Lessons from micro- and macro-modelling linkages: example of linking LCA/DMFA and CGE model for developing Circular Economy scenarios

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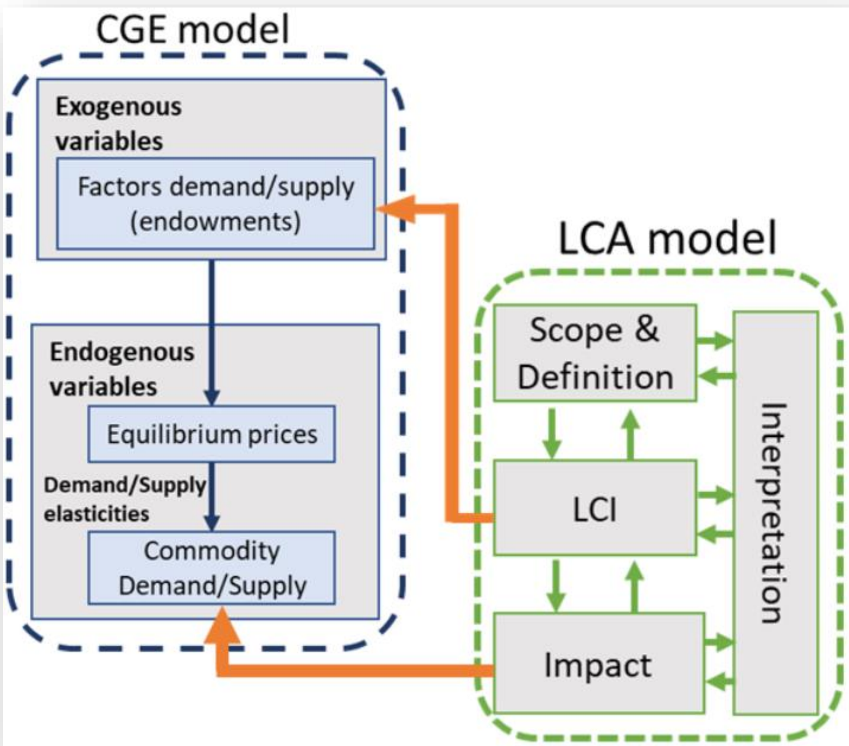

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Introduction

This report aims to provide a primer for CGE practitioners to understand the potential to link micro (i.e., Life Cycle Assessment (LCA) and Dynamic Material Flow Analysis (DMFA)) and CGE models to model circular economy strategies. The report offers an overview of the state-of-the-art of LCA/DMFA and CGE model linkages (including 8 archetypes), key lessons from LCA/DMFA studies to macro-modelling approaches, and an example of substituting internal combustion engine vehicles with electric vehicles, considering the circularity potential of Li-ion batteries to illustrate the application of micro- and macro-modelling linkages towards circular economy scenarios.

Macroeconomic models have emerged as an important tool to understand, manage, and forecast economy-wide effects of policy measures and scenarios. Computable General Equilibrium (CGE) models are the main tool used towards this end. CGE are commonly based on an economic social accounting matrix (SAM) with an input-output tables (IOTs) core. An example is the GTAP model built around the GTAP database, or EXIOMOD built around the EXIOBASE database. A CGE model consists of a set of equations describing responsive and dynamic relationships between economic processes (e.g., production, consumption, and trade) and production factors (e.g., labour, capital, investment). These sets of equations allow for calculation of economy-wide effects arising from, for instance, a significant price change of an imported product, a change in taxes, or the levy of a new tax such as a carbon tax. Long-run models try to ensure consistency over time – for instance that future capital stock and capital productivity depends on current capital investment. Although capable of assessing sector-wide outcomes of industrial policy and their associated environmental impacts, current CGEs are poorly suited to dynamically assess Circular Economy (CE) interventions.

Since CGEs are based on SAMs and IOTs, they have two characteristics that make them difficult to use in dynamic analyses on CE interventions. First, the sector resolution of SAMs and IOTs is quite limited – at best 100 to 150 sectors. CE strategies are however highly product specific – re-use of mobile phones requires different technologies and will yield different secondary components or materials such as the re-use of washing machines. However, in a SAM or IOT one may find at best one product category, such as 'Electrical and electronic products', that aggregates all such products together. Second, SAMs and IOTs define flows and stocks in monetary units, whereas CE strategies require closing physical material loops. Although monetary information can often be considered a good proxy for physical production information, SAMs and IOTs are insufficiently detailed for processing of end-of-life product components or waste products.

These two reasons – the need for a higher granularity and the need for understanding physical flows – have led CE analysts to use Dynamic Material Flow Analysis (DMFA) to create consistent stock-flow information of specific products-in-use, production input, and end-of-life output per year over time, combined with (futurized or ex-ante) Life Cycle Assessment (LCA) that gives information on emissions and other environmental pressures of production and end-of-life management per year over time (see, for example, Li et al., 2022; Carlos Pablo Sigüenza et al., 2021; Zhong et al., 2021).

While DMFA coupled with LCI data resolves the issues of granularity and the need for insight into physical material flows, it ignores the economy-wide effects of CE measures, such as economic consistency and behavioral responses that CGE models offer. In a CE modelling, new secondary products, components, and resources are made available for the market, but the databases underlying CGE models in most cases do not have information on their prices, potential available 'production' volumes, and substitution elasticities in relation to traditional production inputs. Moreover, there is the need to explore the connection between LCA/DMFA and CGE models in way that the detailed information from micro-modelling approaches can provide the kind of information that normally is used in CGE models (i.e., price elasticities, substitution curves, etc.).

In this report, we aim to provide a quick start guide for CGE practitioners focusing on the linkages between micro- and macro- modelling approaches and illustrate the potential application of Life Cycle Assessment (LCA) and Dynamic Material Flow Analysis (DMFA) to CGE models for modelling CE strategies. The report is structured in four chapters as follows:

- **Chapter 1** focuses on the state-of-the-art of LCA/DMFA and CGE model linkages from a conceptual viewpoint.
- **Chapter 2** explores LCAs and DMFAs that analyze transport as a case study (owing to its key role in decarbonization, material resource reduction, and a transition to a circular economy), and identifies the key insights from micro models that can be useful for CGE modelling.
- **Chapter 3** proposes 8 linkages archetypes based on the existing literature that enable us to describe LCA/DMFA and CGE linkages in a systematic way.
- **Chapter 4** shows an example of replacing internal combustion engine vehicles (ICEVs) with EVs to illustrate the application of LCA/DMFA and CGE linkages for modelling circular economy strategies in transport systems.

Chapter 1: Linking LCA/(D)MFA and CGE models

Several studies have developed linkages between LCA/(D)MFA and CGE models. In general, researchers refer to two types of links (or coupling) between the models: low-level, and high-level linkages.

Low-level (or 'soft') linkages are those where micro and macro models are run separately, and outputs from one model are used as data inputs in other models[18]. In most cases, CGE models are used to estimate economic outputs and are used as inputs for LCA-based models to calculate environmental impacts (Guo et al., 2022; Igos et al., 2015; Machado et al., 2020; Wang et al., 2018). For example, Lee (2018) investigated the development of CO_2 emissions in the Japanese hydrogen production by combining the economic outcomes of a dynamic GTAP model with the emissions coefficients (e.g., CO_2 equivalent per unit dollars of production value) from an LCA model. This is also the case when coupling LCA/(D)MFA with MRIO. Another such example is presented by Pauliuk et al. (2017) where technical coefficients from MRIOTs are used as inputs for a DMFA that enables to trace the material use per sector through time.

There are a few studies where soft linkages are established by using outputs from LCA/(D)MFA as inputs to CGE models. For example, Cao and colleagues (2019) studied the development of the Chinese building sector by connecting the outcomes of a DMFA into a recursive dynamic CGE model. A soft linkage between the models was made thought 6 steps (see textbox A). Similarly, Soderman et al. (2016) connects a dynamic CGE and an LCA-based model with multiple iterations to integrate the outcomes of the LCA model to the CGE, and vice versa.

Textbox A. Example soft DMFA + CGE linkages using the 6 steps procedure from Cao et al.(2019)

- **Step 1:** Run DMFA to estimate the newly built floor area.
- **Step 2:** Estimate value added of construction sector based on newly built floor area.
- **Step 3:** Iteratively run CGE by changing parameters of investment demand for the construction sector until value added is equates to DMFA results.
- **Step 4:** Balance the change in investment demand for the construction sector and the demands of investment and consumers under the constraint of market balance.
- **Step 5:** Re-run CGE model with the different sectoral outputs and changes in the distribution of capital and labor onto sectors under the constraint of given capital and labor supply.
- **Step 6:** Chosen production functions capture the substitution of capital, labor, and energies in different sectors.

High-level (or 'hard') linkages are used when LCA/(D)MFA and CGE models are run together so that the behavioral changes from a CGE model are environmentally driven. For instance, hard linkages allow us to include environmental impacts as part of the production function or consider environmental assets as part of economic sectors in a CGE model (Beaussier et al., 2019). Gacia et at.(2018) developed an integrated CGE and LCA model that includes a set of equations that constrain the model to minimize environmental impact and production costs simultaneously. According to Beaussier et al.(2019), this type of linkage is useful when:

a) environmental impacts have endogenous effects on the stock of capital and/or the production factors;
b) economic agents incorporate environmental policies in their decision process; and
c) comparing the environmental impacts of multiple environmental policy instruments.

It is important to notice that in both (soft and hard) linkages the CGE model often drives the coupling of models (Beaussier et al., 2019). This is because CGE models provide constraints in terms of the level of sectoral, spatial, and temporal resolution. Furthermore, as micro and CGE models present different resolutions, a harmonization/matching between economic sectors and product categories is made before coupling CGE and LCA/DMFA models (see for example, Peng et al.(2019); and Steubing et al.(2022)).

Developing models that link LCA/DMFA and CGE models depends on multiple aspects such as modelling skills, computational power, and data availability. The latter is particularly important to understand to what extent micro and macro models can be integrated. In **Chapter 2**, we synthesize the key lessons from LCA and (D)MFA studies on transport systems as case study, emphasizing what kind of insights can be learned from micro models that can be useful to create the linkages with CGE models.

Chapter 2: Lessons from linking LCA and (D)MFA to CGE modelling

Textbox B. Three key lessons from micro-modelling to CGE modelling

LCA and (D)MFA provide relevant information about the environmental impacts of products' production methods and use, as well as material flows and stocks. Beyond the outcomes of those methods, we identify three key lessons that can be useful for macro-modelling practitioners:

1. **Supply and demand granularity:** Both methods offer the capability to study determinants of material flows and stocks, from supply and demand perspectives, and how these vary spatially, sectorally, and temporally. For example, technology changes, production, and use costs, and future material demand. Table 1 shows the coverage of these factors in each method, qualitatively.
2. **Data compilation and standardization:** LCA and MFA lend themself to the compilation of new, detailed datasets, known as Life Cycle Inventories and Material Flow Accounts, LCI, and MFA datasets where multiple parameters of resource use are recorded, as shown in table 2 and 3.
3. **Uncertainty validation:** LCA and (D)MFA data usually have a high level of uncertainty (especially for scenario analyses). Nevertheless, LCA and MFA researchers have managed to quantify the scale and nature of uncertainties from model and data by using statistical analyses that enable the identification of key parameters contributing to their uncertainty (e.g., sensitivity analysis), and providing probabilistic functions on model outcomes (e.g., by developing Monte-Carlo analysis). Notwithstanding their use by macro-modelling practitioners as well, probabilistic methods are critical in the linkage of macro- and micro-modelling approaches where multiple macro-economic scenarios can relate to micro-modelling data considering their probabilistic function due to additional variables and sources of uncertainties.

Life Cycle Assessment (LCA) is a method for assessing the environmental impacts of a product's life cycle (including extraction, production, transformation, use, and end-of-life). The LCA approach usually consists of 3 phases: 1) scope and definition, 2) inventory assessment, 3) impact assessment, and 4) interpretation. The advantage of LCAs is that it allows comparison of two or more products and determines which product is preferable from an environmental viewpoint. A few LCAs also consider the production and use costs, which provides insights into economic aspects of a product's life cycle and its feasibility from a market and consumer perspective.

From a supply and demand side, LCA provides insights on:

- **Technology options:** For example, LCA is used to assess the environmental impacts of internal combustion vehicles (fueled by diesel and petrol), plug-in hybrid vehicles, and electric vehicles (Cusenza et al., 2019; Nordelöf et al., 2014; Shafique et al., 2022; Yang et al., 2021). Some LCA studies that looked at technological changes consider the changes in the energy mix in different years (Shafique et al., 2022). Furthermore, comparisons between Li-ion battery technologies for e-mobility have been made extensively. A review paper showed over 79 available papers that study Li-ion batteries, mostly focusing on the production phase of the life cycle (Peters et al., 2017). Regarding LCI, the study showed that there is a limited amount of LCIs, and researchers usually (re-) used existing LCIs (for more details about the LCIs for Li batteries, check out Fig 2 in Peter et al.(2017)).
- **Production and use cost:** Regarding production and use cost, Khan and Onat (2022) found 41 articles related to comparing different types of fuels or vehicles, where most of the studies focused on electrification of public transport. In general, life cycle costing (LCC) considers the impacts of new infrastructure (e.g., new charging stations for e-vehicles), price changes due to technological changes, and the cost of maintenance.
- **Circular strategies/activities:** There is a growing body of literature that focuses on circular strategies, especially by considering different end-of-life strategies (e.g., with multiple recycling options) (Cusenza et al., 2019). Furthermore, other circular practices (such as impacts of sharing economy) have been evaluated from a LCA perspective, for example, Hollingworth et al. (2019) assessed the environmental impacts of e-scooters in a sharing economy scheme, having insights on the impacts of manufacturing, charging scooters, and transporting e-scooters to overnight stations.
- **Diffusion rates:** Some LCA-based studies have employed technological diffusion rates to assess the temporal dynamics in environmental intensities of production based on adoption phases (i.e., replacing old technology and adopting the new technology). This type of model can be done by combining diffusion of innovations models with stock-flows dynamics linked to LCA (C.P. Sigüenza et al., 2020).

Table 1. Summary of insights from LCA and (D)MFA

	Insights	LCA*	(D)MFA*
Supply side	Technology changes	•••	
	Production cost	•	
	Circular strategies	••	
	Material use		•••
	Supply risk		•
Demand side	Material/energy use	•••	••
	Future material demand		•••
	Use cost	•	
	Circular strategies	•	•••
	Product/material lifetimes	••	•••
	Diffusion rates	•	•

- * Colors and ellipses indicate the degree of application of respective methods and the key insights, as follows:

•	••	•••
Low	Medium	High

Material Flow Analysis (MFA) is a method that allows the quantification of flows and stocks of materials throughout multiple systems (e.g., within and between industries, and across multiple economic sectors). In contrast with LCA (which is implemented at the product level), MFA is used to assess industrial activities as well on a sectoral or economy-wide scale, considering national and global scales from bottom-up data. MFA method can be implemented in a static (i.e., as a screenshot in a specific period), or dynamic (i.e., quantifying flows and stock through time). In both cases, MFA approaches use mass balance principles to measure and attribute specific material flows/stocks.

From supply and demand side, (D)MFA can provide insights:

- **Future material demand:** Several DMFAs have developed scenarios for future material demand, considering multiple materials (e.g., lithium, cobalt, steel), and strategies (e.g., renewable energy mix, e-mobility, and other sustainability scenarios) (Carmona et al., 2021; Fischer-Kowalski et al., 2006; Kamran et al., 2021; Tang et al., 2021). For example, Nurdiawati et al. (2022) developed stock-driven MFA to estimate the future volume of EV battery waste to be potentially generated in Sweden. These types of studies offer insights into future material demand that can inform how the production of goods will develop in the future. The time horizon varies between studies; however, it is usually mentioned scenarios towards 2030 and 2050.

- **Material use:** DMFA researchers also assess the total material requirements for energy transition, and transport systems. For instance, Watari et al. (2019) applied a DMF to the International Energy Agency's scenarios up to 2050, targeting 15 electricity generation and 5 transport technologies. Recent interest in time-based evaluation of consumer carbon footprints has also become an emergent metric to better understand demand-side climate mitigation measures (Smetschka et al., 2019).
- **Product/material lifetime:** Stock-driven DMFA uses lifetime distributions for materials/products, offering information about their lifespans and how different scenarios would influence material inflows-to- and outflows-from- stocks.
- **Circular strategies/activities:** DMFA is used to determine the dynamic of material stocks through time and allows for measurement of how much and when materials from durable goods are disposed of as waste(C.P. Sigüenza et al., 2020; Tang et al., 2021). This is particularly important when considering circular strategies as it provides information about future material availability from secondary/recovery sources.
- **Supply chain resilience:** Some MFA studies have been focused on assessing the flows and stocks of critical raw materials and evaluating multiple scenarios to improve supply chain resilience. For example, Bobba et al. (2020) developed a DMFA model to explore the future lithium demand based on 3 scenarios: extension of Lithium batteries through second use, recycling improvements on Li batteries from vehicles, and renewable energy for Li battery manufacturing.

Considering the lessons from Chapters 1 and 2, we can now think of multiple ways to create linkages between micro and macro models. Each modelling development depends on the type of questions addressed by the modelers, and, thus, the need (or usefulness) of developing linkages between the models. Although modelling linkages are case dependent, we can use the lessons from Chapter 1 and 2 to create a framework that allows to quickly identify linkages archetypes based on common practices in the literature. In **Chapter 3**, we propose a list of linkages archetypes that allow us to investigate the micro and macro linkages in a systematic way.

Chapter 3: Linkages archetypes

Overall, we found several examples that offer the common practices of researchers for linking micro- and macro-modelling approaches. Here we propose 8 archetypes that synthesize the most common linkages between micro and macro models: four archetypes for LCA + CGE models and four archetypes (D)MFA + CGE models (see Figure 1). In general, each archetype is classified in terms of:

- **Low-level (soft), and high-level (hard)**: as mentioned above, the main difference between soft and hard linkages is that soft linkages are made by running each modelling approach individually and using data outputs of a model as an input for the other model, whereas hard linkages usually imply that models are integrated, and micro and macro models are co-dependent and run simultaneously. Low-level (or soft) linkages occur when data of one model is used and input for the other. For example, when a modeler uses the evolution of GDP from a CGE model as one of the parameters to estimate the evolution of GHG emissions of a product using a LCA model. High-level (or hard) linkages are more complex for modelers as it requires changing the structure of a model to merge both micro and macro models. For instance, the hard-linkage archetypes from LCA/DMFA to CGE models couple a micro-modelling component (e.g., impact assessment for LCA, or material flow/stocks for DMFA) with the endogenous variables of the CGE model (e.g., factor demand and factor supply, otherwise defined economically), which means that an equation (or a condition within the production function) should include the micro-modelling components (see example in **Chapter 4**).
- **Foreground, and background systems**: this classification enables us to distinguish which approach is taken as the core model. For example, if an LCA-CGE linkage is developed with an LCA as a foreground system (i.e., CGE as a background), this means that the LCA is the core modelling approach, and CGE data/insights are selected and adapted to provide information for the LCA core model. The foreground /background classification is particularly important to identify soft linkages because defining a foreground (or background) system would indicate which model is used as a data input for the other model. Although foreground/background classification can be found within hard linkages, it is difficult to identify a foreground/background system in a hard-linked model because both micro, and macro models should be already integrated, ideally providing feedback links between both modelling approaches.

As in any other modelling development, the level of linkage depends on the research/policy questions that modelers aim to address with their models. In this report, we use an example of circular economy strategies in transport systems to describe how practitioners can use the linkages archetypes depending on their own research interest. Combining the lessons from Chapters 1-3, the following section illustrates an example of modelling CE strategies for transport systems using the proposed linkages archetypes.

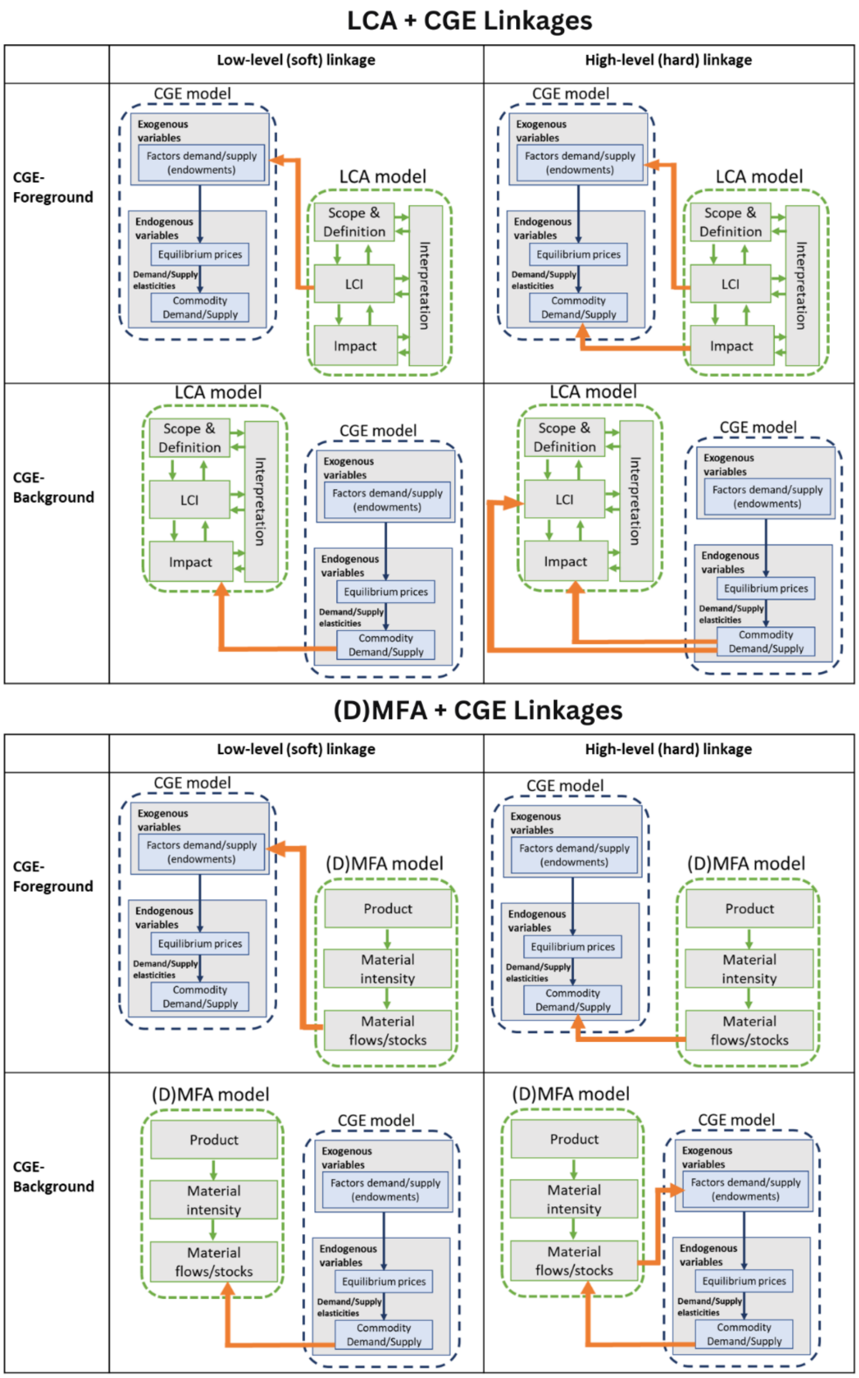

Figure 1. Linkages archetypes for LCA + CGE, and (D)MFA + CGE model

Chapter 4: Applying linkages archetypes - The case of replacing ICEVs with EVs

This chapter shows an example of micro and macro modelling linkages within the context of circular economy strategies. We use the case of replacing internal combustion engine vehicles (ICEVs) with electric vehicles (EVs), considering the circularity potential of Li-ion batteries and the diffusion of such technologies.

- **Background:** The EVs market is growing rapidly in response to the need to reduce GHG emissions, improv air quality, and satisfy consumers' needs for sustainable transport options (Harper et al., 2019). At the same time, EV demand leads to increasing Li-ion batteries, creating growing demand for raw materials (e.g., lithium, cobalt, etc.) required in the production of EVs, and a challenge of dealing with end-of-life EVs and waste in a sustainable way (Baars et al., 2021). As such, CE strategies play an important role in a transition of sustainable transport systems by replacing ICEVs with EVs.
- **Defining policy/research questions:** As mentioned in Chapter 2 – 3, the selection of a linkage modelling approach depends on the policy/research question that modelers need to address. In this case, we provide two questions and associated linkages archetypes from Chapter 3:
  A. What are the changes in GHG emissions due to the replacement of ICEVs with EVs in a given country considering the circularity potential of Li-ion batteries?
  B. What are the changes in GHG emissions due to the replacement of ICEVs with EVs if a government establishes environmental policies based on the GHG lifetime emissions of ICEVs and EVs?
- **Model setting/assumptions:** We assume the presence of a CGE model that contains a sector called *'motor vehicle and transport equipment'*. As in conventional CGE model, our model contains a set of exogenous and endogenous variables. Exogenous variables include fixed factors of supply, endowment, and demand that can be shocked through three parameters: tax/tariff rates, supply/demand elasticities, and shift/share parameters (Burfisher, 2020). Endogenous variables involve consumption and production values, as the solutions of the price equilibrium equations (Burfisher, 2020).

Both questions require calculation of changes in GHG emissions at a national level. For this reason, a CGE model serves as the foreground system. For **Question A**, the circularity potential of Li-ion batteries requires modelling of the dynamics of Li-ion battery stocks and flows, thus, it is most suitable for a linkage with DMFA. For **Question B**, life cycle emissions of ICEVs and EVs are required, lending itself to coupling with an LCA model.

The subsequent sections illustrate how the modelling linkages would be achieved in each case, based on the insights of Chapters 1 -3.

A. Replacing ICEVs with EVs considering the circularity potential of Li-ion batteries

Lithium (Li) is the most common raw material used in the manufacture of batteries for electric vehicles and faces increasing demand against the backdrop of a wide-scale shift away from internal combustion engines (Ambrose & Kendall, 2019). However, the extraction and use of lithium poses significant adverse environmental and social impacts in mining sites, such as water over-exploitation and pollution, biodiversity loss, poor working conditions, and land grabbing from local communities (Agusdinata et al., 2018; Petavratzi et al., 2022). The share of primary (i.e., virgin) and secondary lithium in Li-ion batteries will determine the scale of these impacts and the sustainability of electric vehicle use over the coming decades. The need for secondary lithium use has also become increasingly urgent due to the prospect of global lithium demand outstripping supply over the coming decades (Greim et al., 2022); between 2018 and 2019 lithium consumption increased by 18% (Bae & Kim, 2021). The Critical Raw Materials Act of the European Commission exemplifies global concern about the long-term security and sustainability of lithium supply to satisfy growing appetite for renewable energy infrastructure (EC, 2022).

The use of primary (i.e., virgin) or secondary lithium in the production of Li-ion batteries will be determined by their respective prices and availability, factors influenced *inter alia* by production technologies, procurement policy, and the scale of lithium mining operations. Intermediate Input Substitution Elasticity (σ^{INT}) is a CGE parameter which quantitatively denotes the extent of substitutability between two inputs within a given production process for the same good or service. Within the context of ***Scenario A***, MFA accounts offer data on the relative volume (i.e. tonnes) of both primary and secondary lithium. In combination with price per quantity data (e.g., from COMTRADE or BACI databases), MFA can be used to calculate the potential substitution of primary and secondary inputs within a conventional CGE production function, as follows:

$$\sigma^{INT} = \frac{\%\Delta \frac{Qty\_Li\_recycled}{Qty\_Li\_primary}}{\%\Delta \frac{Price\_Li\_recycled}{Price\_Li\_primary}}, \qquad \textit{equation 1}$$

where σ^{INT} denotes the scale (low to high) of factor substitution between primary and secondary lithium in the production of batteries for EVs. Within this equation, substitutability reflects the extent of change in demand for primary and secondary materials arising from a change in their relative prices, a shift from one to the other. Increasing availability of secondary lithium will make lower its cost, which causes a decrease in its relative price compared to primary lithium. This leads to the replacement of primary lithium with secondary lithium for batteries, given the $\sigma^{INT}$from combining MFA and price data.

Dynamic MFA (DMFA) offers a unifying methodological framework to assess changes in the availability and use of raw materials within production processes at an economy-wide scale (Ziemann et al., 2018), quantity components of σ^{INT}. Due to the use of lithium in other industries (e.g., ceramics, glass, and grid storage applications), the macroeconomic perspective of resource stocks offered by DMFA is advantageous to LCI/LCA. Enriched by price data on primary and second lithium, from σ^{INT} ,DMFA can be used to assess the substitution elasticity between these intermediate inputs in electric vehicle batteries, as an input into a CGE model.

Such a soft-coupled model can be used for scenario analysis to assess the environmental burden associated with circularity of lithium use in li-ion batteries for electric vehicles, within the context of large-scale and long-term economic and material trends. For example, Baars et al. (2021) developed an MFA model to assess the global cobalt flows for the future development of EVs. Furthermore, they developed circular economy scenarios by considering multiple factors relating to resource availability and use, such as batteries replaced before end-of-life vehicle, end-of-life vehicle collection, battery collection, recovery rate, and new chemistry adoption. In a similar way, Chen et al. (2021) assessed the economic and environmental impacts of adopting EVs in the US context using an upgraded version of a Computable General Equilibrium for the US economy. The authors estimated three key parameters for each type of passenger vehicle: purchase price, annual fuel equivalent cost, and annual CO_2 emissions. Purchase price and fuel equivalent cost were determined through a consumer survey, while CO_2 emissions factors were retrieved from the CO_2 emissions per year for each scenario, calculated using emissions from the US Environmental Protection Agency (EPA)'s annual Inventory of US Greenhouse Gas Emissions and Sinks. The latter can be replaced by more granular LCI data for specific countries depending on the modeling requirements. For example, LCIs can bring emission factors related to different car technologies, and energy mix (which important when considering life cycle emissions of EVs). Figure 2 depicts the nature and scope of these soft-coupled models.

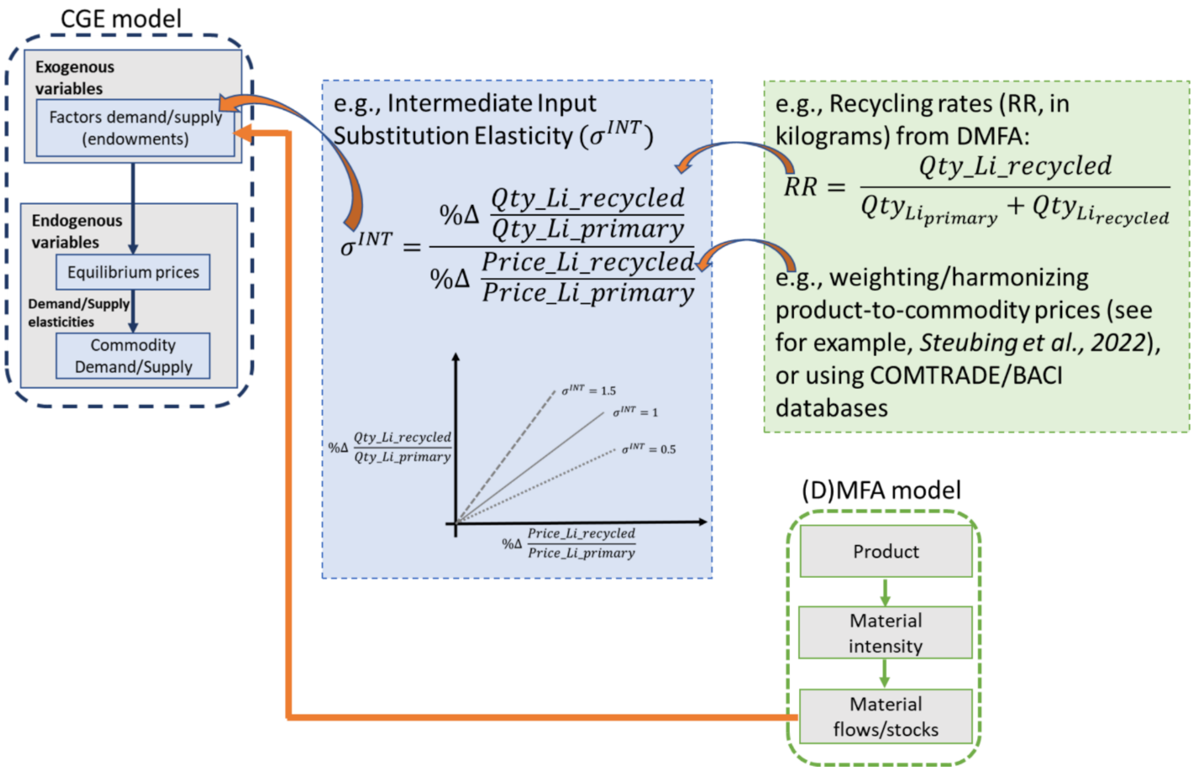

Figure 2. Example of CGE foreground, soft linkage with DMFA for the case of replacing Li-ion batteries from primary (virgin) Li to recycled Li.

In a soft-linked between CGE and Dynamic MFA, where the former serves as the foreground model, consumption and production of electric vehicles would be calculated by economic equilibrium of demand and supply factors, endogenous variables. However, the relative share of primary and secondary lithium in the production recipe (i.e., direct requirements matrix of an I-O table) would be determined by their substitution elasticity, as calculated by the DMFA, and recomputed each time step, based on changes in lithium availability, recycling and price. Satellite accounts connected to the CGE could be subsequently used to assess the greenhouse gas emissions footprint of electric vehicle use where the use and recyclability of secondary lithium varies in time. Relevant scenarios within this context, in which dynamic MFA studies and data can be directly utilized, include: changing consumption trends for electric vehicles (Baars et al., 2021); and studying of lithium availability based on the development time (approximately 16 years) of lithium mines, from discovery to first production (IEA, 2022b).

Although out of the scope of this report, other possible linkages between DMFA and CGE could be examined and better-suited to other research questions. For example, endogenisation of material stocks as production constraints, by combining DMFA with CGE (remaining as a foreground model) production function, could give preferential selection of secondary lithium compared with primary lithium, until secondary reserves are depleted. Supposing DMFA functioned as a foreground model, material stocks and use could be generated using biophysical constraints (e.g., mass balance, recoverability, and resource quality), then soft-linked to a CGE model to equilibrate demand and supply for resources within the economy. A hard linkage between DMFA (foreground) and CGE (background) models within this context, could involve explicit traceability of waste flows (in intermediate and end-use stages) in a CGE model, within a waste input-output framework where the waste sector receives economic and physical representation (Nakamura & Kondo, 2018). Studying environmental rebound effects of production and consumption decisions also invites further integration of physical and financial models (Duarte, et al. 2018).

B. Replacing ICEVs with EVs considering environmental regulations

Environmental restrictions on life cycle impacts of ICEV and EV supply, in ***Scenario B***, introduces a non-price factor production constraint in the output of the automobile industry. The limited granularity of product-level information in CGE models prevents scenario modelling of ICEVs and EVs based on their respective production requirements and life-cycle impacts. Life-cycle inventories (LCIs) offer such information, for example: product-level input and output factors, market penetration rates, and purchase prices as the price per ICEV and EV unit (see table 2, Appendix, for further factors). The latter can be used to make changes in exogenous variables from the CGE model. Commodity Output Transformation Elasticity (σ^Q) is a CGE parameter which quantitatively captures the flexibility of a single industry to produce two different outputs given a set of production endowments and constraints. It is important to mention that σ^Q is used as one of several variables that can be shocked within the CGE model. In practice, it should not matter whether the EVs are made by the same companies/plants; rather, it is crucial to consider which other inputs are needed for EV production as well as production costs (after price adjustments) and corresponding demand (which might depend on specific policies). Within the context of ***Scenario B***, product-level price, and quantity data from LCIs can be used to calculate the potential substitution of IC and EV production within the output of the automobile industry, as follows:

$$\sigma^Q = \frac{\%\Delta \frac{Qty\_EVs}{Qty\_ICEVs}}{\%\Delta \frac{Price\_EVs}{Price\_ICEVs}}, \quad \textit{equation 2}$$

where σ^Q denotes the scale (low to high) of substitution between outputs of the automobile industry. Within this equation, the automobile industry will become able to better satisfy demand for EVs if their price increases (e.g., due to increased consumer demand or rising fuel costs of ICEVs) or expectantly, if their quantity produced increases (e.g., due to new government subsidies and providing affordable prices for consumers). Traditionally, elasticity of substitution is measured by econometric techniques, such as Kmenta-approximation, Bayesian, and Generalized Maximum Entropy methods. However, those approaches are usually difficult to apply in the case EVs because of the lack of data (Guo et al., 2021). To resolve this issue, Guo et al. (2021) estimated a substitution elasticity that represents the willingness of consumers to replace ICEV for EV in China (in the same way as expressed equation 2). The authors used commercial databases to determine the EV price per quantity.

From a CGE perspective, the propensity of ICEVs replacement with EVs is more likely if the latter attracts a lower market price (e.g., due to shifting transport habits or lower affordability of new cars) or its supply is limited (e.g., due to government quotas or in response to greater market opportunities for EVs). Such equation can be used to assess the rate of substitution between ICEVs and EVs over time in production of the automobile industry and represents a soft coupling between CGE (foreground) and LCA (background) models.

Although not traditional factors in the price-based determination of industry output in a CGE model, environmental constraints, such as life-cycle greenhouse gas emissions of ICEVs and EVs from LCI can be endogenized to a CGE industry production function, as follows:

$\min \sum[cf \cdot d]$, $\min \sum[pc]$, *equation 3*

where cf = environmental characterization factors, and d = products inputs/outputs from LCA, and pc = production cost from equilibrium price functions. Figure 3 shows the integration of hard linkages for ***Scenario B*** based on the linkages archetypes.

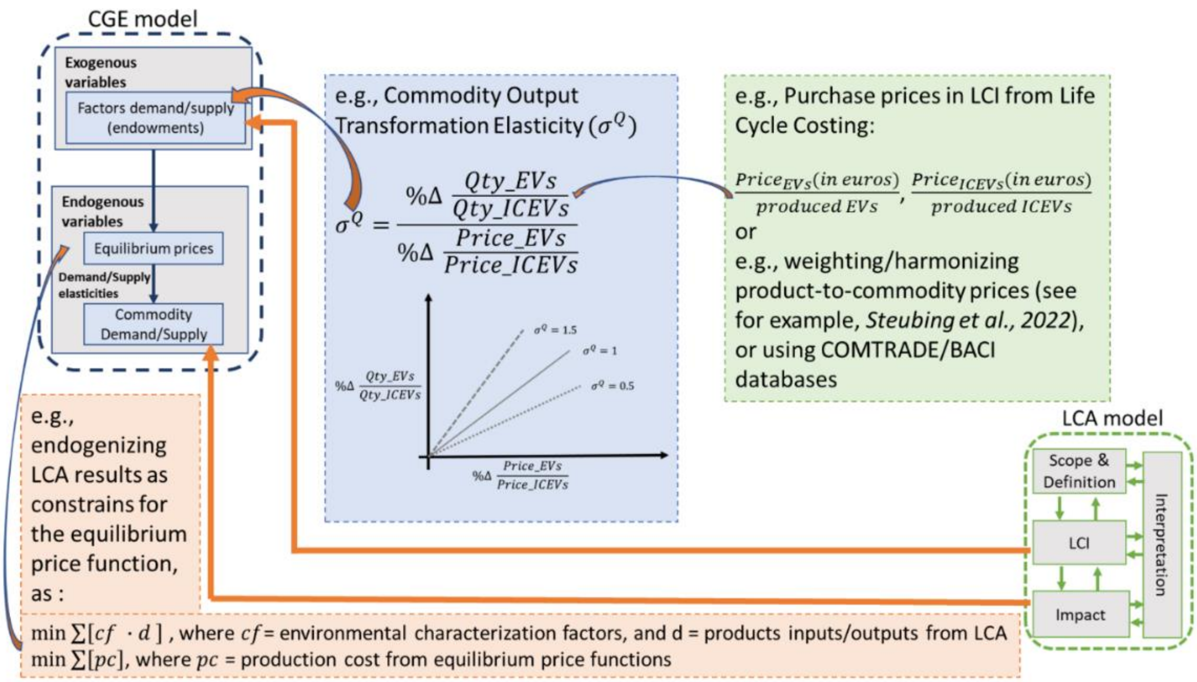

Figure 3. Example of CGE foreground, hard linkage with LCA for the case of replacing ICEVs with EVs considering the life cycle environmental impacts.

Within this context, the LCA model becomes hard-linked to the CGE model that provides the quantity and price information to determine the ICEVs and EV production factors in the output of automobile industry. Such information on the production technology of ICEVs and EVs can be used by CGE modelers to fill production data in CGE models and distinguish between ICEV and EV production. Karplus et al. (2013) developed a CGE model for analyzing the behaviour of passenger vehicle transport. The authors used engineering and fleet data to estimate multiple parameters such as the representation of alternative vehicles (e.g., ICEs vs. EVs), in which income and substitution elasticities, and adoption rates were embedded in the CGE model. In terms of data source and resolution, the engineering/fleet data is equivalent to the LCI data (in terms of sectoral resolution, which implies that hard-linkages between CGE-LCA are straightforward to undertake/perform.

Further endogenization of environmental production constraints or policies could be made via inclusion of greenhouse gas emissions as a shadow price in the general equilibrium function, additional to traditional production costs (as shown in Fu et al., 2021):

$Q^* = F(P, Y, E) = G(P, PO, E)$, *equation 4*

where Q^* = Equilibrium quantity of EVs and/or ICEVs, Y = income, P = Market price, PO = inputs price, and E = Environmental cost. Such a practice is already being adopted within the car industry with manufacturers setting an internal carbon price to inform their production investments (Jessop et al., 2021). It is important to notice that the internal carbon price should be paid by a specific sector in the CGE model (e.g., by government), a common practice in CGE models used for climate policy analysis.

Final remarks

To provide robust and actionable insights for decision makers, circular economy modelling must be based on an understanding of large-scale and long-term interactions between industries, products, and technologies, in both the economic and material world. Linkage of micro and macro modelling approaches is critical towards this end. This report examined the scope for and benefits of linking micro (i.e., Life Cycle Assessment (LCA) and Dynamic Material Flow Analysis (DMFA)) and CGE models to model circular economy strategies. Within this context, micro and macro models offer different vantage points on pathways of material extraction, use and circularity.

Micro models, such as LCA and DMFA, capture fully changes in biophysical stocks and flows across a wide range of production and consumption systems. Macro models provide an insight into how pressures on these systems evolve over time based on economic drivers (e.g., household consumption, labour, investment, and resource prices). Within this report we show how connecting these two modelling frameworks and underlying data offers tremendous potential to study circular economy priorities and impacts, otherwise hidden by the coarse sectoral resolution of macro models and limited economic information in micro models.

Using the example of transport (in **Chapter 4**), we illustrate various options for linking these models to assess replacement of internal combustion engine vehicles (ICEVs) with electric vehicles (EVs), applied to two relevant circularity strategies: use of recycled lithium in EV batteries (***Scenario A***) and shifting production of ICEVs to EVs in the automobile industry (***Scenario B***). In both cases, we identify how information from DMFA and LCA models contain important product- and sector-level data to calculate key CGE model components (input and output substitution) to model economy-wide environmental impacts of circular economy measures.

Invariably, DMFA-LCA-CGE linkages rely on common methodological procedures, such as (i) sectoral concordance between models, (ii) temporal updating and communication between model parameters, and (iii) disaggregation of CGE sectors, their production recipes, and final outputs. The complexity of these procedures will be determined by the scale (soft or hard) of coupling between models and the research questions of interest. A further challenge is understanding and reconciling the unique (and sometime contradictory) biophysical and economic principles and data which underpin macro and micro models. To this end, development of hybrid physical-financial models would help establish a unifying framework for micro-macro linked models.

Although not covered in this report, various factors will also influence the impacts of circular economy measures and our ability to study them. First, the energy mix of countries is of major consequence to environmental burden of EV use and energy efficiency measures more generally (Faria et al., 2013).

Second, in addition to price, consumer and producer decisions emerge from a complex web of social, cultural, interpersonal interactions and feedbacks. Yet, large-scale models of pro-environmental consumption and production shifts remain limited to price-driven, rational, and homogenous models of behaviour change (e.g., CGEs and IAMs), or ignore their determinants entirely (e.g., LCA, (D)MFA, MRIOA scenarios). In contrast, Agent-based Models (ABMs) employ heterogeneous individuals and groups with imperfect information and multiple preferences, who are adaptive in a dynamic setting (Axtell & Farmer, 2022). In exploring linkage of dynamic micro-models to CGE, ABMs deserve greater attention. Nevertheless, it is important to notice the challenge of providing a proper validation/calibration for CGE and ABMs due to the lack of data.

Lastly, temporal mismatch between data and parameters which underpin micro and macro models invite careful sensitivity analysis and collaborative efforts to update databases on the economic and material basis of production and consumption systems. Although non-trivial, the environmental footprinting community is making significant inroads into tackling these challenges (Wiedmann & Lenzen, 2018), providing novel frameworks to connect data, models, and empirical insights to identify novel solutions to the urgent ecological crisis humanity faces.

List of abbreviations

ABMs	Agent-based Models
CE	Circular Economy
CGE	Computable General Equilibrium model
DMFA	Dynamic Material Flow Analysis
EVs	Electric vehicles
GDP	Gross domestic product
GHG	Greenhouse gases
IAMs	Integrated Assessment Models
ICEVs	Internal combustion engine vehicles
IOT	Input-Output Table
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
MFA	Material Flow Analysis
MRIOT	Multi-regional Input-Output Table
SAMs	Social Accounting Matrices

Appendix

Table 2. Summary relevant parameters from LCA and MFA approaches useful for macro-modelling

Supply side	Demand side
• Product-level production • Energy mix scenarios • Cost, e.g., – Vehicle purchase price – Infrastructure cost • Other general econometric data, e.g., discount rate, inflation, and inflation-adjusted discount rate) • Market share and penetration rates • Energy production • Material intensity • Recycling rates	• Total distance traveled by vehicles • Vehicle, batteries and other components lifetimes • Passenger car maintenance • Total energy use • Cost, e.g., – Vehicle (e.g., bus) purchase price – Fuel efficiency – Vehicle maintenance and repair – Battery replacement cost – Insurance • Energy consumption • Material intensity • Lifetime distribution • Time allocation

Table 3. LCI and MFA data sources from the selected studies

LCI accounts	MFA source
• Ecoinvent • For EV, Electric Vehicle Database, 2019 • CATRC, MIIT, Sae-China (in Chinese, in Yang et al.(2021)) • For Li-ion batteries, see fig 2 in Peters et al.(2017) • Empirical data from disassembling products (see, for example, Hollingsworth et al. (2019))	• IEA database and reports (e.g., Global EV Outlook 2022(IEA, 2022a)) • For personal mobility, see table 2 in Virag et al. (2022) • Governmental agencies and statistical bureaus (e.g., RDW and CBS used by Tang et al. (2021))

References

Agusdinata, D. B., Liu, W., Eakin, H., & Romero, H. (2018). Socio-environmental impacts of lithium mineral extraction: towards a research agenda. *Environmental Research Letters*, *13*(12), 123001.

Ambrose, H., & Kendall, A. (2019). Understanding the future of lithium: Part 1, resource model. *Journal of Industrial Ecology*, *24*(1), 80–89. https://doi.org/10.1111/jiec.12949

Axtell, R. ., & Farmer, J. . (2022). *Agent-Based Modeling in Economics and Finance: Past, Present, and Future*. https://www.inet.ox.ac.uk/files/JEL-v2.0.pdf

Baars, J., Domenech, T., Bleischwitz, R., Melin, H. E., & Heidrich, O. (2021). Circular economy strategies for electric vehicle batteries reduce reliance on raw materials. *Nature Sustainability*, *4*(1), 71–79. https://doi.org/10.1038/s41893-020-00607-0

Bae, H., & Kim, Y. (2021). Technologies of lithium recycling from waste lithium ion batteries: a review. *Materials Advances*. https://doi.org/https://doi.org/10.1039/d1ma00216c

Beaussier, T., Caurla, S., Bellon-Maurel, V., & Loiseau, E. (2019). Coupling economic models and environmental assessment methods to support regional policies: A critical review. In *Journal of Cleaner Production* (Vol. 216, pp. 408–421). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2019.01.020

Bobba, S., Bianco, I., Eynard, U., Carrara, S., Mathieux, F., & Blengini, G. A. (2020). Bridging tools to better understand environmental performances and raw materials supply of traction batteries in the future EU fleet. *Energies*, *13*(10). https://doi.org/10.3390/en13102513

Burfisher, M. (2020). *Introduction to Computable General Equilibrium Models*. Cambridge University Press. https://doi-org.ezproxy.leidenuniv.nl/10.1017/9781108780063

Cao, Z., Liu, G., Zhong, S., Dai, H., & Pauliuk, S. (2019). Integrating Dynamic Material Flow Analysis and Computable General Equilibrium Models for Both Mass and Monetary Balances in Prospective Modeling: A Case for the Chinese Building Sector. *Environmental Science and Technology*, *53*(1). https://doi.org/10.1021/acs.est.8b03633

Carmona, L. G., Whiting, K., Haberl, H., & Sousa, T. (2021). The use of steel in the United Kingdom's transport sector: A stock–flow–service nexus case study. *Journal of Industrial Ecology*, *25*(1), 125–143. https://doi.org/10.1111/jiec.13055

Chen, Z., Carrel, A. L., Gore, C., & Shi, W. (2021). Environmental and economic impact of electric vehicle adoption in the U.S. *Environmental Research Letters*, *16*(4). https://doi.org/10.1088/1748-9326/abe2d0

Cusenza, M. A., Bobba, S., Ardente, F., Cellura, M., & Di Persio, F. (2019). Energy and environmental assessment of a traction lithium-ion battery pack for plug-in hybrid electric vehicles. *Journal of Cleaner Production*, *215*, 634–649. https://doi.org/10.1016/j.jclepro.2019.01.056

EC. (2022). *Critical Raw Materials Act: securing the new gas & oil at the heart of our economy I Blog of Commissioner Thierry Breton*. https://ec.europa.eu/commission/presscorner/detail/en/STATEMENT_22_5523

Faria, R., Marques, P., Moura, P., Freire, F., Delgado, J., & de Almeida, A. T. (2013). Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles. *Renewable and*

Sustainable Energy Reviews, *24*, 271–287. https://doi.org/https://doi.org/10.1016/j.rser.2013.03.063

Fischer-Kowalski, M., Gaube, V., & Rainer, G. (2006). *F O R U M MEFASPACE A Model Predicting Freight Transport from Materials Flows, and Transport Activity in Europe* (Vol. 10, Issue 4). www.mitpressjournals.org/jie

Fu, Y., Huang, G., Liu, L., & Zhai, M. (2021). A factorial CGE model for analyzing the impacts of stepped carbon tax on Chinese economy and carbon emission. *Science of the Total Environment*, *759*, 143512. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.143512

Garcia, D. J., & You, F. (2018). Addressing global environmental impacts including land use change in life cycle optimization: Studies on biofuels. *Journal of Cleaner Production*, *182*, 313–330. https://doi.org/10.1016/j.jclepro.2018.02.012

Greim, P., Solomon, A. A., & Breyer, C. (2022). Assessment of lithium criticality in the global energy transition and addressing policy gaps in transportation. *Nature Communications*, *11*(1). https://doi.org/https://doi.org/10.1038/s41467-020-18402-y

Guo, Z., Li, T., Peng, S., & Zhang, H. (2021). Environmental and economic consequences of the incentive policy on electric vehicle industry: A CGE based study in China. *Resources, Conservation and Recycling*, *169*. https://doi.org/10.1016/j.resconrec.2021.105542

Guo, Z., Li, T., Shi, B., & Zhang, H. (2022). Economic impacts and carbon emissions of electric vehicles roll-out towards 2025 goal of China: An integrated input-output and computable general equilibrium study. *Sustainable Production and Consumption*, *31*, 165–174. https://doi.org/10.1016/j.spc.2022.02.009

Harper, G., Sommerville, R., Kendrick, E., Driscoll, L., Slater, P., Stolkin, R., Walton, A., Christensen, P., Heidrich, O., Lambert, S., Abbott, A., Ryder, K., Gaines, L., & Anderson, P. (2019). Recycling lithium-ion batteries from electric vehicles. In *Nature* (Vol. 575, Issue 7781, pp. 75–86). Nature Publishing Group. https://doi.org/10.1038/s41586-019-1682-5

Hollingsworth, J., Copeland, B., & Johnson, J. X. (2019). Are e-scooters polluters? the environmental impacts of shared dockless electric scooters. *Environmental Research Letters*, *14*(8). https://doi.org/10.1088/1748-9326/ab2da8

IEA. (2022a). *Global EV Outlook 2022 Securing supplies for an electric future*. www.iea.org/t&c/

IEA. (2022b). *The Role of Critical World Energy Outlook Special Report Minerals in Clean Energy Transitions*. https://iea.blob.core.windows.net/assets/ffd2a83b-8c30-4e9d-980a-52b6d9a86fdc/TheRoleofCriticalMineralsinCleanEnergyTransitions.pdf

Igos, E., Rugani, B., Rege, S., Benetto, E., Drouet, L., & Zachary, D. S. (2015). Combination of equilibrium models and hybrid life cycle-input-output analysis to predict the environmental impacts of energy policy scenarios. *Applied Energy*, *145*, 234–245. https://doi.org/10.1016/j.apenergy.2015.02.007

Jessop, S., James, W., & Nasralla, S. (2021). *Volvo Cars sets carbon price to assess sustainability of new projects*. Reuters. https://www.reuters.com/business/cop/volvo-sets-carbon-price-assess-sustainability-new-projects-2021-11-10/

Kamran, M., Raugei, M., & Hutchinson, A. (2021). A dynamic material flow analysis of lithium-ion battery metals for electric vehicles and grid storage in the UK: Assessing the impact of shared mobility and end-of-life strategies. *Resources, Conservation and Recycling*, *167*. https://doi.org/10.1016/j.resconrec.2021.105412

Karplus, V. J., Paltsev, S., Babiker, M., & Reilly, J. M. (2013). Applying engineering and fleet detail to represent passenger vehicle transport in a computable general equilibrium model. *Economic Modelling*, *30*(1), 295–305. https://doi.org/10.1016/j.econmod.2012.08.019

Khan, M. J. A., & Onat, N. C. (2022). Comprehensive Total Cost of Ownership Framework for Alternative Fuel Public Transportation Buses. *Transportation Research Record: Journal of the Transportation Research Board*, 036119812211227. https://doi.org/10.1177/03611981221122783

Lee, D. (2018). Building evaluation model of biohydrogen industry with circular economy in Asian countries. *International Journal of Hydrogen Energy*, 1–12. https://doi.org/10.1016/j.ijhydene.2018.09.069

Li, C., Mogollón, J. M., Tukker, A., Dong, J., von Terzi, D., Zhang, C., & Steubing, B. (2022). Future material requirements for global sustainable offshore wind energy development. *Renewable and Sustainable Energy Reviews*, *164*(May). https://doi.org/10.1016/j.rser.2022.112603

Machado, P. G., Cunha, M., Walter, A., Faaij, A., & Guilhoto, J. J. M. (2020). The potential of a bioeconomy to reduce Brazilian GHG emissions towards 2030: a CGE-based life cycle analysis. *Biofuels, Bioproducts and Biorefining*, *14*(2), 265–285. https://doi.org/10.1002/bbb.2064

Nakamura, S., & Kondo, Y. (2018). Toward an integrated model of the circular economy: Dynamic waste input–output. *Resources, Conservation and Recycling*, *139*, 326–332. https://doi.org/https://doi.org/10.1016/j.resconrec.2018.07.016

Nordelöf, A., Messagie, M., Tillman, A. M., Ljunggren Söderman, M., & Van Mierlo, J. (2014). Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? In *International Journal of Life Cycle Assessment* (Vol. 19, Issue 11, pp. 1866–1890). Springer Verlag. https://doi.org/10.1007/s11367-014-0788-0

Nurdiawati, A., & Agrawal, T. K. (2022). Creating a circular EV battery value chain: End-of-life strategies and future perspective. *Resources, Conservation and Recycling*, *185*. https://doi.org/10.1016/j.resconrec.2022.106484

Pauliuk, S., Kondo, Y., Nakamura, S., & Nakajima, K. (2017). Regional distribution and losses of end-of-life steel throughout multiple product life cycles—Insights from the global multiregional MaTrace model. *Resources, Conservation and Recycling*, *116*, 84–93. https://doi.org/10.1016/j.resconrec.2016.09.029

Peng, S., Yang, Y., Li, T., Smith, T. M., Tan, G. Z., & Zhang, H. C. (2019). Environmental Benefits of Engine Remanufacture in China's Circular Economy Development. *Environmental Science and Technology*, *53*(19), 11294–11301. https://doi.org/10.1021/acs.est.9b02973

Petavratzi, E., Sanchez-Lopez, D., Hughes, A., Stacey, J., Ford, J., & Butcher, A. (2022). The impacts of environmental, social and governance (ESG) issues in achieving sustainable lithium supply in the Lithium Triangle. *Mineral Economics*, *35*(3–4), 673–699. https://doi.org/10.1007/s13563-022-00332-4

Peters, J. F., Baumann, M., Zimmermann, B., Braun, J., & Weil, M. (2017). The environmental impact of Li-Ion batteries and the role of key parameters – A review. In *Renewable and Sustainable Energy Reviews* (Vol. 67, pp. 491–506). Elsevier Ltd. https://doi.org/10.1016/j.rser.2016.08.039

Shafique, M., Azam, A., Rafiq, M., & Luo, X. (2022). Life cycle assessment of electric vehicles and internal combustion engine vehicles: A case study of Hong Kong. *Research in Transportation Economics*, *91*. https://doi.org/10.1016/j.retrec.2021.101112

Sigüenza, C.P., Steubing, B., Tukker, A., & Aguilar-Hernández, G. A. (2020). The environmental and material implications of circular transitions: A diffusion and product-life-cycle-based modeling framework. *Journal of Industrial Ecology*, 1–17. https://doi.org/10.1111/jiec.13072

Sigüenza, Carlos Pablo, Cucurachi, S., & Tukker, A. (2021). Circular business models of washing machines in the Netherlands: Material and climate change implications toward 2050. *Sustainable Production and Consumption*, *26*, 1084–1098. https://doi.org/10.1016/j.spc.2021.01.011

Smetschka, B., Wiedenhofer, D., Egger, C., Haselsteiner, E., Moran, D., & Gaube, V. (2019). Time Matters: The Carbon Footprint of Everyday Activities in Austria. *Ecological Economics*, *164*. https://doi.org/10.1016/j.ecolecon.2019.106357

Söderman, M. L., Eriksson, O., Björklund, A., Östblom, G., Ekvall, T., Finnveden, G., Arushanyan, Y., & Sundqvist, J. (2016). Integrated Economic and Environmental Assessment of Waste Policy Instruments. *Sustainability*, *8*(411), 1–21. https://doi.org/10.3390/su8050411

Steubing, B., de Koning, A., Merciai, S., & Tukker, A. (2022). How do carbon footprints from LCA and EEIOA databases compare? A comparison of ecoinvent and EXIOBASE. *Journal of Industrial Ecology*, *26*(4), 1406–1422. https://doi.org/10.1111/jiec.13271

Tang, C., Sprecher, B., Tukker, A., & Mogollón, J. M. (2021). The impact of climate policy implementation on lithium, cobalt and nickel demand: The case of the Dutch automotive sector up to 2040. *Resources Policy*, *74*. https://doi.org/10.1016/j.resourpol.2021.102351

Virág, D., Wiedenhofer, D., Haas, W., Haberl, H., Kalt, G., & Krausmann, F. (2022). The stock-flow-service nexus of personal mobility in an urban context: Vienna, Austria. *Environmental Development*, *41*. https://doi.org/10.1016/j.envdev.2021.100628

Wang, H., Dai, H., Dong, L., Xie, Y., Geng, Y., Yue, Q., Ma, F., Wang, J., & Du, T. (2018). Co-benefit of carbon mitigation on resource use in China. *Journal of Cleaner Production*, *174*, 1096–1113. https://doi.org/10.1016/j.jclepro.2017.11.070

Watari, T., McLellan, B. C., Giurco, D., Dominish, E., Yamasue, E., & Nansai, K. (2019). Total material requirement for the global energy transition to 2050: A focus on transport and electricity. *Resources, Conservation and Recycling*, *148*. https://doi.org/10.1016/j.resconrec.2019.05.015

Wiedmann, T., & Lenzen, M. (2018). Environmental and social footprints of international trade. *Nature Geoscience*, *11*(5), 314–321. https://doi.org/10.1038/s41561-018-0113-9%0A

Yang, L., Yu, B., Yang, B., Chen, H., Malima, G., & Wei, Y. M. (2021). Life cycle environmental assessment of electric and internal combustion engine vehicles in China. *Journal of Cleaner Production*, *285*. https://doi.org/10.1016/j.jclepro.2020.124899

Zhong, X., Hu, M., Deetman, S., Steubing, B., Lin, H. X., Hernandez, G. A., Harpprecht, C., Zhang, C., Tukker, A., & Behrens, P. (2021). Global greenhouse gas emissions from residential and commercial building materials and mitigation strategies to 2060. *Nature Communications*, *12*(1), 1–10. https://doi.org/10.1038/s41467-021-26212-z

Ziemann, S., Müller, D. B., Schebek, L., & Weil, M. (2018). Modeling the potential impact of lithium recycling from EV batteries on lithium demand: A dynamic MFA approach. *Resources, Conservation and Recycling*, *133*, 76–85. https://doi.org/10.1016/j.resconrec.2018.01.031%0A