in the present study, compared to data on the physical lifetime of residential buildings in the literature.

In addition, although previous studies did not distinguish between detached houses and apartment buildings, this study focused on detached houses. Based on these statistics,

⁴ $\operatorname{erf}(x)$ denotes the error function defined as $\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt (-\infty < x < \infty)$.

it can be concluded that the average economic lifetime of residential buildings in Japan is approximately 35 years. This result indicates a 13-year discrepancy between the statutory useful life (22 years) and economic life of residential buildings, which aligns with the fact that the Japan Housing Finance Agency (JHF), an independent administrative institution under the Ministry of Land, Infrastructure, Transport, and Tourism and the Ministry of Finance, sets the maximum lending/borrowing period for housing loans at 35 years (JHF, 2023). The economic lifespan outlined in this study appears to be consistent with real-world practices, in which residential buildings are typically used for 35 years or more.

Table 4-2. Parameter estimations for the probability functions of the economic lifetime of detached residential buildings

Parameter	Distribution type				
	Normal	Weibull	Gamma	Rayleigh	Log-normal
μ	34.99* (0.87)	-	-	-	3.42* (0.05)
σ	13.35* (0.62)	-	-	-	0.7* (0.03)
α	-	2.66* (0.99)	-	-	-
β	-	38.79* (0.14)	-	-	-
δ	-	-	3.78* (0.34)	-	-
ε	-	-	9.25* (0.88)	-	-
ξ	-	-	-	26.48* (0.87)	-
Mean	34.99	34.48	34.99	33.19	39.04
S.D.	13.35	13.95	17.99	17.35	31.25
AIC	1880.86	1913.54	1976.5	1937.52	2102.72
Number of obs.	234	234	234	234	234

Note: Numbers in parentheses indicate standard deviation. * indicates significance at the 1% level. The probability density function of normal distribution, Weibull distribution, Gamma distribution, Rayleigh

distribution, and Log-normal distribution are formulated as $f(t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(t-\mu)^2}{2\sigma^2}\right\}$, $f(t) =$

$\frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left\{-\left(\frac{t}{\alpha}\right)^\beta\right\}$, $f(t) = \frac{t^{\delta-1}}{\Gamma(\delta)\varepsilon^\delta} \exp\left(-\frac{t}{\varepsilon}\right)$, $f(t) = \frac{t}{\xi^2} \exp\left(-\frac{t^2}{2\xi^2}\right)$, and $f(t) =$

$\frac{1}{\sqrt{2\pi}\sigma t} \exp\left\{-\frac{(\ln t - \mu)^2}{2\sigma^2}\right\}$, respectively.

4.3.2 Residential buildings stock and CO₂ emissions from manufacturing and use phases

Figure 4-2 illustrates the stock of residential buildings in Japan, categorized by 10-year construction periods, built between 1951 and 2020. Focusing on stocks post-2005, when the first energy-saving standard was introduced, the proportion of buildings constructed after 1980 ranged from 65% to 79% of the entire stock.

Figure 4-3 illustrates the CO₂ emissions during the manufacturing and use phases of detached residential buildings in Japan in 2005, 2011, and 2015. The uppermost layer shows the direct and indirect CO₂ emissions induced by the demand for manufacturing residential buildings. From the second upper layer to the bottom layer, CO₂ emissions induced the consumption of energy during the use phase of residential building stocks categorized by 10-year construction periods. Compared to the stock built after 1980, when the first energy-saving standard was introduced, which ranged from 65% to 79% of the entire stock, CO₂ emissions from the residential building stock constructed during that period accounted for 62-79%. The more recent the energy-saving standards, the smaller the residential building envelope performance parameters, including the U-value (i.e., heat transfer coefficient) and solar heat gain coefficient. In 1980, the national average specified a U-value under 1.83, and from 1999 to the present, the national average specified a U-value under 0.77 (Ministry of Land, Infrastructure, Transport and Tourism, 2024a). The smaller the residential building envelope performance parameters, such as the U-value, the greater the thermal comfort provided, allowing control over the use of energy, such as air conditioner operation (Ozel, 2014; Chen et al., 2024). These findings suggest that the difference in the ratios may have occurred because the CO₂ emission

intensities of residential buildings constructed after the energy-saving standard was introduced were lower than those of buildings built before the standard.

Furthermore, in terms of overall CO₂ emissions from residential buildings in Japan during the manufacturing and use phases, emissions during manufacturing contributed significantly, accounting for approximately 9–13% of annual emissions. Therefore, in the analysis of the extended lifetime of houses, considering the influence of CO₂ emissions during manufacturing is crucial, as is the tradeoff between the impact of the manufacturing-phase emissions and the impact of CO₂ emission intensities during the use of residential buildings constructed under new energy-saving standards.

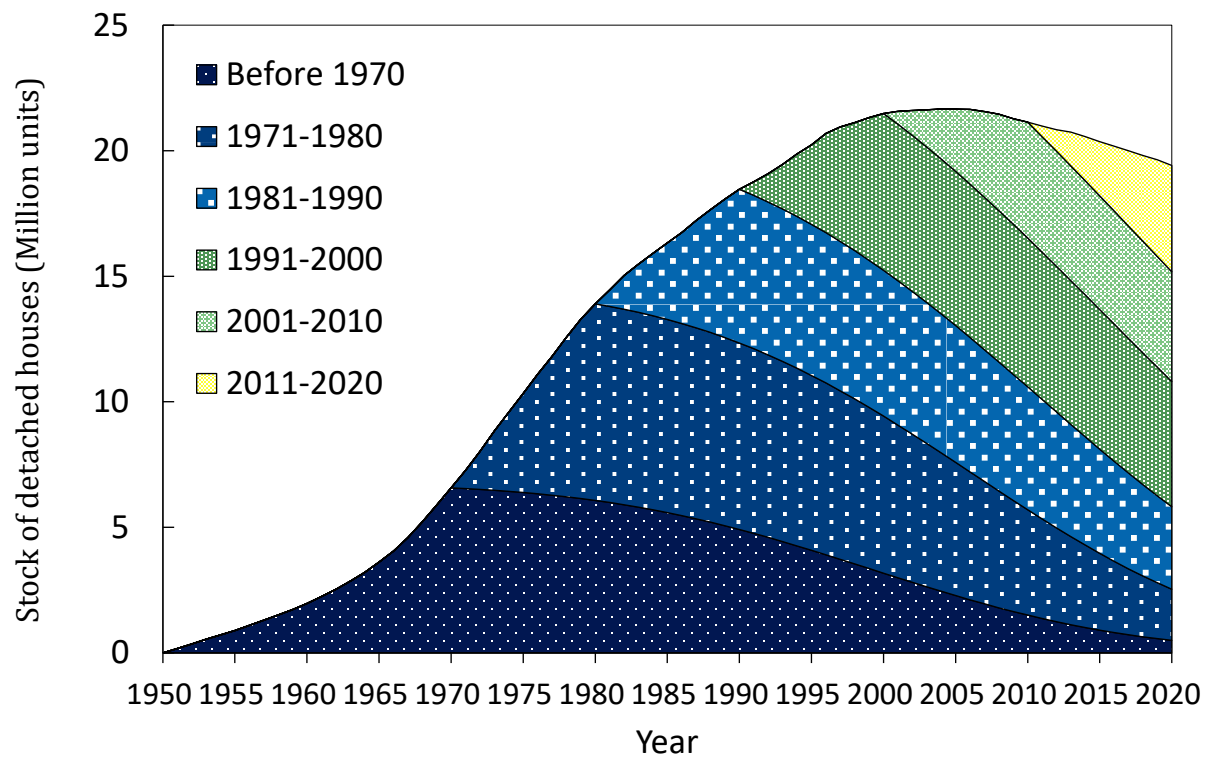


Figure 4-2. Dynamics of the stock of detached residential buildings, categorized by construction periods in 10-year intervals, with economic value retained, from 1950 to 2020.

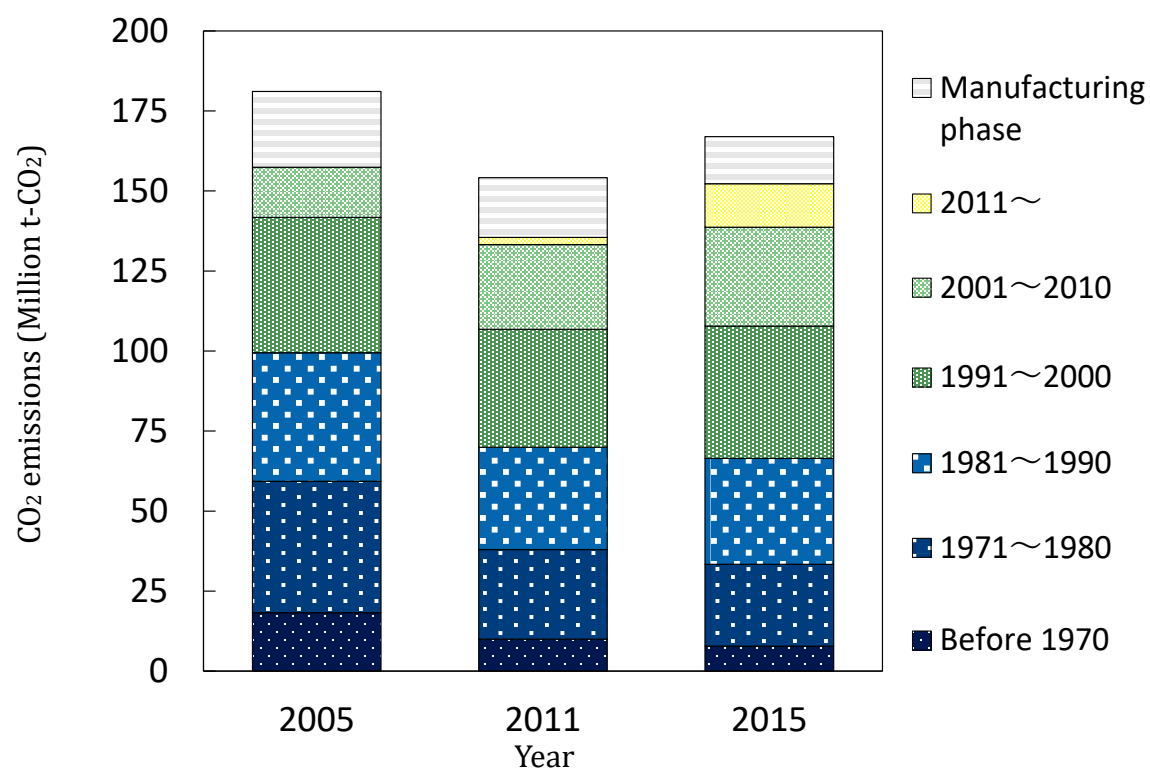


Figure 4-3. CO₂ emissions from the manufacturing and the use phases, categorized by construction periods in 10-year intervals of detached residential buildings in Japan for the years 2005, 2011, and 2015.

4.3.3 Impact of changing the period of use on CO₂ emissions from residential buildings

Figure 4-4 illustrates the differences in CO₂ emissions from the manufacturing and use of residential buildings in Japan in 2015. This variation occurs by altering the average economic lifetime of residential buildings from -25 years to +50 years, demonstrating the contrast with CO₂ emissions under an unchanged lifetime scenario (BAU). The red diagonal lines indicate the increase and decrease in CO₂ emissions resulting from the manufacturing of residential buildings, whereas the blue horizontal lines indicate the increase and decrease in CO₂ emissions arising from the use of residential buildings. Circular marks indicate the overall increase or decrease in CO₂ emissions from residential buildings, summing the variations during both the manufacturing and use phases.

The results indicate that shortening the average economic lifetime of residential buildings increases CO₂ emissions during the manufacturing phase, decreases emissions during the use phase, and leads to an overall increase in total CO₂ emissions. For example, a 5-year reduction was found to result in the construction of 91,321 additional new residential buildings, causing CO₂ emissions to increase by 21.8%. However, CO₂ emissions during the use phase could be reduced by promoting residential buildings with superior energy-saving performance, which results from a shortened average economic lifetime. In the case of a 5-year reduction, emissions decreased by 1.7%. If the economic lifetime were to be shortened to match the statutory useful life of 22 years (a reduction of 13 years from the estimated average economic lifetime), 312,565 new residential buildings would be required, leading to a 74.5% increase in CO₂ emissions during the manufacturing phase and a 3% overall increase.

However, extending the average economic lifetime of residential buildings decreases CO₂ emissions during the manufacturing phase but increases emissions during the use phase. For example, a 5-year extension reduced the demand for 73,859 new residential buildings compared with the business-as-usual (BAU) scenario, resulting in a 17.6% decrease in CO₂ emissions during the manufacturing phase. However, CO₂ emissions during the use phase increased by 1.8%, owing to the continued use of older, less energy-efficient buildings. Extending the lifespan by 35 years resulted in a reduction of 516,987 buildings in the stock and a 1.5% decrease in total CO₂ emissions across both the manufacturing and use phases. Extending the lifespan by 50 years resulted in a reduction of 599,760 buildings in the stock and a 2.3% decrease in total CO₂ emissions. In other words, extending the average lifespan to 85 years (an increase of 50 years) represents the optimal lifespan for minimizing CO₂ emissions within the assumed scenario.

Thus, extending the economic lifespan of residential buildings beyond the current limits could result in greater environmental benefits from a CO₂ perspective. Cai et al. (2015) demonstrated the impact of the service life (i.e., “physical” lifetime) of buildings in China on the environmental load associated with building construction. Their study showed that a shorter service life increased the environmental footprint of building construction, whereas a longer service life decreased it. However, it is important to note that Cai et al. (2015) did not conduct a comprehensive analysis that includes CO₂ emissions from the use phase of buildings. Thus, their findings are not fully supported by a complete life cycle analysis. By contrast, in this study, we provide a more comprehensive assessment of the impact on life cycle CO₂ emissions, including the use phase. The results of this study indicate that a shorter economic lifetime increases CO₂

emissions during the manufacturing phase of residential buildings, and a longer lifetime decreases them, supporting Cai et al.'s findings from a whole life cycle perspective. The Japanese government announced support measures to promote the construction of new residential buildings with high-quality energy-saving performance (Ministry of Finance, 2024). However, as highlighted by the UNEP-IRP (2020), which emphasizes the necessity of material efficiency strategies, including extending the lifetime of durable commodities such as residential buildings, policymakers should emphasize the promotion of longevity.

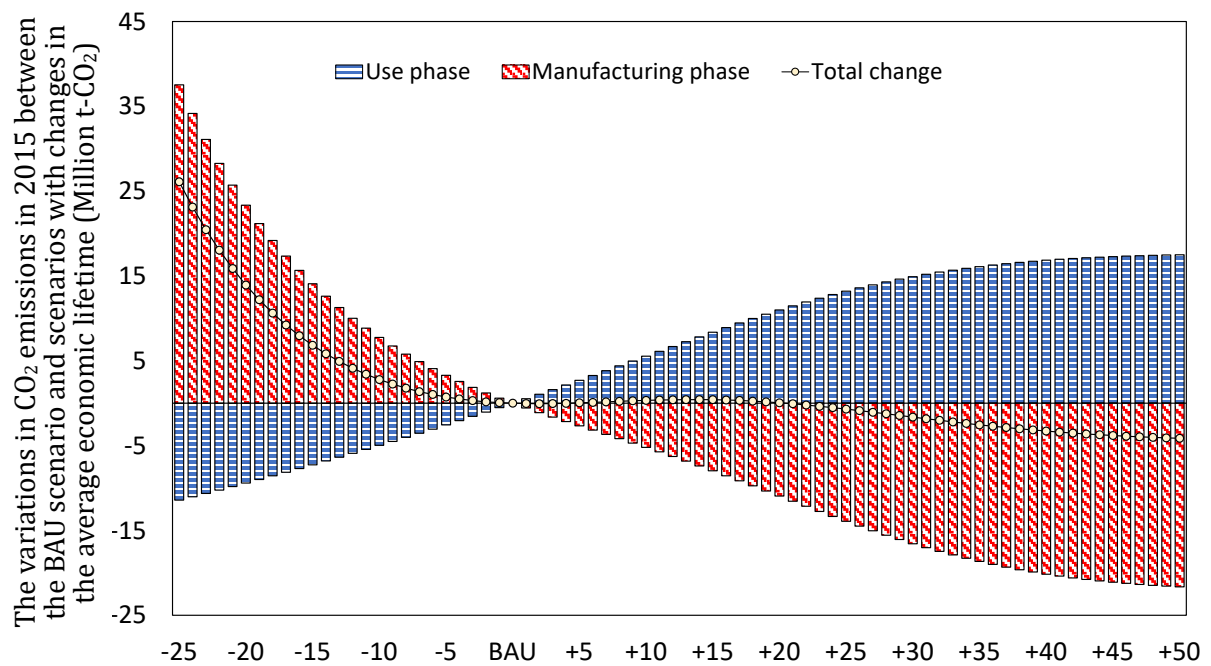


Figure 4-4. Variations in CO₂ emissions in 2015 under an unchanged lifetime scenario (BAU) compared to the CO₂ emissions resulting from altering the average economic lifetime of residential buildings from -25 years to +50 years.

4.4. Limitations of this study

Chang et al. (2014) highlighted the potential for errors in estimating the embodied energy consumption of buildings due to sectoral aggregation in the input-output table. Similarly, Matsushima et al. (2024) developed a time-series dataset of environmentally extended input-output tables and found that embodied sectoral CO₂ emissions calculated using input-output tables with “lower” sectoral resolution were more susceptible to biases introduced by price deflation. Consequently, these aggregation biases can distort carbon footprint estimates and obscure hotspots within supply chain structures. As a result, policies might misallocate resources, such as budgets, or impose regulations on incorrectly specified sectors, whereas industrial practices may also be driven by misguided decisions regarding supplier relationships. Therefore, when using input-output models for analysis, it is essential to utilize input-output tables with as much sectoral detail as possible to ensure more accurate policy implementation. This study attempted to develop an analytical framework based on environmentally extended input-output tables with the highest sectoral resolution available in Japan.

However, this study has some critical limitations. As noted by Lenzen (2011), many analyses using input-output models have relied on the average production technology within a specific aggregated sector, as well as the average environmental load intensity within the same sector. The production technology (i.e., intermediate input vector) for the wooden residential building sector, which is the focus of this study, similarly reflects only the average production technology (i.e., intermediate input structure) of a wide variety of domestic wooden residential buildings. This makes it difficult to capture housing characteristics at the company or product level. As a result, the government may face

challenges in evaluating company-specific efforts without detailed results at the company level, and may misallocate resources, such as subsidies. It may also be difficult to compare companies' efforts and set efficient targets in the housing industry. A detailed product-level input-output approach or an enterprise input-output approach would lead to more accurate analyses and better informed decision making. However, these important follow-up studies are beyond the scope of the present study.

This study lacked data on the lifespan and energy-efficiency improvements of furniture and appliances, as well as data on house renovations and their impact on energy efficiency. Owing to the absence of these data, it was challenging to conduct a detailed assessment of recurrent embodied energy and the impact of deep energy-efficient renovations. Therefore, the scope of this research was limited to two aspects, namely the manufacturing phase and the operational phase of buildings, and primarily analyzed the impacts of building replacement. Incorporating data on embodied energy and energy-efficiency improvements associated with renovations in future research would enable a more comprehensive evaluation.

Moreover, this study assumes that the energy consumed during the operational phase of residential buildings is electricity. This assumption is based on the fact that electricity will account for more than half (66.4%) of residential energy consumption in Japan in 2021 (Ministry of the Environment, 2023). However, other energy sources, such as gas, also play a role. The lack of a detailed analysis of the impact of these energy forms on the overall energy consumption represents a limitation of this study. Thus, future research should include data on energy sources other than electricity to enhance our understanding

of operational energy consumption and facilitate a more accurate analysis.

4.5. Conclusions

Using a parametric method, this study demonstrates that the economic lifetime of Japanese residential buildings follows a normal distribution, with an average of 35 years. Additionally, a shorter lifetime resulted in an increase in CO₂ emissions. The results have the following implications. First, it is important not to shorten the lifespan of residential buildings beyond the current limit. Second, an ambitious extension of the lifetime of residential buildings is necessary to reduce CO₂ emissions through longevity policies. The promotion of the second-hand market has been shown to be effective in extending the lifetime of products (Oguchi and Fuse, 2015; Amatuni et al., 2023). Expanding renovation and second-hand housing markets can be crucial initiatives for promoting longevity and improving the environmental performance of existing detached residential buildings in Japan.

However, the fact that residential buildings that have exceeded the statutory useful life of 22 years have little value and cannot be resold (Fukumoto, 2012) prevents the expansion of renovation and second-hand housing markets. Residential buildings relinquished by their final owners during the 13-year period between the statutory useful life of 22 years and the economic lifetime of 35 years retained their demand as residences. However, this supply is constrained because of a lack of value. Extending the statutory useful life to 35 years is necessary to fill this 13-year gap. The ministerial order for establishing a statutory useful life was issued in 1965 and has not yet been revised

(National Tax Agency, 2017). The basis for these years was not explicitly stated, and it also did not reflect an increase in the value of housing due to renovations or refurbishments. Preserving the value of existing residential buildings by extending their statutory useful life leads to the preservation or extension of their economic lifetime, making them a crucial policy goal aimed at reducing energy consumption and CO₂ emissions in the residential and construction sectors.

Chapter 5: Conclusions

This Ph.D. dissertation reports on the development and implementation of a comprehensive residential LCA framework by integrating a database developed through the advancement of Japan's input-output tables with a stock-flow model. Its aim is to provide a foundation for effectively reducing CO₂ emissions from the residential sector, a critical area in Japan.

Chapter 3 estimates a new dataset of embodied CO₂ emission intensities by applying two non-survey methods used for deflating Japan's input-output tables (IOTs): the double-deflation method (DD method) and a combined method (CD method) that integrates the DD method with the generalized RAS method. These methods were used to deflate Japan's 2005, 2011, and 2015 IOTs to constant prices from 2015. By comparing the estimated data for specific years (2005 or 2011) across 367 sectors, it was revealed that the embodied CO₂ emission intensities for certain sectors, such as the tobacco and nuclear fuel sectors, were larger when calculated using the CD method compared to the DD method. This indicates that differences in methodology lead to discrepancies in emission intensity data for some sectors. In the comparison of embodied CO₂ emission intensities among groups categorized by major industry classifications, methodological differences were observed. Significant discrepancies were found in groups such as non-ferrous metals and other manufactured goods, which include products widely used in large-scale manufacturing industries like construction, automotive, and aerospace. These results highlight that emission intensities for specific sectors and aggregated sector groups, such as non-ferrous metals, exhibit biases due to the extreme price homogeneity assumption

inherent in the DD method. Based on these findings, this chapter recommends that life cycle assessment (LCA) practitioners, especially those analyzing changes in the carbon footprint of industries with significant transactions with biased sector groups (e.g., the construction industry), utilize the newly provided open database from this dissertation.

In Chapter 4, the embodied CO₂ emission intensity dataset developed in Chapter 3 was incorporated into a framework for time-series LCA analysis of residential buildings in Japan. This chapter investigates the impact of the economic lifespan of detached wooden residential buildings in Japan on CO₂ emissions during the manufacturing and use phases. The economic lifespan of these residential buildings was estimated based on real estate transaction data, and the effects of changes in the average lifespan on CO₂ emissions in the manufacturing and use phases were evaluated. It was found that the average economic lifespan of detached wooden residential buildings in Japan is approximately 35 years. Shortening the average lifespan leads to increased CO₂ emissions during the manufacturing phase due to the need for new construction, while emissions during the use phase decrease. On the other hand, extending the average economic lifespan reduces the need for new construction, leading to lower emissions during the manufacturing phase, but increases emissions during the use phase. These findings strongly emphasize the importance of extending the lifespan to reduce CO₂ emissions and highlight the need to reevaluate the statutory useful life of residential buildings in Japan. Based on these insights, this chapter demonstrates that actively extending the maintenance and economic lifespan of buildings is a crucial element of environmental policy.

However, this paper evaluates the environmental performance of residential buildings based on the average insulation performance of buildings constructed during the relevant period, and does not analyze the impact of changes in the spread of energy-saving technologies such as ZEH (net zero energy house). In this regard, by incorporating insulation performance and diffusion rates into the emission intensity dataset as scenarios, using tools such as the Input-output table for analysis of next-generation energy system for 2015 (Institute for Economic Analysis of Next-generation Science and Technology, 2020), it will be possible to assess the impact of environmental policies other than those aimed at extending lifespan.

Furthermore, the estimation in this paper assumed that the size of the house was reflected and aggregated in the emission intensity data. To address this, by using data on the number of units categorized by the size of residential buildings and insulation effects data corresponding to the size for CO₂ emission estimates during construction and operation, it will be possible to conduct an emission analysis that considers the size of residential buildings.

Supplementary materials

S.3.1

```
%Load data
%Z2005n=xlsread('Linked IO tables', 'Nominal IOT_2005', 'C3:ON513');
%Z2005d=xlsread('Linked IO tables', 'Deflated IOT_2005', 'C3:ON513');
Z2011n=xlsread('Linked IO tables', 'Nominal IOT_2011', 'C3:ON513');
Z2011d=xlsread('Linked IO tables', 'Deflated IOT_2011', 'C3:ON513');
%Z2015n=xlsread('Linked IO tables', 'Nominal IOT_2015', 'C3:OR513');

%Number of rows
m=496;
%Number of columns
n=401;

%Intermediate and final consumptions of goods and services
A=Z2011n([1:m],[1:n]);
P=A.*(A>0);
N=-A.*(A<0);

%Row and column sums vectors
u=Z2011d([1:496],402); %Row sum vector
v1=Z2011d(511,[1:376])-sum(Z2011d([498:508],[1:376])); %Column sum for intermediate inputs
v2=sum(Z2011d([1:496],[377:401])); %Column sum for final demand
v=[v1 v2]; %Column sum vector

%GRAS algorithm
r{1}=ones(m,1);
for k=1:500; %Number of iterations
pr_j=r{k}'*P;
nr_j=sum(inv(diag(r{k}))*N,1);
for j=1:n;
    if pr_j(j)==0;
        sigma(j)=1;
    else
```

```

        sigma(j)=(v(j)+(v(j)^2+4*pr_j(j)*nr_j(j))^0.5)/(2*pr_j(j));
    end
end
s{k}=diag(sigma);
ps_i=P*diag(s{k});
ns_i=sum(N*inv(s{k}),2);
for i=1:m;
    if ps_i(i)==0;
        rho(i)=1;

    else
        rho(i)=(u(i)+(u(i)^2+4*ps_i(i)*ns_i(i))^0.5)/(2*ps_i(i));
    end
end
r{k+1}=rho';
if (norm(diag(r{k+1})*P*s{k}*ones(n,1)-inv(diag(r{k+1}))*N*inv(s{k})*ones(n,1)-u)>0.00001)...
    &&(norm(ones(1,m)*diag(r{k+1})*P*s{k}-ones(1,m)*inv(diag(r{k+1}))*N*inv(s{k})-
v)>0.00001);
X{k}=(diag(r{k+1})*P*s{k}-inv(diag(r{k+1}))*N*inv(s{k}));
else
XX=(diag(r{k+1})*P*s{k}-inv(diag(r{k+1}))*N*inv(s{k}));
end
end

%Optimized matrix
XX;

```

S.3.2

The 2005, 2011, and 2015 current and constant Input-Output matrices are shown in Table S3-1, S3-2, S3-3, S3-4, S3-5, and S3-6 at

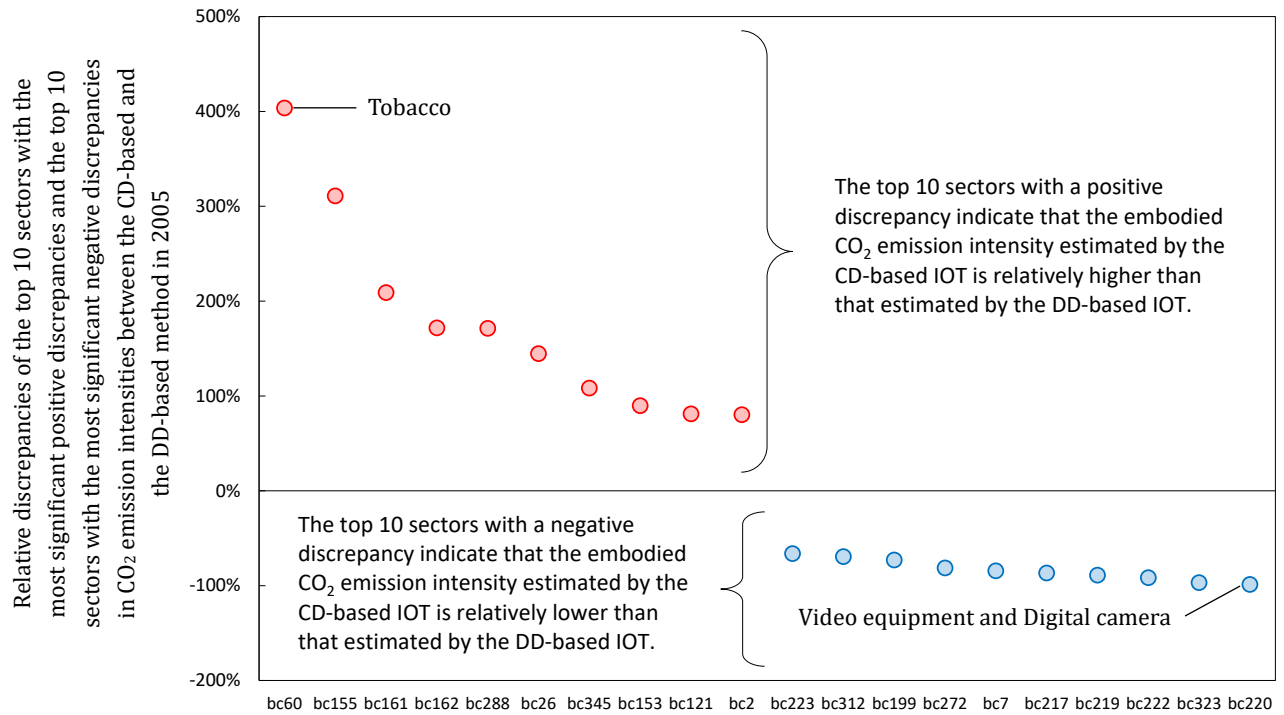
URL: <https://www.dropbox.com/scl/fi/kqv4vgwn3yq9zl0sgzqbp/Supplementary-Material-3.2.xlsx?rlkey=gfa3bmlbebh2tbkae0qwb4buz&dl=0>

S.3.3

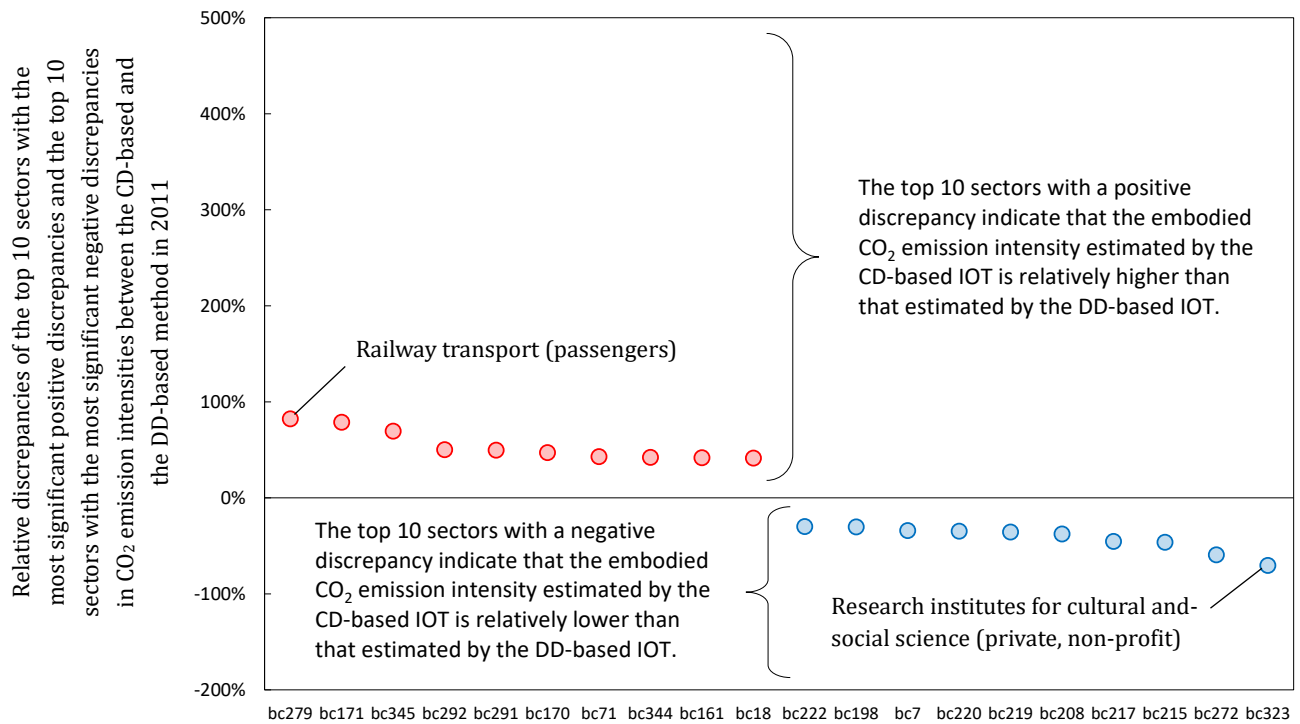
Embodied CO₂ emission intensities based on the 2005 and 2011 IOT at constant prices of 2015 are shown in Table S3-7, S3-8, S3-9, S3-10, and S3-11 at

URL: <https://www.dropbox.com/scl/fi/wp71hqitme075l9sd3vtg/Supplementary-Material-3.3.xlsx?rlkey=6mk61g0xkk833dne8lso847cw&dl=0>

S.3.4



(a) The plots of 2005.



(b) The plots of 2011.

Figure S3-1. The plots of discrepancies for non-competitive-import type embodied CO₂ emission intensities of 367 sectors of Japan estimated by the DD-based and the CD-based IOTs of 2005 and 2011 in 2015 constant prices. The plots of relative discrepancies of the top 10 sectors with the most significant positive discrepancies and the top 10 sectors with the most significant negative discrepancies in non-competitive-import type embodied CO₂ emission intensities of 367 sectors of Japan between the CD-based the DD-based IOTs of 2005 and 2011 in 2015 constant prices.

S.4.1

Table 4-2. Parameter estimations for the probability functions of the economic

Lifespan change	Notation of each scenario	Lifespan change	Notation of each scenario
-25 year	k=1	+13 year	k=39
-24 year	k=2	+14 year	k=40
-23 year	k=3	+15 year	k=41
-22 year	k=4	+16 year	k=42
-21 year	k=5	+17 year	k=43
-20 year	k=6	+18 year	k=44
-19 year	k=7	+19 year	k=45
-18 year	k=8	+20 year	k=46
-17 year	k=9	+21 year	k=47
-16 year	k=10	+22 year	k=48
-15 year	k=11	+23 year	k=49
-14 year	k=12	+24 year	k=50
-13 year	k=13	+25 year	k=51
-12 year	k=14	+26 year	k=52
-11 year	k=15	+27 year	k=53
-10 year	k=16	+28 year	k=54
-9 year	k=17	+29 year	k=55
-8 year	k=18	+30 year	k=56
-7 year	k=19	+31 year	k=57
-6 year	k=20	+32 year	k=58
-5 year	k=21	+33 year	k=59
-4 year	k=22	+34 year	k=60
-3 year	k=23	+35 year	k=61
-2 year	k=24	+36 year	k=62
-1 year	k=25	+37 year	k=63
-0 year	k=26	+38 year	k=64
+1 year	k=27	+39 year	k=65
+2 year	k=28	+40 year	k=66
+3 year	k=29	+41 year	k=67
+4 year	k=30	+42 year	k=68
+5 year	k=31	+43 year	k=69
+6 year	k=32	+44 year	k=70
+7 year	k=33	+45 year	k=71
+8 year	k=34	+46 year	k=72
+9 year	k=35	+47 year	k=73
+10 year	k=36	+48 year	k=74
+11 year	k=37	+49 year	k=75
+12 year	k=38	+50 year	k=76

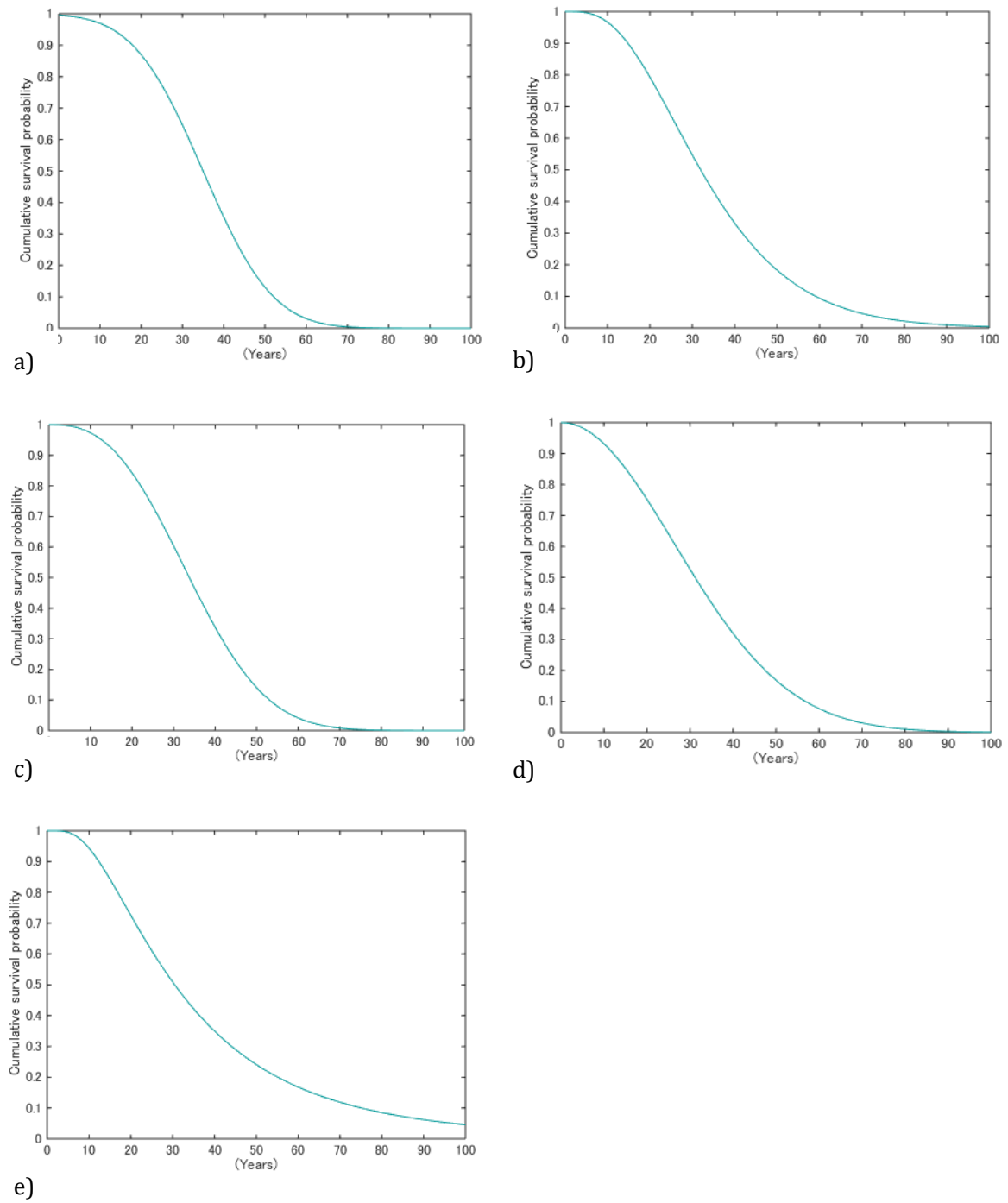


Figure S4-1. Cumulative survival probability distribution curves for detached residential buildings in Japan, based on five lifetime distribution probability densities:

- a) normal distribution, b) gamma distribution, c) Weibull distribution, d) Rayleigh distribution, and e) log-normal distribution.

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Lara Matsushima

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