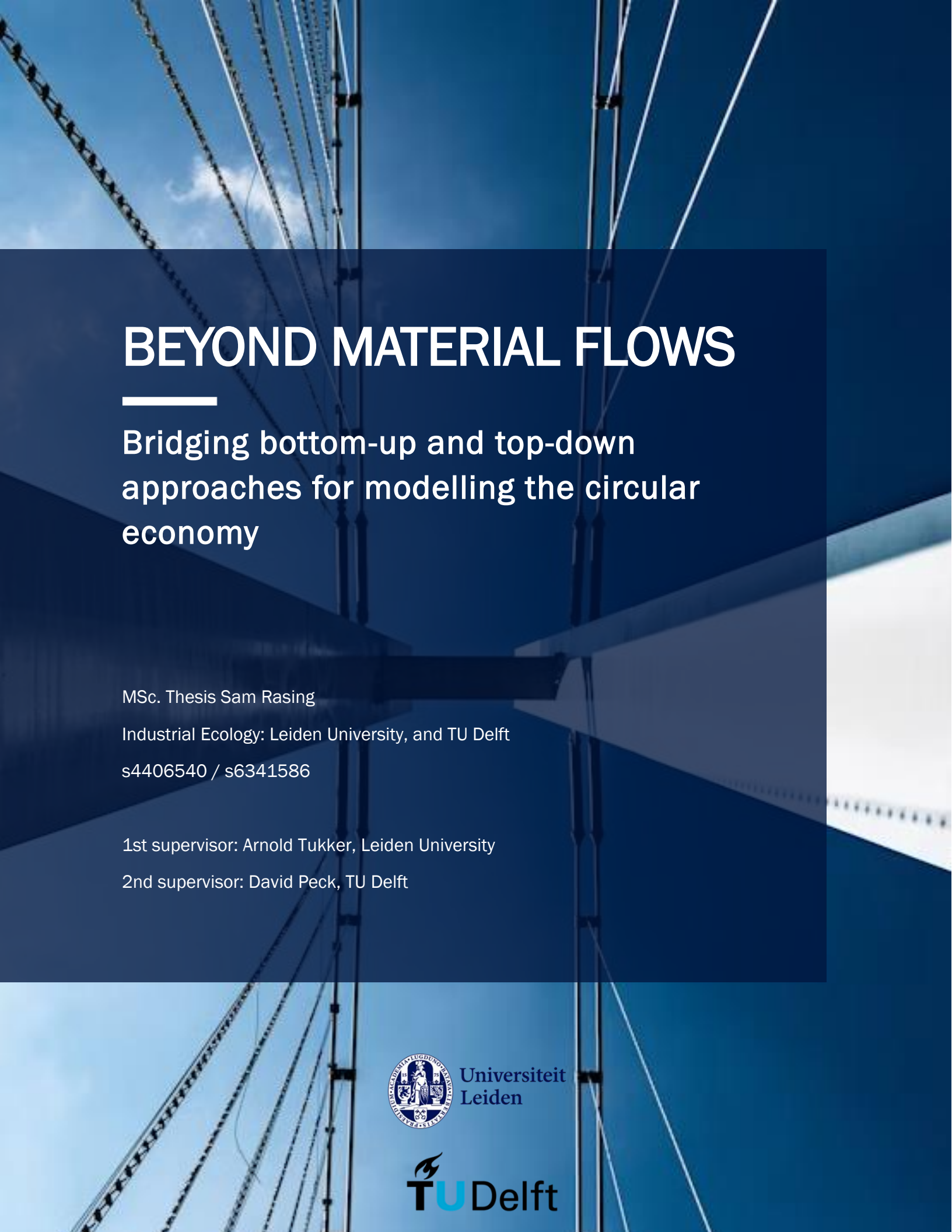


BEYOND MATERIAL FLOWS

Bridging bottom-up and top-down approaches for modelling the circular economy

MSc. Thesis Sam Rasing

Industrial Ecology: Leiden University, and TU Delft

s4406540 / s6341586

1st supervisor: Arnold Tukker, Leiden University

2nd supervisor: David Peck, TU Delft

Universiteit Leiden

TU Delft

Abstract

The global use of natural resources continues to increase, contributing to the transgression of planetary boundaries. The circular economy (CE) is seen as a way to address this by reducing, reusing, recycling, and recovering materials within the economy. However, these CE strategies affect prices, demand, and other economic dimensions beyond material flows, creating economy-wide effects that remain poorly understood. To capture these dynamic impacts, Computable General Equilibrium (CGE) models are increasingly used, as they incorporate price and substitution effects to model the economy-wide dynamics of CE strategies. However, CGE models are highly aggregated and use monetary units, meaning they are not good at capturing flows to waste and recycling, due to their low and often highly fluctuating value, and thus, cannot model physical material flows at the level of detail required for CE modelling. Material Flow Analysis (MFA) is better suited to capturing these material flows, but cannot capture the economy-wide dynamics of a CE strategy. The limitations of both models demonstrate the need for a linked MFA-CGE approach capable of modelling CE strategies with enough product-level detail, while also capturing the generated economy-wide effects.

A literature review shows that previous MFA-CGE linkages have provided valuable insights but are not suited to assessing CE strategies at the product level, since they focus on single materials rather than products, neglect the stock-flow dynamics that determine future material availability, or remain theoretical without empirical validation. To address this gap, this thesis explores the possibilities of linking a product-oriented dynamic MFA (dMFA) with a CGE model to assess the economy-wide impacts of product-specific CE strategies. This is done by developing a proof of concept for a soft-linking approach between a product-level dMFA and a CGE model, demonstrated through a case study on the lifetime extension of electrical and electronic equipment (EEE) through repair in the European Union (EU).

Based on inflow data for 54 EEE categories covering 1980–2022, a dual-stock dMFA model is developed, in which the stocks of new and repaired products are separated to account for the shorter lifetime of repaired products. The model is run under two scenarios: a baseline without additional repair and a repair scenario, driven by household preference change in which a product-specific repair rate is applied to each EEE category. The resulting flows for 2017 are then soft-linked to a CGE model (GREEN-R), aggregated into two regions: the EU and the rest of the world. The soft-linking approach allocates the changes in material inflows derived from the dMFA to a shift in household final demand, away from new EEE and towards repair services. The physical inflows of the dMFA are translated into monetary flows at basic prices, using price data obtained from production and trade statistics. The linkage is then implemented by applying a relative reduction to the household's consumption of EEE in the CGE model, with all expenditure no longer spent on new EEE redirected towards EEE repair services.

The results of the repair scenario are as follows. First, the dMFA provides the material foundation for the CE scenario, showing how an increase in repair reduces both the inflow of new EEE and generated waste by 10.1% and 10.9%, respectively. It also reveals that the volume of repaired products exceeds the inflow of new EEE it replaces, due to the shorter lifetimes of repaired products. Translated into

monetary terms, the 10.1% reduction in inflow corresponds to a 14.1% reduction in household consumption of EEE. Second, by applying this monetary inflow reduction to the CGE model, the economy-wide dynamics of the increase in repair are identified. Wages rise by 0.08% as labour demand increases, but since labour is an important factor of production, this also drives inflation. Real household income therefore falls by 0.01%, while less labour-intensive sectors become relatively cheaper, shifting the composition of household consumption through substitution and income effects. The CGE model also reports GHG emissions, showing that repair delivers a climate benefit, with global emissions falling by 2.76 Mt.

Together, these results demonstrate that soft-linking a product-level dMFA to a CGE model provides insights that neither model could generate in itself. By doing so, this thesis demonstrates the value of soft-linking and provides directions for future research, since the method rests on simplifications and leaves certain dynamics outside its scope that would need to be addressed.

Statement on the Use of Generative AI

During the development of this thesis, I have used generative AI tools to support language editing and code development. All outputs were reviewed and revised by me, and I take full responsibility for the content of this work.

Acknowledgement

Since the start of my thesis research project in February 2026, I have worked very hard on my thesis, but without the help of others, the final result would not be what it is now. I would therefore like to thank several people who helped me a great deal during this process. First, I want to thank Corjan and Xinyu (Planbureau voor de Leefomgeving) for the opportunity to collaborate with them in making the dMFA-CGE linkage work. Without their input, I would not have been able to develop this methodology, as their experience and knowledge of CGE modelling were crucial in making it possible. I would also like to thank both my supervisors for the critical feedback I received, which greatly improved my thesis. I particularly appreciate having been able to join the ACT! project, which opened doors I would never have found on my own and brought me into contact with people and opportunities such as working with PBL to implement the linkage. The last person I would like to thank is my girlfriend Suus for the love and support I received during these six months. You were there in all the moments when I was stuck or in over my head, and with your support, you always helped me get back on track. You also gave me valuable feedback throughout the writing process and helped me find structure in the maze of researching and writing.

List of abbreviations

ABM: Agent-Based Model
CE: Circular Economy
CES: Constant Elasticity of Substitution
CGE: Computable General Equilibrium
CIF: Cost, Insurance and Freight
COMEXT: Eurostat database on international trade in goods
CPB: Netherlands Bureau for Economic Policy Analysis
CPC: Central Product Classification
DIY: Do It Yourself
dMFA: dynamic Material Flow Analysis
EEE: Electrical and Electronic Equipment
ELS: EEE and Lifetime-extension Services (nested CES composite)
EoL: End-of-Life
EU: European Union
EU-6: EU WEEE classification into six categories
EU-10: EU WEEE classification into ten categories
EU27: The 27 member states of the European Union
EUR: Europe region in GREEN-R
FOB: Free On Board
GDP: Gross Domestic Product
GHG: Greenhouse Gas
GREEN-R: CGE model developed by PBL and CPB
GTAP: Global Trade Analysis Project
HS: Harmonized System
IE: Industrial Ecology
IO: Input-Output
IRENA: International Renewable Energy Agency
ISIC: International Standard Industrial Classification
LCA: Life Cycle Assessment
LTE: Lifetime Extension
MFA: Material Flow Analysis
NACE: Statistical Classification of Economic Activities in the European Community
PBL: Netherlands Environmental Assessment Agency
PE: Partial Equilibrium
POM: Put On Market
PRODCOM: Eurostat statistics on the production of manufactured goods
RECC: Resource Efficiency–Climate Change
ROS: Recreation and Other Services, including repair (GTAP sector)
ROW: Rest of World
RR: Repair rate
SAM: Social Accounting Matrix
SBS: Structural Business Statistics
SD: System Dynamics
SFA: Substance Flow Analysis
SQ: Sub-question
UN: United Nations
UNU: United Nations University
USD: United States Dollar
VAT: Value Added Tax
WEEE: Waste Electrical and Electronic Equipment

Contents

1 Introduction 8
1.1 Problem statement 8
1.2 Research gap 9
1.3 Research questions 11
1.4 Thesis scope 11
1.5 Thesis outline 12
2 Literature review 13
2.1 MFA and CGE modelling 13
2.1.1 Material Flow Analysis 13
2.1.2 Computable General Equilibrium 14
2.2 Linking MFA with CGE models 15
2.2.1 Linkage archetypes 16
2.2.2 Existing linkage approaches 17
2.3 Conclusions of the literature review 19
3 Methods 21
3.1 Introducing the case 21
3.1.1 Relevance of EEE repair 21
3.1.2 Scope of the case study 22
3.2 dMFA methodology 22
3.2.1 Modelling repair in dMFA 23
3.2.2 Dual-stock dMFA model 23
3.2.3 Stock data 25
3.2.4 Implementation of baseline and repair scenarios 26
3.3 CGE methodology 27
3.3.1 Set up of the CGE model 27
3.3.2 Regional and sectoral aggregation of GREEN-R 29
3.4 Linking MFA to CGE 31
3.4.1 Allocating the dMFA inflows within the SAM 31

3.4.2 Transforming physical inflows into monetary values 34
3.4.3 Implementing the preference shock in the CGE model 36
3.4.4 Analysing the CGE results of the linkage approach 38
3.5 Final Remarks 39
4 Results 40
4.1 Material impacts from the dMFA 40
4.1.1 Changes in inflows and outflows 40
4.1.2 Monetary equivalent of the material reduction 44
4.2 Economy-wide impacts from the CGE model 45
4.2.1 Macroeconomic effects of the repair scenario 45
4.2.2 Decomposition of final demand 47
4.2.3 Impact on GHG emissions 49
5 Discussion 52
5.1 Interpreting the impact of the repair scenario 52
5.2 Benefits of the linkage approach 53
5.3 Limitations of the linkage approach 55
5.3.1 Scope constraints and data limitations 55
5.3.2 Unaccounted dynamics in the linkage approach 57
5.3.3 Temporal misalignment between the two models 58
5.3.4 Scenario design 58
6 Conclusion 60
6.1 Recommendations for further research 61
7 References 63
8 Appendices 70
8.1 A1 Correspondence between UNU-keys and the NACE sectors 70
8.2 A2 Aggregation NACE sectors 71
8.3 A3 Data processing and code documentation 73

1 Introduction

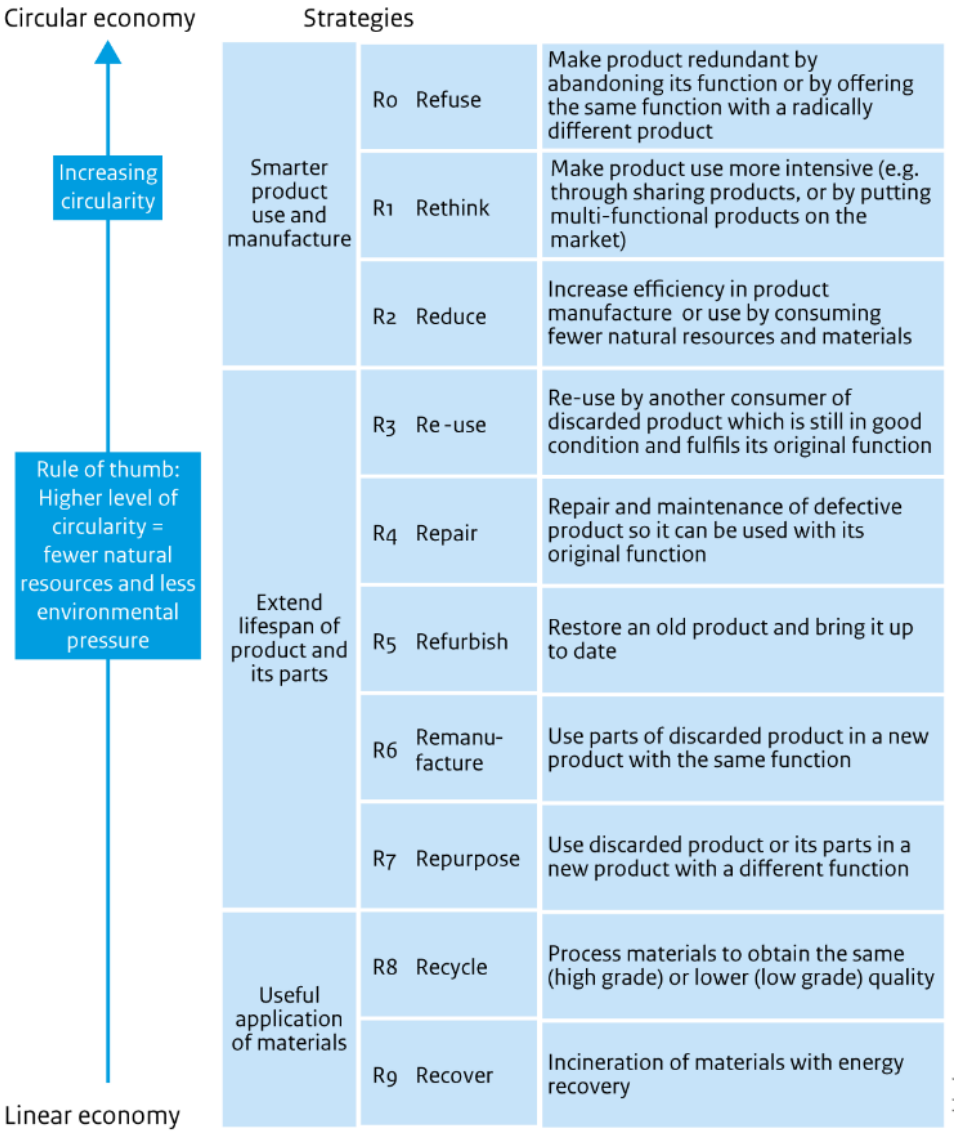
1.1 Problem statement

Around the globe, the consumption of natural resources continues to grow and is expected to increase by 60% from 2020 to 2060 based on the current model of material use (United Nations Environment Programme, 2024). Without switching to sustainable resource use, these current trajectories will further contribute to the surpassing of planetary boundaries (Rockström et al., 2023; Steffen et al., 2015). Beyond these environmental pressures, there is growing concern about the resilience of materials supply chains due to increased demand for critical raw materials driven by the energy transition (IRENA, n.d.) and recent disruptions such as the Russia-Ukraine war and the COVID-19 pandemic (Jiang, 2026). As a result, resource security is higher on the political agenda, most notably through the European Union's Critical Raw Materials Act (European Commission, n.d.-a).

To address the challenges of unsustainable resource use and supply-chain resilience, academics, policymakers, and companies have increasingly turned their attention to the concept of the circular economy (Ellen MacArthur Foundation, 2013; Geissdoerfer et al., 2017). The circular economy (CE) can be understood as a new economic system that replaces the current end-of-life (EoL) practices through the reduction, reuse, recycling, and recovery of materials within the production, distribution, and consumption processes to achieve sustainable development (Kirchherr et al., 2017).

Achieving the CE requires changes on various system levels, including technology markets, organisations, institutions, regulations, infrastructures, and culture (Jackson et al., 2014). Within this broader transition, reduce, reuse, recycling, and recovery are part of a broader set of CE strategies (R-strategies, see Figure 1) that are developed to reduce resource and material consumption throughout product chains and make the economy more circular (Potting et al., 2017). The waste hierarchy is a key aspect of this framework, as not all CE strategies are equally effective, as some contribute far more to reducing material consumption than others (Kirchherr et al., 2017).

However, as stated, the promises of a CE are beyond material and environmental flows alone, since it aims to achieve sustainable development and incorporates social equity and economic prosperity (Ghisellini et al., 2016). It is therefore important to understand whether the implementation of CE strategies is also able to deliver on these social and economic dimensions. This understanding matters because CE does not operate as a closed system: it has direct and indirect effects on the wider economy, including changes in prices and demand, that remain relatively poorly understood (Castro et al., 2022; Zink & Geyer, 2017). Given this limited understanding of the economic impacts of a CE transition, it remains uncertain whether implementing CE strategies will result in a win-win outcome across the environmental and economic dimensions of CE (Aguilar-Hernandez et al., 2021). To have a better understanding of the economic impacts, it is important to move beyond the sole pursuit of waste prevention and incorporate the dynamic macroeconomic effects of CE strategies (Fevereiro et al., 2025).



Smarter product use and manufacture	R0	Refuse	Make product redundant by abandoning its function or by offering the same function with a radically different product
	R1	Rethink	Make product use more intensive (e.g. through sharing products, or by putting multi-functional products on the market)
	R2	Reduce	Increase efficiency in product manufacture or use by consuming fewer natural resources and materials
Extend lifespan of product and its parts	R3	Re-use	Re-use by another consumer of discarded product which is still in good condition and fulfils its original function
	R4	Repair	Repair and maintenance of defective product so it can be used with its original function
	R5	Refurbish	Restore an old product and bring it up to date
	R6	Remanu-facture	Use parts of discarded product in a new product with the same function
	R7	Repurpose	Use discarded product or its parts in a new product with a different function
Useful application of materials	R8	Recycle	Process materials to obtain the same (high grade) or lower (low grade) quality
	R9	Recover	Incineration of materials with energy recovery

Figure 1: R-strategy framework, from Potting et al. (2017)

1.2 Research gap

Drawing on the field of energy and climate economics focused on modelling the effects of climate mitigation policies (Babatunde et al., 2017; Nikas et al., 2019), the CE literature has increasingly turned to economy-wide modelling frameworks (Fevereiro et al., 2025) to capture these dynamic macroeconomic impacts associated with the implementation of CE strategies. Of these frameworks, Input-Output (IO) models and Computable General Equilibrium (CGE) models are the most used to model the economy-wide impacts of CE strategies (Donati et al., 2020; Fevereiro et al., 2025).

Since 2010, there has been a big increase in the usage of IO models to model the CE (Aguilar-Hernandez et al., 2018). The IO model allows the user to compute value-added, employment, and environmental footprints based on given levels of final demand and technologies (Fevereiro et al.,

2025). Using an IO approach, Wiebe et al. (2019) demonstrate that repair would significantly reduce material extraction globally, with a small positive effect on employment. De Boer et al. (2021) compared the impact of CE across regions and found that the gained value added and income are unequally distributed across the world. These studies provide valuable insights, but the underlying IO model relies on fixed prices and exogenous final demand, making it unable to capture the complex dynamics and impacts associated with CE strategies (Fevereiro et al., 2025).

The alternative approach is the computable general equilibrium (CGE) models, which address these limitations of IO models. CGE models describe economic processes as responsive and dynamic relationships between supply and demand (Hosoe et al., 2010). Compared to the IO approach, the CGE models include prices and substitution elasticities and therefore allow for a more dynamic analysis involving price dynamics (Fevereiro et al., 2025). An example of a CGE approach is provided by Masui (2005). He finds that extending the product lifetimes of electrical machinery is able to reduce the generation of waste, while positively contributing to Gross Domestic Product (GDP). A more recent CGE study by Brusselaers et al. (2022) modelled fiscal policies designed to stimulate CE behaviour of consumers. Their findings indicate that labour demand increases in the repair sector at the expense of other sectors.

By incorporating price dynamics, CGE models are better suited to representing economic behaviour and identifying the dynamic, economy-wide spillover effects of CE strategies (Tukker & Rueda-Cantuche, 2024). However, CGE models also come with two significant limitations. First, the majority of CGE models tend to have highly aggregated materials sectors and therefore lack sufficient detail at the product level (Winning et al., 2017). When modelling energy and climate policies, such levels of aggregation are not problematic, as this involves only a few energy carriers and energy-intensive sectors (Babatunde et al., 2017). CE strategies, by contrast, are highly product-specific, since production recipes differ substantially between reused, refurbished, and primary products (Aguilar Hernandez et al., 2023). Given this limited sector resolution, these models provide only a limited view of the impacts of a given CE strategy. Second, CGE models represent stocks and flows in monetary units, which serve as a poor proxy for the physical flows essential to CE modelling, given that waste often has no value or a highly fluctuating value per kilogram processed or recycled (Tukker & Rueda-Cantuche, 2024). Due to this lack of granularity and material flows, the CGE (and IO) models are not able to model the macroeconomic impacts of CE strategies applied at the micro level (i.e., product level).

To obtain this higher granularity and the need for understanding physical flows, the field of Industrial Ecology has developed various models to analyse resource flows at scales ranging from individual products to entire economies, evaluating circularity from a material-centric perspective (Blomsma & Brennan, 2017). One of these models is called Material Flow Analysis (MFA), which traces the stocks and flows of materials across systems to identify inefficiencies and circularity potentials based on consistent stock-flow information (Zanon-Zotin et al., 2026). However, MFA fails to capture economy-wide dynamics, as its static approach ignores market mechanisms and economy-wide economic balances as a result of changes in the material cycles (Zink & Geyer, 2017).

This presents a challenge for CE modelling. On one hand, there are macro-level (i.e. top-down) models such as CGE that are able to model the dynamic macroeconomic effects of CE strategies, but don't have the level of detail required for modelling product-level CE strategies. On the other hand, there are micro-level (i.e. bottom-up) models such as MFA that can capture the detailed material stocks and flows at the product level, and changes therein as a result of applying CE strategies, but these fail to incorporate economy-wide dynamic effects. Therefore, as standalone models, they are unable to assess the material and economic dimensions of the CE strategies. This shows that there is a need for a model that integrates MFA with a CGE model, linking micro- and macro-level models to capture economy-wide dynamics of CE strategies with sufficient product-level resolution (Tukker & Rueda-Cantuche, 2024).

1.3 Research questions

To address this research gap, this thesis aims to develop a proof of concept for linking MFA with a CGE model, in order to assess the economy-wide impacts of product-specific circular economy strategies at a sufficient level of product resolution. This objective will be pursued through the following research question:

To what extent can linking an MFA model with a CGE model improve the assessment of product-specific circular economy strategies?

The main question is addressed through three sub-questions, each focused on a specific stage of the research process:

SQ1: What lessons can be drawn from existing MFA-CGE linkage approaches for the development of a micro-macro linkage suitable for assessing circular economy strategies at the product level?

SQ2: What data and methods are required to enable a consistent linkage between MFAs and CGE models for assessing circular economy strategies at the product level?

SQ3: What static and dynamic impacts of circular economy strategies at the product level are generated by linking an MFA with a CGE model?

1.4 Thesis scope

Through the development of an MFA–CGE linkage, this thesis touches upon a range of interesting and relevant topics. By linking material flows with macroeconomic dynamics, this thesis touches upon debates on geopolitics and supply chain dynamics (Nygaard, 2023; Shiquan & Deyi, 2023), as well as broader socioeconomic dimensions such as well-being, welfare, health, human rights, inequality and democracy (Al Haj Eid et al., 2025; Padilla-Rivera et al., 2020). The linking method developed in this thesis is also relevant for the degrowth/post-growth debate, as it is able to analyse the impact of CE strategies and GDP-based indicators (Kirchherr & Jones, 2026). Beyond this, such models are generally shaped by major societal developments currently underway, such as AI, digitalisation, robotization, and demographic change (Acemoglu & Restrepo, 2019).

While all of these topics are highly relevant, this thesis is primarily concerned with the development of a proof of concept and is therefore mainly focused on methodological development in the context of CE strategies. The results shed light on material and economic impacts, but the broader concepts and subjects mentioned above fall outside the scope of this thesis and are not addressed in detail or incorporated in the research design.

1.5 Thesis outline

Following this introduction, this thesis conducts a brief literature review to answer SQ1. This review begins with a short introduction to the MFA and CGE methodologies, before reviewing past articles that conducted MFA-CGE linkages. The findings of this review show that MFA-CGE linkages are not a new development, but that current approaches are not suited for assessing the CE strategies at the level of products.

Building on these findings, this thesis develops a proof-of-concept method for linking a product-oriented dMFA with a CGE model, addressing SQ2. The methodology is illustrated using lifetime extension through repair of electrical and electronic equipment (EEE) as an exemplifying case. The chapter first sets out the methods and data underlying the standalone dMFA and CGE models. After which the linkage methodology is then developed through three barriers that must be overcome to enable linking of these models. Together, these define the modelling approach to analyse the case on repair of EEE.

The results of this modelling approach are presented in the subsequent chapter to provide an answer to SQ3. The results of the dMFA are presented first and cover the impacts on material inflows and outflows associated with an increased repair of EEE. Then, the results of the CGE are presented to demonstrate the economic dynamics that can be revealed with the linkage approach. This includes macroeconomic impacts on income, prices, and demand, as well as the changes in GHG emissions from both a production-based and a consumption-based perspective.

The final chapters are dedicated to the discussion of the results and the conclusion. The discussion begins with the impacts of increased repair in the case of EEE, before turning to the benefits of the linkage approach relative to standalone models and earlier MFA-CGE couplings, and closing with the limitations of the method and the directions for further research these suggest. The conclusion provides answers to the main research question and the three sub-questions, reflects on the methodological approach, and sets out recommendations for future research.

2 Literature review

This research starts with a brief literature review on MFA-CGE linkages. This review aims to gain a better understanding of how previous studies were able to link an MFA with CGE and to identify whether these approaches provide relevant starting points for an MFA-CGE linkage at the product level. The relevant literature was obtained through snowballing of various meta-review studies on micro-macro modelling, including Baars et al. (2022) and Beaussier et al. (2019). The approach of this review is described in more detail at the start of Section 2.2. However, before discussing the literature on MFA-CGE linkages, it is necessary to establish an understanding of the underlying concepts and methods of MFA and CGE.

2.1 MFA and CGE modelling

2.1.1 Material Flow Analysis

Mapping material stocks and flows is important because they provide physical services to society in the form of buildings, infrastructure, and consumer products (Pauliuk & Müller, 2014). To have a better understanding of this relationship between materials and society, the field of Industrial Ecology (IE) developed the MFA methodology to map the flows and stocks of any material within the economy and society (Graedel, 2019). The goal of an MFA is to provide a complete overview of all flows and stocks of a particular material over time within a spatially defined system, which is a group of processes connected by flows, bounded in space and time (Brunner & Rechberger, 2016). These processes involve all transformations, transport, or storage of materials throughout the economy from mining and production processes to consumption and waste processes. The principle of mass conservation is applied to every process. See figure 2 for an example (Graedel et al., 2004)

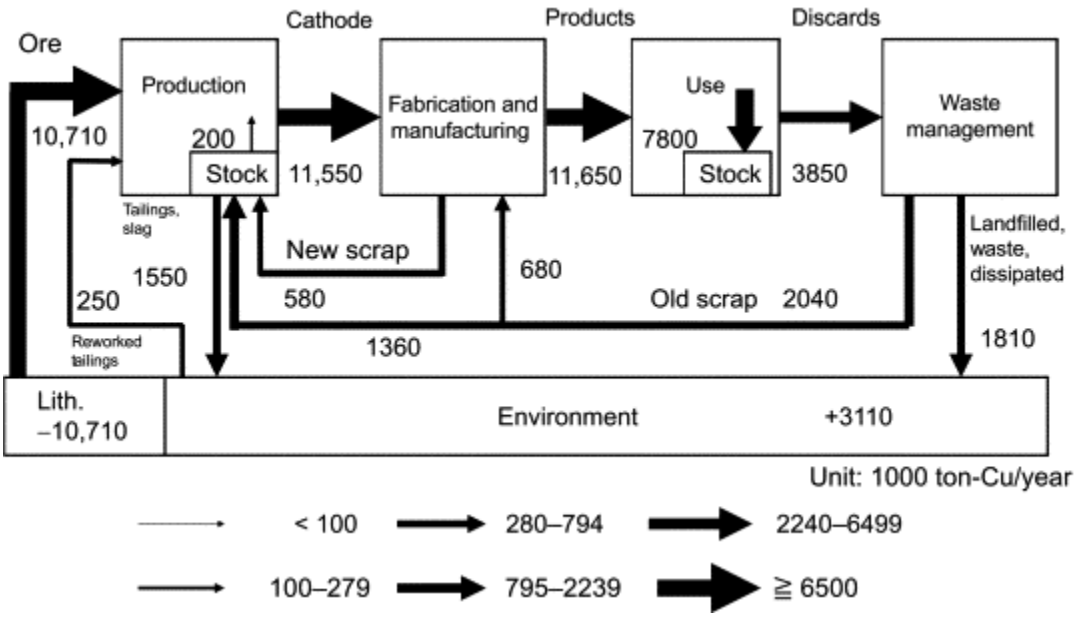


Figure 2: Example of a MFA on copper, obtained from Graedel et al. (2004)

MFA is an umbrella term that covers various approaches. Instead of focusing on a specific material such as copper, it is also possible to analyse the aggregated material flows within a national economy, which is called an Economy-wide MFA. An alternative approach is to look at the flows and stocks of substances (i.e., phosphorus, nitrogen) with a substance flow analysis (SFA).

All these MFA approaches are generally static, which means that they take a snapshot of material stocks and flows at a specific point in time (Chen & Graedel, 2012). These snapshots provide valuable insights into the anthropogenic metabolisms of materials, but lack information about the dynamics of resource use and the impact of this on stocks and flows (Müller et al., 2014). To be able to do so, people started to develop dynamic MFAs (dMFA) that analyse the stocks and flows over a time interval (Chen & Graedel, 2012). By incorporating the dimension of time, the dMFA is able to analyse historical and future stocks and flows by using historical data and data extrapolation (Müller et al., 2014).

There are two approaches to dMFA. The flow-driven approach takes estimated inflow data as an exogenous variable and calculates the in-use stock data by taking the cumulative difference between inflows and outflows (Gerst & Graedel, 2008). The alternative stock-driven approach does this in an opposite way, by calculating the inflows and outflows based on the collected data on stocks and stock vintages (Gerst & Graedel, 2008). The flow-driven approach is the most common method, as it is in most cases difficult to find stock data for a specific material or product. The stock-driven approach requires information on materials or products in use, including their vintages (Müller et al., 2014).

The focus of a dMFA is often on different end-uses of materials. However, it can vary in the level of detail, ranging from whole end-use sectors such as transportation, construction, and electrical appliances, to specific products within these sectors (Müller et al., 2014), such as passenger cars (Modaresi & Müller, 2012) or washing machines (Boldoczki et al., 2021). By applying dMFA at the product level, it provides the most detailed estimations of when products (and the materials embedded in those products) reach their end of life, providing relevant information about future material availability from secondary/recovery sources, making dMFA very relevant to assess the potential of circular strategies (Aguilar Hernandez et al., 2023).

2.1.2 Computable General Equilibrium

The other methodology that needs further introduction is CGE. Where an MFA is interested in the material stocks and flows within a defined system, a CGE model models the whole economy and the interactions among its parts by modelling all economic activities in an economy simultaneously, including production, consumption, employment, taxes, savings, and trade (Burfisher, 2017). The CGE model is a large system of non-linear equations that describe the economy as a set of optimization problems where the behaviour of economic agents (households, firms, and government) is driven by optimizing the allocation of their resources (Hosoe et al., 2010). For example, households maximize their utility subject to their budget constraints, while firms maximize their profits subject to their production technology constraints. The model solves these optimization equations via the price mechanisms within markets (Figure 3), which affect both demand and supply of goods by adjusting

the prices (Hosoe et al., 2010). This price mechanism dictates that when there is excess supply, prices will decrease, but when there is excess demand, prices will rise. The overall outcome, driven

A simple CGE model consists of two components. The first one is the Social Accounting Matrix (SAM). The SAM is the representation of the macroeconomic account of a socio-economic system in a given year, which includes all transactions between economic agents in an economic system (Miller & Blair, 2009). The SAM is an extension of the basic symmetric Input-output-table, by including accounts on income, savings, and taxes to have a complete overview of all economic behaviour (Mainar-Causapé et al., 2018). The SAM is used to calibrate all the coefficients and exogenous variables in the CGE model's equations (Hosoe et al., 2010). The second component of a CGE model is a set of elasticity parameters. These elasticity parameters describe producer and consumer responses to changes in prices and income (Burfisher, 2017) and are therefore important aspects in the assessment of optimization behaviour of economic agents. Together, these parameters allow the model's equilibrium output to replicate the economic structure empirically observed in the base year, as represented by the given SAM (Ziesmer et al., 2023). The description above fits the standard calibration process of a static CGE model. However, it should be noted that there are also dynamic approaches, such as recursive dynamic CGE models, which require parameters to be calibrated for multiple time periods to incorporate time (Ziesmer et al., 2023). It should be noted that a static CGE model still captures dynamic economic behaviour, as "static" refers only to the fact that it models the impact within a single time period.

These calibrated parameters, given the SAM and elasticities, provide the baseline scenario of the CGE model, and this makes it possible to create counterfactual scenarios. To understand the impact of policies or changes in the economy, the modeller can make changes to, or shock, the calibrated parameters and run the CGE model and observe how this shock affects the market equilibrium due to the changing behaviour of economic agents in response to this shock (Burfisher, 2017). This makes it possible to identify how agents reallocate expenditure towards goods that have become relatively cheaper, known as the substitution effect, and how a change in real income raises or lowers the overall level of consumption, referred to as the income effect. (Burfisher, 2021). By incorporating these dynamics, it makes a CGE highly relevant for CE strategies, as it is able to identify the dynamic impacts induced by behavioural responses of the economy.

2.2 Linking MFA with CGE models

Both MFA and CGE models have their respective strengths. However, as stated in section 1.2 of this thesis, each model also carries limitations that this thesis aims to address by linking the two. Given the other objectives of this thesis and the constraints of an MSc thesis, a fully comprehensive literature review was deemed not feasible. Instead, illustrative studies were identified through a snowballing approach, starting from two key meta-review articles (Baars et al., 2022; Beaussier et al., 2019). These two articles were selected because both studies conducted relatively recent, a systematic literature review on micro-macro modelling. The review by Beaussier et al. (2019) examined the linking of economic models and environmental assessment methods, which included MFA, but also other types of environmental assessment methods such as Life Cycle Assessment

(LCA) and Footprint methods. Baars et al. (2022), on the other hand, focused exclusively on the integration of MFA into a wide range of models such as IO, CGE, Partial Equilibrium (PE), System Dynamics (SD), and Agent-Based Models (ABM).

Despite their broader scope, both studies present a good overview of all studies that have developed MFA-CGE linkages till 2023. However, the insights provided by Beaussier et al. (2019) and Baars et al. (2022) remain largely conceptual and do not address the methodological detail of the linking approaches themselves. As the aim of this literature review is to develop a better methodological understanding of previous linking approaches, the insights generated by these reviews are insufficient. Therefore, this literature review uses these meta-reviews to select all studies on MFA-CGE couplings to provide a good overview of all linking approaches developed in the past.

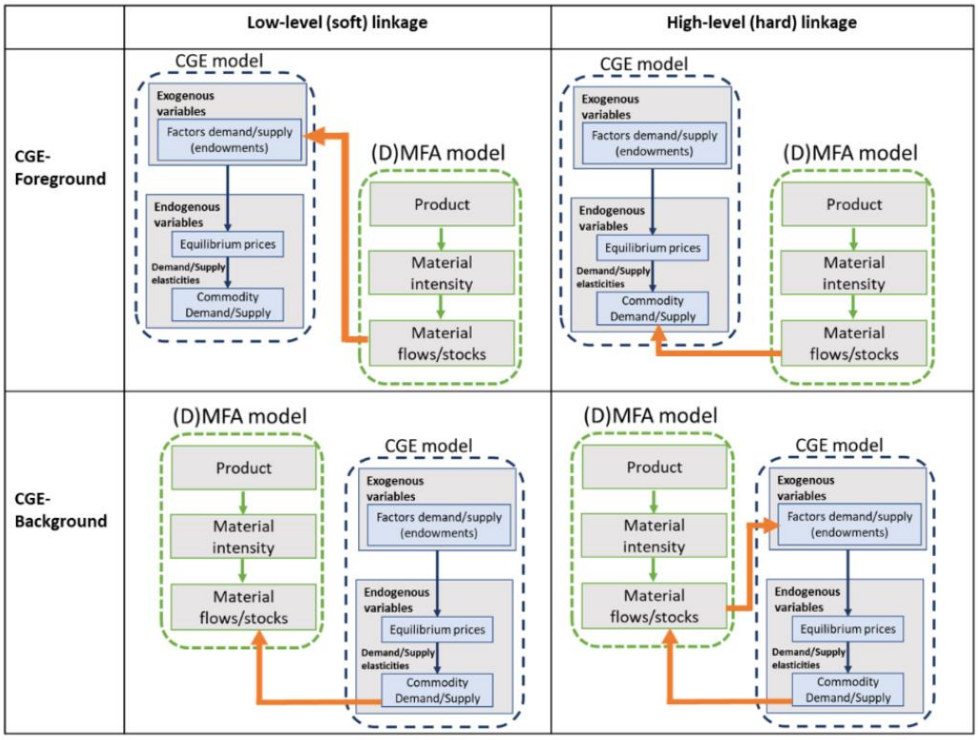
Based on this snowballing approach, 20 studies were initially identified as establishing an MFA-CGE linkage. However, closer inspection of each individual methodology of the 20 studies revealed that not all studies seem to have developed a true MFA-CGE linkage. In many cases, these models were run separately, with neither model's outputs used as an input for the other, making these articles irrelevant given the goal of the literature review. For this reason, these studies were excluded from the review, leaving six studies that establish a sufficient link between an MFA and a CGE model (Aguilar Hernandez et al., 2023; Cao et al., 2019; Dellink & Kandelaars, 2000; Grames et al., 2019; Nechifor et al., 2020; Wang et al., 2018).

2.2.1 Linkage archetypes

To structure the different linkage approaches found in this literature review, I will use the linkage archetypes for MFA and CGE models, developed by Aguilar Hernandez et al. (2023). According to them, the linkages between MFA and CGE models can be classified based on two dimensions: Background-Foreground and Hard-Soft linkage (see Figure 4):

- **Soft vs. Hard linkage**: This dimension is focused on how the two models are linked together. A soft link is established when the two models run separately, and the output of the first model functions as an input for the second model. With a hard link, the MFA and CGE models run together in an integrated manner, which means that the equations within these models are co-dependent, with feedback between the two models.
- **Foreground vs background systems**: The second dimension is focused on which model is taken as the core model and functions as the foreground system. This is important because it tells us the direction of the linkage, as it shows which outputs (background) are taken to be used as inputs for the foreground system. This distinction mainly applies to soft-linkages because hard-linkages state that the model runs integrated, so it is harder to distinguish which model serves as the foreground model.

Figure 3: Linkage archetypes for dMFA and CGE model, from Aguilar et al. (2023)



2.2.2 Existing linkage approaches

Having established the linkage archetypes, the findings of the literature review are discussed below. This will involve all six studies that established a sufficient level of MFA-CGE linkage, organised by common characteristics.

2.2.2.1 Static MFA approaches

The first approach to link MFA to CGE dates back to the beginning of the century, which shows that the importance of linking material flows with a CGE is not something of the last few years. In this study, Dellink and Kandelaars (2000) link a static MFA to a static CGE model ("static" referring to a single time period; see Section 2.1.2) to assess the effects of material taxation on zinc use. With this approach, the MFA inflows are linked to the CGE sectoral outputs to calculate material intensities per sector. Subsequently, these material intensities are used to develop a material tax policy to shock the CGE model. Based on the dynamic impacts, a new material demand is calculated based on changes in output in combination with the old material intensities. With this approach, the study demonstrates that economic flow data and material flow data can be made compatible, providing a valuable material foundation to apply a shock to the CGE model. However, the approach also comes with limitations as the material intensities remain fixed, which is highly unlikely given the dynamic impacts on sectoral inputs and outputs associated with the shock. A similar approach developed by Wang et al. (2018) tries to model this by using a material reduction rate. Similar to Dellink and Kandelaars (2000), they use historical data to calculate a base-year material intensity, but rather than fixing the material intensity, they also estimate future annual reduction rates of material consumption based on historical development. By linking the material intensities and the annual material reduction rate to the endogenous sectoral output, a recursive CGE model is able to project future

resource use. However, these material intensities are only applied to the output of the CGE model and do not affect any of the exogenous or endogenous parameters within the CGE model. The material flows therefore have no influence on the economic dynamics, so this linkage remains rather limited. Besides these individual shortcomings, both studies do not incorporate any stock dynamics of a dMFA, as they only incorporate annual inflow data, which is generated without considering stock-flow dynamics of a dMFA. This makes these approaches less relevant for CE modelling, as CE strategies are very much dependent on future inflows and outflows, which are very much dependent on stocks.

2.2.2.2 Dynamic MFA approaches

Other studies do account for stock-and-flow dynamics by linking outputs of a dMFA to a CGE. A good example of this is Cao et al. (2019), who soft-link a dMFA to a recursive CGE model to assess the future socioeconomic metabolism for the Chinese building sector. dMFA inflows are converted to a value-added target, used to calibrate the construction sector's investment-demand share parameter iteratively. This linkage approach extends the analysis beyond physical material flows, incorporating the economy-wide dynamic impacts associated with China's building stock development, showing the clear contributions of this soft-linking approach. Nechifor et al. (2020) take a different route in linking these models. This study uses outflow data on obsolete scrap obtained from a dMFA. This annual outflow represents the annual scrap-availability trajectory, which is imposed as a hard exogenous ceiling on the production function of secondary steel. This provides a promising method for establishing a material foundation for CGE demand, ensuring that scrap use never exceeds the scrap availability calculated by the dMFA. Another soft-linking approach is proposed by Aguilar Hernandez et al. (2023), who calculate the relative volume in tonnes of primary and secondary lithium with the dMFA and, via international trade data, calculate the price per quantity. Based on these relative volumes and prices, the potential substitution of primary and secondary materials for the CGE production function is calculated. This is a clever way to model material substitution behaviour based on relative price and availability, though it should be noted that the approach has only been demonstrated theoretically and has not yet been applied empirically. Thus, all three dMFA-CGE linkage methods demonstrate that soft-linking is a valuable approach for capturing the economy-wide dynamics associated with the output of the MFA, to provide a more material foundation for the CGE model.

2.2.2.3 Hard linkage

All studies discussed so far have relied on soft-linking. However, Grames et al. (2019) pursue a more fully integrated approach by developing a hard link between a substance flow analysis (SFA) and a dynamic CGE. They have developed a recursive analytical general equilibrium model that integrates a two-sector closed economy with an SFA of the phosphorus cycle. At each timestep, the obtained equilibrium determines the physical phosphorus flows in the MFA, while the stocks and flows of the SFA simultaneously feed back into the production and utility functions through the phosphorus in soil, manure, and the environment. The approach in this study is very promising as it is able to establish concrete dependencies between material and monetary flows. This represents a significant advantage compared to the soft-linking approach, since it captures the dynamic feedback between

economic and material systems that soft-linked approaches are structurally unable to represent. A hard linking approach is thus preferable, but this has its limitations. The model of Grames et al. (2019) relies heavily on various simplifications, such as exogenous determination of the price of mineral phosphorus, so it fails to incorporate all the dynamic feedback of a normal CGE model. Therefore, it currently lacks empirical applications using real-world data.

2.2.2.4 Scope of existing linkages

Besides their distinct modelling approaches, these studies also share a similar characteristic in the cases they apply to. Almost all focus on only one or two materials, such as zinc (Dellink & Kandelaars, 2000), lithium (Aguilar Hernandez et al., 2023), steel (Nechifor et al., 2020; Wang et al., 2018), and phosphor (Grames et al., 2019). The only study in this exception is Cao et al. (2019), as they look at the end-use of the construction sector. Based on these cases, the approaches are very relevant for CE strategies applied at the material level, such as steel scrap recycling or increased material efficiency. However, modelling CE strategies applied to products is much more difficult, as products are far more heterogeneous than a material such as steel. For this reason, some of these approaches are much more difficult at the product level. For example, the approach developed by Nechifor et al. (2020) relies on a very detailed production function for the steel sector. Doing this for a very heterogeneous product category (e.g. furniture, EEE) would be far more difficult.

2.3 Conclusions of the literature review

As stated in the introduction, the goal of this study is to link MFA with a CGE model to analyse the economy-wide impacts of CE strategies at the product level. The conducted literature review provides several relevant insights for the remainder of this thesis.

It shows that hard linking is the only way to incorporate the complete dynamic feedback between the material and the economic system. However, this has not been established beyond a theoretical demonstration. Soft-linking approaches, by contrast, show already promising methods that demonstrate that material and economic flows can be made compatible and are able to provide additional insights beyond the stand-alone models. A soft-linking approach is therefore still worth pursuing, particularly given that this thesis aims to provide a proof of concept rather than a fully developed model.

It also demonstrates the importance of incorporating stock-flow dynamics in the linkage approach, as various studies have failed to do so. This is important for modelling CE strategies, as these are very dependent on the dynamics of stocks, which determine the potential outflow of materials to be recycled, for example. Therefore, a dMFA is better suited for this kind of linkage.

Another notable point concerns the scope of the studies. The linkage approaches identified are almost entirely focused on single materials, such as steel or zinc. The only approach that goes beyond the material level uses annual build floor-area as a proxy for the total end use of the construction sector (Cao et al., 2019). This suggests that existing MFA-CGE linkage approaches have not yet been extensively demonstrated at the level of detail required for a product group consisting of heterogeneous products with varying material compositions.

Taken together, this shows that a soft-linked dMFA-CGE approach is, particularly in the constraints of an MSc thesis, the most promising way forward to provide a proof-of-concept method that helps to understand the macroeconomic impact of CE strategies for products. However, despite the range of relevant linkage approaches identified, none have been developed at the product level. A new linking approach is therefore needed to be able to assess the impacts of CE strategies at the product level.

3 Methods

To address the methodological gap stated at the end of the previous chapter, this chapter develops a soft-linking approach between a product-oriented dMFA and a static CGE model (single time period) to capture the dynamic, economy-wide impacts of circular economy strategies at the product level. The approach is demonstrated through a case study on the lifetime extension of electrical and electronic equipment (EEE) via repair. Building on this case, a dMFA model is developed to quantify the material flows associated with the repair of EEE, based on two scenarios. Thereafter, I will introduce the CGE model used in this study to assess the dynamic, economy-wide impacts associated with these scenarios. With both models outlined, the soft-linking approach is developed by addressing the main methodological obstacles in translating the dMFA scenario results into inputs for the CGE model.

Before I continue with the rest of this chapter, I should note that the goal of this study is to demonstrate a proof of concept for a dMFA-CGE linkage, rather than to develop a fully validated empirical model. This goal has influenced the research design, as various decisions made throughout the development of this methodology were based on simplified assumptions and data availability. Some of these decisions would not be sufficient for a full empirical study, but given the constraints of an MSc thesis, they are considered acceptable.

3.1 Introducing the case

3.1.1 Relevance of EEE repair

The case used to demonstrate this linkage approach between a dMFA and CGE will be the lifetime extension (LTE) of electrical and electronic equipment (EEE) in the European Union. The decision behind this case selection was mainly due to practical reasons. In the first place, there was already a comprehensive stock-flow dataset, covering a large number of EEE categories for each EU member state. Second, focusing on a single, well-defined CE strategy (LTE) allowed for relatively straightforward linkage between the two models.

However, this does not mean that analysing EEE repair in the EU lacks broader relevance. Reducing the amount of generated waste of EEE (WEEE) has been on the EU's agenda already for quite some time, with the implementation of the WEEE directive to tackle the issue of the growing amount of WEEE in 2012 (European Commission, n.d.-c). In the last few years, product lifetime extension (LTE) has been increasingly seen as a promising strategy to delay product replacement and reduce waste generation (Maldini et al., 2025). The promise of repair has also been recognised by the European Union, which has adopted a range of ambitious initiatives such as the Right to Repair Directive (European Commission, n.d.-b). In this context, analysing the impact associated with increasing the repair of EEE is deemed a relevant case for this study.

3.1.2 Scope of the case study

EEE refers to all items used by households or businesses with circuitry or electrical components with a power or battery supply (Baldé et al., 2024). It consists of diverse sets of products of different sizes and purposes (see Table 1), ranging from small products like lamps and mobile phones to large equipment such as washing machines and fridges (Islam et al., 2021). When discussing the dMFA, CGE, and linkage approach, a narrower focus is developed where certain EEE products are excluded.

Table 1: Overview of WEEE categories based on EU-6 WEEE classification, adapted from Islam et al. (2021)

EU-6	E-waste category	Sample e-waste product
1	Temperature exchange equipment	Refrigerators, freezers, air conditioners, and heat pumps
2	Screens, monitors, equipment with surface screens >100 cm2	Televisions, monitors, laptops, notebooks, and tablets
3	Lamps	Fluorescent lamps, high-intensity discharge lamps, and light-emitting diode (LED) lamps
4	Large equipment	Washing machines (WM), clothes dryers, dish-washing machines, electric stoves, and large printing machines, copying equipment, and photovoltaic panels
5	Small equipment	Vacuum cleaners, microwaves, ventilation equipment, toasters, electric kettles, and electric shavers, scales, calculators, radio sets, video cameras, electrical and electronic (EE) toys, small electrical and electronic (SEE) tools, small medical devices, small monitoring, and control instruments
6	Small IT and telecommunication equipment	Mobile phones (MPs), Global Positioning Systems (GPS), pocket calculators, routers, personal computers (PCs)/desktop computers (DCs), printers, telephones

As stated before, the CE intervention applied to the case study is LTE through repair, as this reflects a single well-defined CE strategy, making it well suited for a proof of concept. In terms of the R-strategy framework, repair entails the repair and maintenance of a defective product so that it can be used with its original function (Potting et al., 2017). Repair can be carried out by different entities such as: Original Equipment Manufacturers (OEMs), Independent Repairers (IRs), and consumers performing repair themselves (do-it-yourself - DIY) (Svensson-Hoglund et al., 2021). However, for this study, the focus will be on repair carried out by an independent repairer. The geographical scope comprises the aggregate of all 27 EU member states (EU27). The intervention is modelled as a what-if scenario, in which the underlying driving force is a preference change among households. On this basis, two scenarios are developed:

- **Baseline scenario**: reflecting the current levels of EEE repair in the EU.
- **Repair scenario**: A gradual increase in EU consumer preference for repairing EEE rather than purchasing new EEE products. Driven by this preference shift, consumers respond to product failure at end-of-life by taking the item to an independent repairer to restore its functionality, rather than discarding it and purchasing a replacement.

The details of scenarios with specific parameters will be discussed in the next section when the dMFA model is introduced.

3.2 dMFA methodology

This section describes the methodology and data underlying the dMFA model used to analyse the material inflows and outflows associated with EEE. It first explains how the increase in repair is modelled, before explaining the underlying mechanics of the model. The data inputs are then discussed, together with the data underpinning the baseline and repair scenarios.

3.2.1 Modelling repair in dMFA

To model CE strategies with a dMFA, the resource efficiency–climate change (RECC) modelling framework has been developed to link material flows to products and the services they provide during their use phase (Pauliuk et al., 2021). Based on the RECC modelling framework, there are two ways to model the preference change of the repair scenario in a dMFA (Pauliuk et al., 2021): increasing the lifetime parameter, or increasing the recirculation rate of the reuse parameter. Increasing the lifetime parameter represents the additional lifetime gained due to repair and maintenance of a product. Adjusting the recirculation rate behaves differently, as it represents an increase in the share of EoL outflow that is repaired and reused, thereby replacing the inflow of new products.

The logic behind the repair scenario described in the previous section is focused on product failure at end-of-life, where consumers do not discard the product to buy a new one, but instead choose to repair and reuse it. For this reason, the reuse parameter is adjusted rather than the lifetime parameter, as this aligns more closely with the preference change of the scenario involving repair and reuse. This choice also creates an advantage later on, because it makes the quantities related to repair more explicit, which becomes important later when linking the dMFA output to the CGE model. The reuse parameter could also include direct reuse of a product without any repair, but it is assumed that the increase in reuse is all contributed to an increase in repair of EoL EEE. For this reason, the recirculation rate is referred to as the repair rate in the remainder of this thesis.

Inflow of repaired and reused products does not have the same characteristics as a new product. Even if they provide the same functionality, repaired and reused products will still exhibit some wear and tear from the years they have been used (Krych et al., 2025). Considering this, it would be unrealistic to assume that new products and repaired products have the same lifetime. To take this into account, the dMFA model attaches a shorter lifetime to a repaired product compared to that of a new product by changing the lifetime parameter for repaired products. More detailed information can be found in section 3.2.4. It is also assumed that after a product is repaired, it will only be used for one additional use cycle and not repaired or reused again. In reality, this would not be the case, but this assumption is made to keep the model and data collection more straightforward, given the exploratory nature of this thesis. Given the single use-cycle and shorter lifetime of repaired products, the standard dMFA model is insufficient and implies a dual-stock dMFA model is to be used.

3.2.2 Dual-stock dMFA model

For the repair scenario, a certain share of a product's outflow is used to replace the inflow of a new product. Using an inflow-driven model results in problems here because the lifetime of a repaired product is shorter than that of a new product. In this case, the total inflows will stay the same, but as repaired products have a shorter lifetime, the outflow of repaired products will increase, and as a result, this will decrease the stock of this product. This is undesirable because the stock in a given year reflects the functionality provided to society (Pauliuk & Müller, 2014). The repair scenario does not assume a change in functionality, but rather that there is the same functionality provided through different means, which is repair instead of a new product. Therefore, it is necessary to develop a

stock-driven MFA, where the stock is treated as the exogenous variable, to calculate the inflows and outflows.

The stock-driven model used in this study adopts a simplified version of the approach developed by Boldoczki et al. (2021), who modelled the impact of washing-machine reuse using a dual stock approach (Figure 5). This approach separates new and reused products to account for the shorter lifetime of repaired products and to make sure that reused products can't be repaired a second time.

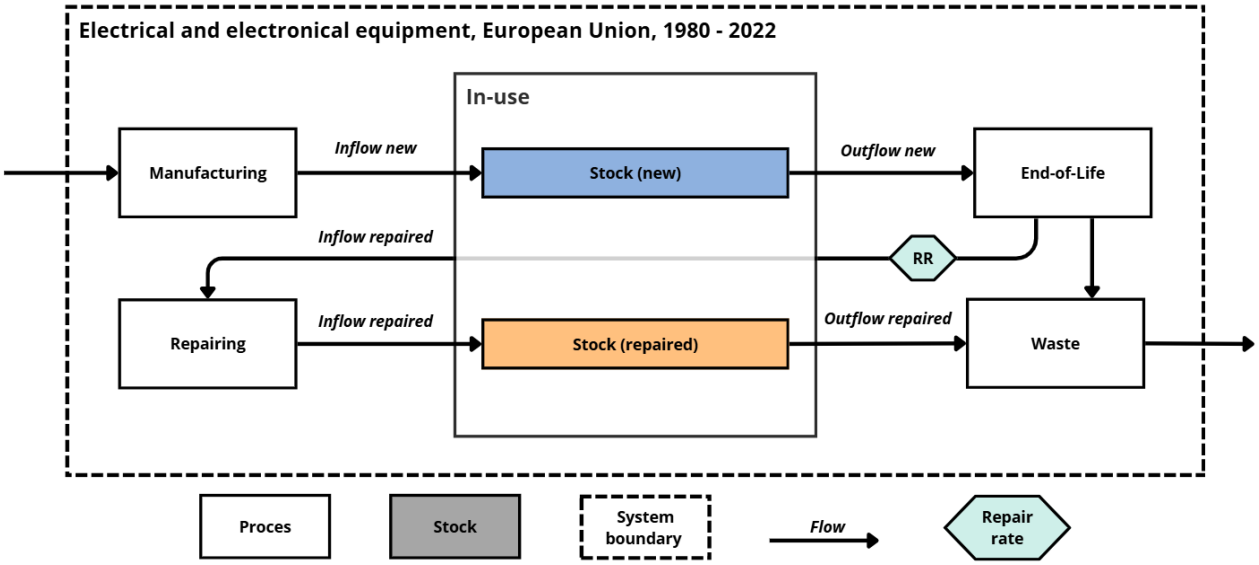


Figure 4: Dual-Stock-flow diagram, adapted from Boldoczki et al. (2021)

For each product category, the model is solved recursively in calculation timesteps t, one for each year, from 1980 to 2022. For each t, the total in-use $Stock(t)$ is given based on the data from Pauliks et al. (2026) and represents the total in-use of new products and in-use of repaired and reused products, according to eq. 1.

$$Stock(t) = Stock_{new}(t) + Stock_{repaired}(t) \quad (1)$$

The in-use stock of new and repaired products at any given t, is determined by eq. 2 and 3. These equations represent the sum of all surviving inflows until t, given the lifetime distribution and the years that have passed since the inflow in the year τ.

$$Stock_{new}(t) = \sum_{\tau=0}^{t} inflow_{new}(\tau) * lifetime_{new}(t-\tau) \quad (2)$$

$$Stock_{repaired}(t) = \sum_{\tau=0}^{t} inflow_{repair}(\tau) * lifetime_{repaired}(t-\tau) \quad (3)$$

Following Pauliks et al. (2026), the model assumes no outflows in the first year. Therefore, for $t = 0$, the inflow of new products equals the entire stock required that year. For all subsequent years, the inflows depend on the outflows, since a share of the outflow of new products is repaired and re-enters

the stock. Therefore, $Stock'(t)$ is introduced, which represents the in-use stock of previous years' inflows, before the inflow at t is added. Eq. 4 and 5 give this for new and repaired products, respectively:

$$Stock'_{new}(t) = \sum_{\tau=0}^{t-1} inflow_{new}(\tau) * lifetime_{new}(t-\tau) \quad (4)$$

$$Stock'_{repaired}(t) = \sum_{\tau=0}^{t-1} inflow_{repaired}(\tau) * lifetime_{repaired}(t-\tau) \quad (5)$$

Based on the surviving stock $Stock'(t)$ of both new and repaired products, eqs. 6 and 7 show how the outflows are calculated. At any timestep (except at $t = 0$), the outflows equal the difference between the in-use stock of the previous year $(t-1)$ and the surviving stock at t.

$$Outflow_{new}(t) = Stock_{new}(t-1) - Stock'_{new}(t) \quad (6)$$

$$Outflow_{repaired}(t) = Stock_{repaired}(t-1) - Stock'_{repaired}(t) \quad (7)$$

The surviving stock also determines the total required inflow, which is equal to the difference between the target stock for that year and the surviving stock of previous years' inflows (eq. 8).

$$Inflow_{total}(t) = Stock(t) - Stock'_{total}(t) \quad (8)$$

This inflow now needs to be filled with repaired and new products. Based on the outflow of new products and the repair rate (RR), the potential inflow of repaired products is determined (eq. 9). This assumes that there is no delay between the outflow of repair and the inflow of a repaired product. However, not all these potentially repairable products are repaired, since the repaired inflow cannot exceed the total required inflow without breaking the mass balance. Equation 10 therefore constrains the repaired inflow so that it cannot surpass the total required inflow.

$$Inflow_{potential\ repair}(t) = Outflow_{new}(t) * RR(t) \quad (9)$$

$$Inflow_{repaired}(t) = \min\{Inflow_{total}(t), Inflow_{potential\ repair}(t)\} \quad (10)$$

The inflow of new products is determined as the difference between the total required inflow and the repaired inflow (Eq. 11). Finally, the total waste outflow is given by eq. 12.

$$Inflow_{new}(t) = Inflow_{total}(t) - Inflow_{repaired}(t) \quad (11)$$

$$Outflow_{waste}(t) = Outflow_{repaired}(t) + Outflow_{new}(t) - Inflow_{repaired}(t) \quad (12)$$

3.2.3 Stock data

The underlying data for both scenarios is obtained from the inflow-driven model developed by Pauliks et al. (2026). In this model, the inflows are treated as the exogenous variables and used to determine the total stock and outflow of a given year, based on the specific lifetime of a product. The inflow data used originates from the European Commission and encompasses the put-on-market data (POM) of EEE products covering the years 1980-2022 for the EU27 countries (Pauliks et al., 2026). The inflow data represent product sales in tonnes of over 900 different products, grouped in 54 different product

categories (UNU-keys), based on similar composition and properties (Lysaght et al., 2026; Pauliks et al., 2026). To determine the lifetime of these products, they use the Weibull distribution with a unique shape and scale parameter for each UNU-key for each region (Magalini et al., 2014). Based on the POM and lifetime for each UNU-key, the model is able to develop a stock-flow dataset for each UNU-key in each EU27 country, for the period 1980-2022. As the regional scope of this thesis is the EU, the EU country data will be aggregated to provide the total inflow in the EU for each UNU-key.

3.2.4 Implementation of baseline and repair scenarios

To keep the focus on linking the dMFA with the CGE model, it was decided not to extend the stock-flow dataset into the future through extrapolation. This means that the implementation of both scenarios takes effect over the period 1980-2022. As a result, the dMFA produces a hypothetical past rather than predictions in the future and should be seen as a retrospective analysis. Using the stock data from Pauliuk et al. (2026) in combination with the lifetimes used in this study, the stock-driven model reproduces the inflows and outflows of the inflow-driven model. By applying the original stock data and lifetimes with the repair rate (RR) set to zero for all products, the baseline scenario is created in which no additional repair takes place. It should be noted that this does mean no repair takes place, but rather that the current state of repair is already covered in the original lifetimes. (Magalini et al., 2014).

Compared to the baseline scenario, the preference change for repair in the repair scenario is modelled by increasing the RR of the reuse parameter. For this reason, the repair scenario requires a repair rate for each individual product category. However, as I mentioned before, the EEE represents a heterogeneous group of products, which makes it very difficult to find a unique repair rate for each of the 54 product groups. Since the main aim of this study is to develop a proof of concept for a soft-linking approach, relying on less detailed data for repair rates is acceptable. For the repair rates, we take an empirical study on household WEEE at civic amenity in Denmark (Parajuly & Wenzel, 2017). They characterized the household WEEE stream by looking at the remaining functionality and reuse potential. Based on this, they determined the potential repair rate for seven of the 10 EU-10 WEEE categories (Table 2). Some categories were not included in this study, so these got the average repair rate of the other categories. The category of lighting equipment was assumed to have a repair rate of 0%, as literature shows that lamps have little repair potential (Bastein et al., 2013).

Table 2: Potential repair rates of EEE categories based on EU-10 WEEE classification

EU-10 WEEE categories	**Repair rate**		**Source**
	Baseline	Repair	
1. Large household appliances	0%	11.54%	(Parajuly & Wenzel, 2017)
2. Small household appliances	0%	11.84%	(Parajuly & Wenzel, 2017)
3. IT and telecommunications equipment	0%	21.09%	(Parajuly & Wenzel, 2017)
4. Consumer equipment	0%	28.23%	(Parajuly & Wenzel, 2017)

5. Lighting equipment	0%	0%	(Bastein et al., 2013)
6. Electrical and electronic tools (except for large-scale stationary industrial tools)	0%	6.67%	(Parajuly & Wenzel, 2017)
7. Toys, leisure, and sports equipment	0%	12.12%	(Parajuly & Wenzel, 2017)
8. Medical devices (except for all implanted and infected products)	0%	15.24%	Average of (Parajuly & Wenzel, 2017)
9. Monitoring and control instruments	0%	15.24%	Average of (Parajuly & Wenzel, 2017)
10. Automatic dispensers	0%	15.24%	Average of (Parajuly & Wenzel, 2017)

Based on these aggregated potential repair rates, each UNU-key is assigned the repair rate of the EU-10 category to which it belongs. The repair rates are assumed to take full effect in 2017, but to represent a gradual development over time, they are initially set to zero and rise over the five years preceding 2017. In 2017, they will reach the defined repair rate, after which it is assumed they remain constant. The repair scenario also introduces new lifetimes for repaired products based on the original lifetime in a similar manner to Boldoczki et al. (2021), where they assume that a repaired washing machine has 25% of its original lifetime. However, that study focused solely on washing machines, whereas this thesis considers a much wider range of EEE categories, many with shorter lifetimes. Using this 25% would make the lifetime of such repaired goods extremely short, and therefore repaired products are assigned a lifetime equal to 50% of the original.

The full code documentation and data processing for the dMFA are described in section A3 of the Appendix. As a final note, it is important to emphasise that the assumptions and data used in this section are rather unrealistic, such as the RRs and a 50% lifetime across all repaired products. However, the main aim of this thesis is to develop a proof of concept for linking MFA and CGE, and for this purpose these simplifications are sufficient.

3.3 CGE methodology

After having established the dMFA methodology and scenarios, this thesis will now focus on the CGE model used to identify the economy-wide dynamic effects associated with the changes in stocks and flows caused by the preference change of the repair scenario implemented in the dMFA model. First, the general setup of the CGE model used in this thesis is described. Thereafter, the underlying data is explained, in combination with the specific model adaptations to model a preference change from EEE to repair.

3.3.1 Set up of the CGE model

To incorporate the economy-wide dynamic effects of both scenarios, the output of the dMFA will be linked to the CGE model called GREEN-R. This is a multi-regional, multi-sectoral global CGE model,

based on the Global Trade Analysis Project (GTAP) database, developed by the Netherlands Environmental Assessment Agency (PBL) and the Netherlands Bureau for Economic Analysis (CPB),

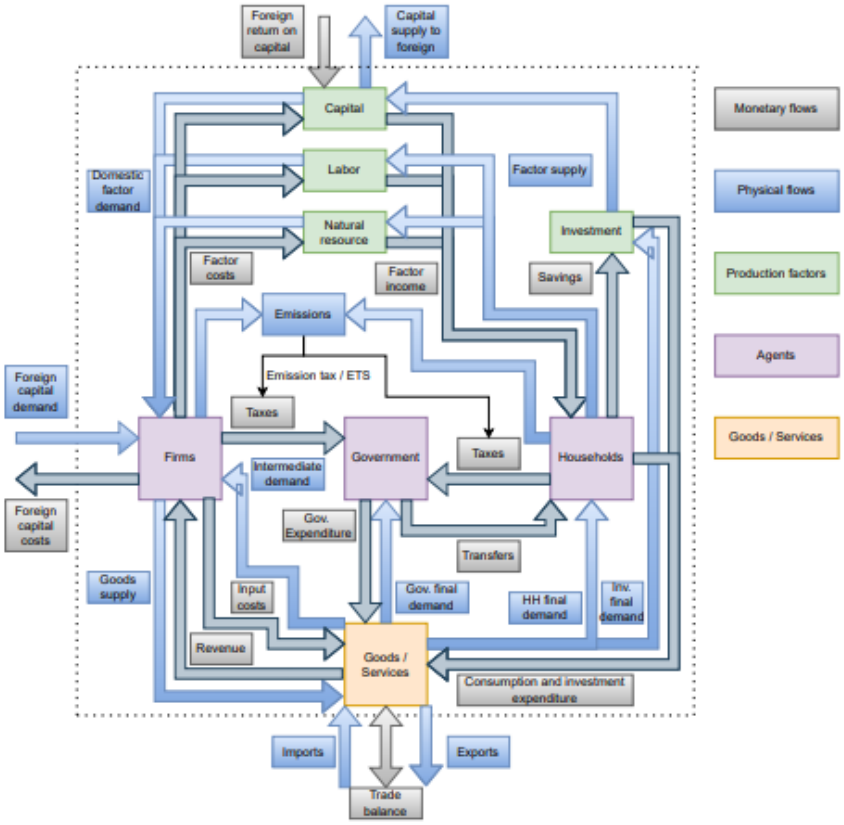


Figure 5: Graphical overview of flows in GREEN-R, from Olijslagers & Brink (2024)

to assess the impact of climate and circular economy policies (Olijslagers & Brink, 2024). The model represents the global economy via the behaviour of three main economic agents active in each region: Firms, government, and households (Figure 6). The setup of this model will now be explained via these agents, based on the GREEN-R documentation by Olijslagers & Brink (2024).

The first economic agents are firms. Each firm represents a sector in the economy, and in GREEN-R, it is assumed that all these sectors produce one unique good. The general rule is that the total output of a firm is equal to the sum of production costs, including taxes and basic prices equal to unit cost prices. Firms strive to maximize profits, and this is modelled via a production function. This production function is constructed using multiple nested layers of Constant Elasticity of Substitution (CES) functions, with all sectors sharing the same production structure and substitution possibilities. This CES function determines firms' production inputs given a specific set of parameters and data inputs. The parameters of the CES-production function are calibrated for each sector based on global input-output data, which is explained in the next section.

The behaviour of consumers is modelled via one representative household per region. These households own the factors of production (labour, capital, land, and natural resources) and receive income from firms in return for their use, for which households pay taxes to the government. It is

assumed that the quantity of labour is fixed and that there is no unemployment. On the other hand, households also receive a transfer from the government. With this income, households consume the goods produced by the firms, and this is modelled via a multi-layered CES, which determines what households consume given a specific set of parameters and data inputs. Besides consumption, a share of household income goes to savings, which fund investment goods such as buildings and machinery. These are allocated across investment categories via a Cobb-Douglas utility function, so each category's share of the total investment budget remains fixed.

The third agent is the government, which receives income via various types of taxes, such as a production tax, income tax, VAT, taxes on capital and labour, imports, and exports. It is assumed that over time, a constant share of the tax revenue is transferred to households. What is left of the tax revenue is used by the government for the consumption of goods and services. Government consumption is modelled via a Cobb-Douglas demand function, which keeps expenditure shares across product groups constant.

GREEN-R also incorporates greenhouse gas (GHG) emissions to assess the climate impact associated with policies, through two types of emissions (Olijslagers & Brink, 2024). First, it accounts for the emissions from fossil fuel combustion by households and firms by multiplying the use of a fossil energy source (coal, gas, or oil) by an emission factor. Second, it also accounts for the emissions produced by the production processes of firms, which are assumed to be proportional to output.

The calibration of the parameters of the functions in the model is done via the GTAP11 dataset with 2017 as the base year (Aguiar et al., 2022). The GTAP dataset contains data on input-output matrices, investment, government and household consumption, taxes, factor use (capital, labour, land, and natural resources), bilateral trade, and transport and trade services. The calibration of these parameters ensures that the equilibrium produced for the base year reproduces the GTAP data. The elasticities are not estimated but are obtained from the literature.

There are more aspects to the GREEN-R model, such as international trade, international capital mobility, and transport and trade services, that fall beyond what is covered here. For these, the reader is referred to the full documentation of GREEN-R, including references to the functions and elasticities underlying the model (Olijslagers & Brink, 2024).

3.3.2 Regional and sectoral aggregation of GREEN-R

The CGE model described above is used for the linkage with the dMFA model, but for the purpose of this research, several changes have been implemented to keep the model simple given the exploratory nature of this thesis. First, the temporal scope of the CGE model is chosen. GREEN-R can be run either statically or recursively, but for this thesis, it is decided to run the model statically as the main aim of this research is to establish and demonstrate a linkage between the dMFA and CGE models, rather than to produce a fully dynamic forecast. This would require linking both models across multiple years, which is highly time-consuming and not necessary to establish a linkage between the models. For this reason, it is decided to connect the dMFA to the most recent available

base year of the CGE model, which means that the base-year parameters are calibrated using a SAM for 2017. With this setup, the CGE operates in a similar fashion to the dMFA, as it produces a hypothetical past rather than a future prediction.

The data for the SAM used by GREEN-R is provided by the GTAP11 database, which contains 65 sectors and 141 regions (Aguiar et al., 2022). It would be possible to run the analysis at this level of detail, but the purpose of this study is to develop a linkage approach rather than to maximise empirical precision. Therefore, the decision was made to make various aggregations to make the model simpler. The first aggregation concerns the regional dimension. As the case study focuses on the repair of EEE in the EU, all EU member states are aggregated into a single region, named EUR. The remaining regions are aggregated into a Rest-of-World region (ROW).

The sectoral dimension has also been aggregated. First, the model requires the sectors related to the manufacturing of EEE products. The relevant GTAP sectors for EEE are Manufacture of Computer, Electronic and Optical Products (ELE) and Manufacture of Electrical Equipment (EEQ) (Aguiar et al., 2022). These two sectors are aggregated into a single sector, which is named Manufacture of Electrical and Electronic Equipment (EEE). Besides the manufacturing of EEE, the scenario also covers the repair of EEE, and therefore, sectors that provide these services need to be included. Based on the Eurostat SBS classification, repair of EEE falls under the sector of Repair of computers and personal and household goods (S95) under the NACE Rev. 2 classification of Eurostat (European Commission, 2008b). Taking this sector would be the most accurate approach for this study. However, in GTAP, this is not a standalone sector but is part of the larger sector called Recreation and Other Services (ROS), which involves recreational, cultural, and sporting activities, other service activities, and private households with employed persons (Aguiar et al., 2022). In the absence of a better alternative, the ROS sector is selected to represent the repair of EEE in this model setup. However, it should be noted that this sector covers a much broader range of activities than repair alone. The remaining sectors are aggregated into broader categories, with particular attention to sectors relevant to EEE, such as metals, chemicals, and mining (Table 3). For a complete overview of the sectoral aggregation, see Appendix A2.

In addition to these regional and sectoral aggregations, further changes are made to the setup of the GREEN-R model to enable the implementation of the dMFA scenario results within the CGE model. These will be discussed in the next section.

Table 3: Sector aggregation of GREEN-R used in the study

CGE Sectors	Sector Code
Agriculture, Forestry and Fishing	AFF
Mining	MIN
Refineries	OIP
Chemicals, plastics and mineral products	CHP
Metals	MET
Electrical and electronic equipment	EEE
Recreation and other services (including repair)	ROS
Machinery and equipment	MEQ

Other manufacturing	OMA
Construction	CNS
Transport	TRA
Services	SER
Coal	COA
Crude oil	COI
Gas	GAS
Power sector	POW

3.4 Linking MFA to CGE

Having introduced the case, the two scenarios, and both models, the next sections will develop the methodology to link the results of the dMFA from both scenarios to the CGE model. This will be structured around the various challenges that occur in linking a dMFA with a CGE model. The first challenge concerns how the changes in UNU-key inflows of the dMFA (driven by a household preference change) relate to the monetary stocks and flows embedded in the CGE model. The next challenge is the translation of the material flows into monetary flows, given the absence of material flows in the CGE model. The final challenge is implementing the preference change of the repair scenario in the CGE model without breaking the equilibrium (supply equals demand). Based on these challenges, a method is constructed where the results of the dMFA based on the repair scenario are combined into a single preference shock applied to the CGE. The outcome of this shock will be the economy-wide dynamic effects caused by the changes at the bottom-up level driven by the repair of EEE.

3.4.1 Allocating the dMFA inflows within the SAM

The first challenge is about understanding how the inflows of the dMFA relate to the monetary stocks and flows of the CGE model. This is important because to create a linkage between the models, it is necessary to understand how changes in inflows in the dMFA, caused by the preference change, affect the CGE model.

To build this understanding, we need to know how the dMFA inflows relate to the flows of the CGE model. In the dMFA, the inflows serve as additions to the in-use EEE stock and are made up of the inflow of new products and the inflow of repaired products. This is different in the CGE model. In the underlying SAM of the CGE model, inflows occur either as the output of one sector delivered to other sectors, in the form of intermediate consumption, or as output delivered to final demand categories, comprising households, government, and investment (United Nations et al., 2009). Based on this, it is already possible to establish that the inflow of new EEE corresponds to the output of the EEE sector, while the inflow of repaired EEE corresponds to the output of the ROS sector, representing the ancillary activities related to the repair strategy (Donati et al., 2020). The origins of the inflows of the dMFA in the SAM are now allocated, but the destinations of these inflows are yet to be determined.

Given the structure of the SAM, the destinations of the inflows could be either intermediate consumption or output delivered to each of the final demand categories (United Nations et al., 2009).

According to input-output theory, intermediate consumption refers only to products consumed within a single year, representing semi-finished products that are further processed into a final product (United Nations et al., 2009). On a conceptual level, this means that intermediate flows do not contribute to the EEE stock, unlike the inflows of the dMFA, which reflect final products added to the in-use stock of EEE. Consequently, the inflows of the dMFA do not link to the intermediate consumption in the SAM, so these should not be affected by the changes in inflows of the dMFA. This does not mean that the inflows to firms are neglected.

If we look at how stocks reside within the CGE model, we see that the CGE model does not contain a physical stock similar to the dMFA, but it does have a monetary equivalent in the form of productive capital stock (Burfisher, 2021; Pauliuk & Müller, 2014). Inflow towards this capital stock comes from household savings via investment, which is then allocated across investment-good categories and added to an economy-wide capital stock each year and consumed by firms (Olijslagers & Brink, 2024). Putting this together, the changes in inflows of the dMFA driven by the preference change for repair should only affect the output of the EEE and ROS sectors delivered to the final demand categories of households, government, and investment in the CGE model, with firms consuming EEE in the form of capital via investment.

However, as explained in Section 3.1.2, the scenario is driven by a shift in consumer preferences, whereby consumers reduce their consumption of new EEE by opting for repair instead. This preference change does not extend to government or firms, so the scenario does not assume any preference change of these actors. This would mean that the inflows from the EEE and ROS sector to investments and the government won't be affected. For the most optimal modelling approach, we need to split the inflows of the dMFA across these three destinations to make sure that only the household share is affected by the preference change. However, the underlying data of the dMFA does not allow for such a split. This is because the dMFA inflows are represented by the annual put-on-market (POM) of EEE. The annual POM is calculated using the apparent consumption method, which combines domestic production with imports, minus exports, to approximate how much EEE enters the market in a region each year (Lysaght et al., 2026). While this method provides geographic information, it does not indicate whether the EEE or EEE repair services are purchased by consumers, firms, or the government. Therefore, based on the inflows of the dMFA alone, it is not possible to distinguish between these different user types.

There may be various ways to potentially split the dMFA inflows by end-user, either through extensive data collection or by using the CGE output shares of EEE. However, as the goal of this research is to establish a proof of concept for dMFA-CGE linkage, these methods are determined to be beyond the scope of the research. Therefore, this thesis assumes that all the dMFA inflows are linked to the final demand for EEE and ROS by households in the CGE model. Because the scenario only affects the repair behaviour of consumers in the EU, the dMFA inflow changes will only have an impact on the final demand of households in the EUR region, and the final demand of ROW won't be affected.

To summarise: the repair scenario assumes that due to a shift in preference, consumers respond to product failure by taking the item to an independent repairer to restore its functionality, rather than

discarding it and purchasing a replacement. This affects the inflows of the dMFA, as a certain amount of new EEE inflow is replaced by an inflow of repaired EEE. Allocating these changes within the CGE model means that household final demand for the EEE sector will decrease, while household final demand for the ROS sector will increase.

3.4.1.1 Aligning UNU-keys with GTAP sectors

By assuming that the dMFA inflow changes are all linked to the final demand of households in the EUR region, it is assumed that all EEE originates from the EEE sector. However, based on the micro-level data, this is not always the case. The next step is to see how the UNU-key product micro-level data actually links to the macro-level data in the CGE model.

As discussed before, the EEE sector in the CGE model is the aggregate of the GTAP sectors ELE and EEQ, which correspond with NACE Rev. 2 sectors of 26 and 27. However, each UNU-key can be split into more detailed product categories based on the Harmonized System (HS) nomenclature of the United Nations (UN), which can be linked to the corresponding GTAP sectors. Based on this, a correspondence table is constructed between UNU-keys and the NACE Rev. 2 sectors. The results and the logic behind this correspondence can be found in Appendix A1.

This table shows that not all UNU-keys are linked to NACE sectors 26 and/or 27. For example, Professional Heating, Non-Cooled Dispensers, and Professional Tools are all EEE, but are not produced by the EEE sector. This means that reducing the inflow of these products does not have a direct impact on the EEE sector. Some products are only partially covered by the EEE sectors. For example, freezers and refrigerators link to both sectors 27 and 28. Changing the inflows of these products would impact the EEE sector, but also other sectors. The CGE model only represents a change in the EEE sector, and to accommodate this mismatch between micro- and macro-level data, it is assumed that only UNU-keys with a link to this sector are included. This means that all UNU-keys with no link to the EEE sector are excluded from the analysis. It also means that, for UNU-keys with a partial link to another sector besides EEE, the full impact of the scenario is attributed entirely to the EEE sector.

Linking the UNU-keys to the repair sector in the CGE model creates another tension between micro- and macro-level data. In the CGE model, the ROS sector is the provider of EEE repair services, but in reality, the repair of EEE falls under "Repair of computers and personal and household goods" (NACE division 95) under the NACE Rev. 2 classification (European Commission, 2008b), which is part of the broader ROS sector. The part is also very minor, since the output of NACE division 95 contributes less than 4% to the annual domestic supply of the entire ROS sector in the EU in 2017 (Eurostat, 2023).

Not only does the ROS sector include non-repair activities, but some EEE repair activities also take place outside the ROS sector according to the Eurostat NACE Rev. 2 classification. For example, the repair of air conditioning falls under "Specialised construction activities" (division 43), while the repair of electrical tools falls under "Repair and installation of machinery and equipment" (division 33) (European Commission, 2008b). This has implications for the dMFA-CGE linkage, since the repair activities related to these UNU-keys are accounted for under NACE divisions 33 and 43, and not the ROS sector. To more accurately reflect reality, these impacts to other sectors should be included in

the model. This, however, would also make the model much more complex. Thus, for simplification, this thesis focuses only on repairs of UNU-keys connected to the ROS sector, by assuming that UNU-keys not related to ROS have an RR of 0 in the repair scenario. These UNU-keys still contribute to the overall inflow of new EEE, but do not contribute to the inflow of repaired EEE provided through the ROS sector, since their repair takes place in a different sector.

3.4.2 Transforming physical inflows into monetary values

After allocating the preference change within the CGE model, the next challenge in linking these models is translating physical inflows into monetary flows. This is essential to be able to quantify this shock, as the dMFA is only able to provide the physical reduction in new EEE on the market in Tonnes, while the CGE model stores all information in monetary terms (Aguilar Hernandez et al., 2023).

3.4.2.1 Developing a conceptual monetary-physical link

For this, it is required to understand the price levels of the SAM of GREEN-R, because it is possible to value the output of the sector based on different types of prices (United Nations et al., 2009). See Table 4 for detailed definitions.

Table 4: Definitions of price levels, from United Nations et al. (2009)

basic price	The amount received by the producer from the purchaser for a unit of a good or service produced as output minus any tax payable, plus any subsidy receivable by the producer as a consequence of its production or sale. It excludes any transport charges invoiced separately by the producer.
producer's price	The amount received by the producer from the purchaser for a unit of a good or service produced as output minus any VAT, or similar deductible tax, invoiced to the purchaser. It excludes any transport charges invoiced separately by the producer.
purchaser's price	The amount paid by the purchaser, excluding any VAT or similar tax deductible by the purchaser, to take delivery of a unit of a good or service at the time and place required by the purchaser. The purchaser's price of a good includes any transport charges paid separately by the purchaser to take delivery at the required time and place.

This shows that not all prices are the same, as they differ in the margins that are incorporated within the price. In GTAP11, the final demand is recorded at market prices, which are described as the price received by the seller of the commodity and are equivalent to basic prices (McDonald & Thierfelder, 2004). Because the shock is applied to the final demand of households, the material inflows of the dMFA need to be translated into prices valued at basic prices. The solution to do this lies within the methods and data to calculate the physical inflows.

As stated before, the inflow data of new EEE is based on the apparent consumption method, which means it is calculated by combining domestic production with imports, minus exports (Lysaght et al., 2026). The data behind this inflow data is PRODCOM for production data and COMEXT for

international trade data (Magalini et al., 2014). Both PRODCOM and COMEXT provide physical data on EEE, but most importantly, these datasets also include the monetary values associated with this material data (European Commission, 2023, 2026). PRODCOM reports the sold production value of a product, which is defined as sold (invoiced) production, which may be carried out under the primary or secondary activities of the enterprise (European Commission, 2023). The value of production excludes the various margins and can therefore be considered to be valued at the basic price.

The valuation of imports and exports should reflect the same as the producer price, but for international trade, this is done in a different manner. The free on board (FOB) valuation is used for exports, while the cost, insurance and freight (CIF) valuation is used for imports, and for both the valuations of import and export, the statistical values do not include taxes on import or export, such as customs and excise duties or VAT (European Commission, 2026). The FOB price includes the value of goods at basic prices, but also the trade and transport services to the border of the exporting country, while the CIF price reflects the price of a good delivered to the border of the importing country, hence including international transport and insurance costs (European Commission, 2008a). The reason for this is to make the prices of imports and exports compatible with domestic production with basic prices (European Commission, 2008a). By reporting import values at CIF and export values at FOB, the values in COMEXT reflect the same valuation as the production values reported by PRODCOM.

Because the monetary flows of production, imports, and exports are now all valued at compatible prices, it is possible to combine these without further price adjustment. This opens the door to using the same data sources and methods to calculate the monetary equivalent of POM for all UNU-keys. By doing this, it is possible to calculate the monetary inflow associated with each UNU-key inflow. How this is done is discussed in the next section.

3.4.2.2 Quantifying the monetary-physical link

As stated in the MFA section, the dMFA model generates annual outputs for all flows and stocks across the entire study period. In this case study, we focus on 2017 as the reference year. Therefore, all reported inflows and outflows correspond to $t = 2017$. By applying the apparent consumption method to the monetary equivalent of the underlying data used to calculate the POM in material weight (eq. 13), it is possible to calculate the inflow value for all UNU-keys (i). The results of this can be found in the Supplementary information S2.

$$Inflow_i^V = Value_i^{prod} + Value_i^{imp} - Value_i^{exp} \quad (13)$$

Equation 13 looks very simple, but it is accompanied by intensive data processing to do it right. Therefore, this thesis adapted the *Waste over Time Script* developed by Van Straalen et al. (2016) to calculate the monetary equivalent of POM. In this script, UNU-key 002, related to photovoltaic panels, lacks the price data needed for translation into monetary terms and is therefore excluded from this study.

In the previous section, the monetary equivalent of POM is calculated through the apparent consumption method. This monetary inflow is now used to connect inflows and outflows of MFA to

monetary values. This is done by various equations. Based on the annual monetary value and the physical quantity of POM, the price per kg is calculated for each UNU-key (eq. 14). The results for this for each UNU-key can be found in section A3 of the Appendix.

$$price_i = \frac{Inflow_i^V}{Inflow_i^Q} \tag{14}$$

By combining the price with the inflows of new products in the baseline and repair, it is possible to calculate the monetary change in expenditure towards new EEE products, based on the reduction in physical quantities sold, and the price per kg (eq. 15):

$$\Delta\text{EEE} = \frac{\sum_{i=1}^{n}(inflow_{i,baseline}^{new,Q} - inflow_{i,repair}^{new,Q}) * price_i}{\sum_{i=1}^{n} inflow_{i,baseline}^{new,Q} * price_i} \tag{15}$$

Following these three equations, the method calculates the reduction in household expenditure on the EEE sector. Section A3 of the Appendix documents the code and data processing for Equations 13 to 15, including the adaptation from the *Waste over Time Script* developed by Van Straalen et al. (2016).

As stated in Section 3.4.1, the reduction in EEE consumption is also accompanied by an increase in household expenditure towards the ROS sector, to pay for the repair activities. This increase is difficult to determine as the trade and production data used to calculate the monetary value of POM is not available for repaired products, since repair constitutes a service rather than a tangible object. The only relevant information covers the annual output of NACE division 95 (Eurostat, 2023), but this is only available at the sector level. Given that there are 54 UNU-keys with widely ranging characteristics (Islam et al., 2021), the method described above cannot be used to calculate a price per kg for repaired EEE. Determining the price for repair for each UNU-key would therefore require additional data collection. This would be very time-consuming given the wide range of UNU-key categories. Given the focus of this thesis on developing a proof of concept, this is considered beyond the scope of this thesis. It is therefore assumed that the monetary household savings from consuming less EEE are entirely redirected to the consumption of repair services, which is a common assumption in macroeconomic CE modelling, given limited information on prices of repair (Wiebe et al., 2019, 2023). This means that in absolute terms, the reduction in demand for new EEE is always equal to the increase in demand for ROS. To express this in absolute terms, the outcome of Equation 15 cannot be used directly, as it is relative to the output of the EEE sector rather than that of the ROS sector. To determine this exact change for ROS, a different approach is required, which will be explained in the next section.

3.4.3 Implementing the preference shock in the CGE model

Having translated the material inflows of the dMFA into a monetary reduction in household expenditure on new EEE and an equal increase in household expenditure towards repair of EEE, the final challenge is to implement this preference shock within the CGE model without breaking its calibration, by altering the changing consumer preferences for new EEE and EEE repair. This part was

developed together with PBL, which provided all the knowledge from the CGE perspective. The main method is outlined below, while a detailed explanation can be found in Chapter 4 of the supplementary information S4.

Since the dMFA repair scenario is driven by a shift in consumer preference rather than by a specific policy, this preference shift needs to be modelled directly within the household's consumption behaviour in the CGE model. This requires adapting the CES utility function of households, which determines how household expenditure is allocated across goods given the preferences of households and the household's budget constraint. Similar to Brusselaers et al. (2022), a nested CES utility function is constructed for household consumption of new EEE and the consumption of ROS, hereafter referred to as the ELS composite (EEE and Lifetime-extension Services). Within this nested utility function, the share of the ELS composite in total household final demand is held constant, so that the preference shift occurs only through a reallocation of expenditure between new EEE and ROS, within the ELS nest itself, and does not increase household spending towards ELS as a whole.

The baseline parameters of α_{EEE} and α_{ROS} of the ELS composite are calibrated using the GTAP11 database. These parameters represent the share of household income spent on ELS that is allocated to the EEE sector (α_{EEE}) or the ROS sector (α_{ROS}). In the baseline scenario, no changes are made to α_{EEE} and α_{ROS} in the ELS composite, because the current levels of repair are already covered by the current household expenditure on ROS. In the repair scenario, the $\Delta\mathrm{EEE}$, based on the dMFA, is applied to the ELS composite by creating a relative change in α_{EEE} equal to the $\Delta\mathrm{EEE}$, while the total share of the ELS composite is held constant. As a result, the savings in household expenditure obtained from reducing EEE consumption can only be redirected to ROS by increasing the α_{ROS} in the ELS composite, rather than the consumption of other goods. This means that the absolute value subtracted from the share of EEE is exactly redirected to the share of ROS, consistent with our assumption that both changes are equal in absolute terms.

3.4.3.1 Linking the dMFA inflow reduction to the CGE efficiency augmenter

To implement this into the model, a naïve approach would be to directly change the α_{EEE} and α_{ROS} in response to the dMFA inflow changes. This approach would break the calibration by creating inconsistencies between price aggregator and demand equations, resulting in the failure of Walras' law, which states that the total value of demand should equal the value of supply (Hosoe et al., 2010). The solution to this problem is to indirectly change the shares by using an efficiency augmenter as recommended by Redding and Weinstein (2020). The efficiency augmenter is a parameter that determines how much utility a household derives per euro spent on a given sector.

By changing the efficiency parameters of EEE and ROS consumption, households will derive more utility from ROS than EEE, causing them to reallocate expenditure from EEE towards ROS. Subsequently, this alters the consumption shares of EEE and ROS within the ELS composite, without breaking calibration. However, the change in efficiency augmenters should be driven by the dMFA to establish a direct linkage between the two models. Given the relationship between the shares and the efficiency augmenters, the latter can be determined from the required input share, based on the

relative reduction in EEE inflow associated with lifetime extension through repair. This procedure consists of the following three steps:

First, we take $\Delta\mathrm{EEE}$ (output of eq.15), which represents the direct reduction in consumption of new EEE as a result of an increase in repair services. Based on this change, a new target share for EEE can be calculated, capturing the direct impact associated with $\Delta\mathrm{EEE}$ (eq. 16).

$$\alpha_{EEE}^{target} = \alpha_{EEE} * (1 - \Delta\mathrm{EEE}) \tag{16}$$

Secondly, by combining α_{EEE}^{target} with the original share and the given elasticity, it is possible to calculate the efficiency augmenter required to achieve the target share (eq. 17).

$$\gamma_{EEE} = \left(\frac{\alpha_{EEE}^{target}}{\alpha_{EEE}}\right)^{\frac{1}{\sigma-1}} \tag{17}$$

Because the α_{ROS} is affected by α_{EEE}^{target} the efficiency augmenter for ROS can be calculated to uphold cost neutrality, given by eq. 18.

$$\gamma_{ROS} = \left(\frac{1 - \alpha_{EEE}^{target}}{\alpha_{ROS}}\right)^{\frac{1}{\sigma-1}} \tag{18}$$

The final element required to calculate the efficiency augmenters for both sectors is the elasticity of substitution between EEE and ROS, which was set to 1.5 based on expert input from PBL. Based on these new efficiency augmenters, the first-order impact produced by the preference shock of the repair scenario can be reproduced at base-year prices.

3.4.4 Analysing the CGE results of the linkage approach

Implementing this preference shock causes the model to produce a new equilibrium reflecting this preference change. The outcome will incorporate the first-order impact of the preference change, but it will also involve dynamic effects such as income and substitution effects, as explained in Section 2.1.2. To understand the extent to which the preference change affects model outcomes compared to these dynamic macroeconomic effects, a decomposition analysis will be conducted focused on household final demand. This decomposition analysis separates the different effects, including the first-order impact caused by the preference change, the substitution effects caused by changes in relative prices, and the income effects caused by changes in household income.

Linking the dMFA to the GREEN-R model also allows us to analyse environmental impacts associated with the repair scenario, beyond the material flows. The repair scenario affects emissions across the supply chain, but the prolonged use of older EEE would also affect environmental impacts during the use-phase of EEE. The current linkage approach already covers the supply-chain emissions related to household consumption of EEE and ROS, but not the use-phase emissions, since the dMFA does not account for energy consumption during use. Since the environmental assessment of EEE is not the core concern of this thesis, the use phase has not been modelled. The changes in GHG emissions can partially be explained by the direct impact related to changes in final demand for ROS and EEE,

but macroeconomic effects play a role here as well. Therefore, a Shapley structural decomposition analysis of emission changes is conducted. This separates the direct impact of the repair scenario from the impact of changes in emission intensities and technology structures. The methods for both decomposition analyses were developed by PBL, and a full explanation can be found in Chapter 4 of the supplementary information S4.

3.5 Final Remarks

In this chapter, the dMFA and CGE methodologies are developed to be able to model an increase in the repair of EEE, driven by a consumer preference change. Bringing this all together creates the following soft-linkage approach to link a dMFA (1980-2022) with a static CGE for the year 2017:

1. Run the dMFA for each UNU-key category under both scenarios to obtain the changes in material inflows and outflows associated with the preference shift toward repair.
2. Calculate the monetary equivalent of POM and combine this with the physical POM across UNU-keys to calculate the price per kg, at basic price valuation, for all EEE products.
3. Apply the price per kg to the change in inflows for each UNU-key to obtain the monetary reduction for each EEE category and combine these into a relative reduction in EEE consumption.
4. Use this relative reduction to calculate the target share parameter of EEE and determine the corresponding target share parameter of ROS based on the assumption that the value of the reduction in EEE is entirely redirected to ROS.
5. Based on these target shares, calculate the efficiency augmenters for EEE and ROS required to achieve them within the nested ELS composite.
6. Apply these efficiency augmenters to the nested ELS composite to model the preference shock.
7. Run the model and perform a decomposition analysis of impacts on final demand, income, and emissions to understand the underlying dynamics.

4 Results

In this chapter, I will present the results of the dMFA-CGE linkage method described in the previous chapter. First, I will describe the changes in stocks and flows from the MFA driven by the repair scenario, and how this translates into a monetary reduction of household consumption of EEE products, which functions as the preference shock to the CGE model. Subsequently, the dynamic impacts generated by the CGE model are presented, based on the preference shock derived from linking the MFA results to the CGE model.

4.1 Material impacts from the dMFA

Starting with the results of the MFA, the changes in inflows and outflows associated with the implementation of the repair scenario are discussed. This is then translated into monetary terms for the preference shock for the year 2017, showing how prices affect the size of the resulting reduction in EEE consumption. The dMFA has a temporal scope from 1980 to 2022, but because the scenario only affects inflows after 2012, only the results between 2010 and 2022 are shown. This means that the repair scenario models a hypothetical past, starting with the introduction of additional repair in 2012, which slowly increases until 2017, after which it remains constant. A complete overview of the annual stock and flow dynamics is provided in Supplementary information S1, while the material and monetary impacts for 2017 are presented in Supplementary information S2.

4.1.1 Changes in inflows and outflows

Figure 7 presents the combined changes in inflows and outflows as a result of the implementation of the repair scenario. The baseline flows are presented with a dotted line, and this tells us that the total annual inflow volume of EEE (based on the selected UNU-keys) is showing a minor increase between 2010 and 2022 from 8.1 to 8.3 million tonnes. During this period, the amount of WEEE generated in the EU steadily increased to 7.7 million tonnes in 2022. If we now focus on the repair scenario, we see that both inflows and outflows are affected by EEE repair. The blue area shows that the inflow of new

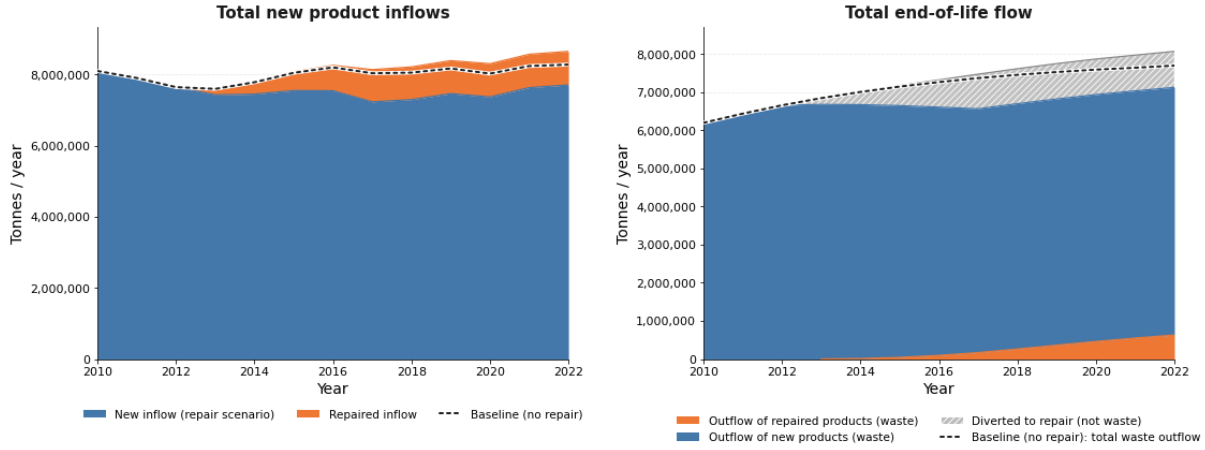


Figure 6: Total new product inflows and end-of-life outflows of EEE under the baseline and repair scenarios (2010–2022)

EEE is reduced from the start of the intervention onward, as it is replaced by the inflow of repaired EEE, shown by the orange area. The figure on the right shows that this has a positive effect on the WEEE generated, as it shows that the total outflow in the repair scenario is below the outflow levels of the baseline.

Besides the positive impact induced by repair, both figures also show that this impact is smaller than the volume of EEE that is repaired and reused. In 2013, the inflow of repaired products was approximately equal to the reduction in new EEE inflow. By 2018, however, a total of 919 thousand tonnes of repaired EEE was replacing only 757 thousand tonnes of new EEE, a difference of 162 thousand tonnes. As a result, total inflows start to rise above the baseline scenario. In 2014, this difference in total inflows is still minor, at 7 thousand tonnes, but in 2022, this has increased to 373 thousand tonnes above the baseline scenario.

The reason for this is the shorter lifetime of repaired products. This shorter lifetime increases the outflow of EEE, resulting in a higher total outflow of EoL EEE. Because the stock should remain the same, the inflows need to increase to compensate for the higher outflows, but when the inflow of repaired products is already fixed by the repair rate, it is only possible to achieve mass balance with an increase in the inflow of new EEE.

Since it is assumed that a product can only be repaired a single time, the outflow of repaired EEE also reduces the future potential for repair of EEE. This shows that as the scenario develops, a growing share of the outflow of EoL can no longer be repaired and is directly diverted to the waste outflow. As a result, by 2022, 944 thousand tonnes were diverted from the waste stream, but this resulted in a net waste reduction of only 571 thousand tonnes. This is visible in the figure as the grey area representing repaired products, which is larger than the difference between the waste outflows of the two scenarios. These differences in the inflows of repaired EEE and the outflow of WEEE show that repaired products should not be seen as a one-to-one replacement for a new product but should instead be seen as a delay in the purchase of a new product. Because the dMFA is run at the UNU-key level, the aggregate totals of Figure 6 can also be disaggregated to the more granular product level. This is shown for both the inflows (Figure 8) and outflows (Figure 9), disaggregated by EU-10 category, consistent with the level at which the repair rate parameters for the repair scenario have been implemented. The disaggregation in Figure 5 shows that there are vast differences in inflows and outflows across the different product categories, in terms of size and dynamics. If we look at the baseline inflow of new products, it shows that the annual inflows can differ enormously. While large household appliances contribute with an annual inflow of around 4 million tonnes per year, which presents almost 50% of total EEE inflows, medical devices don’t even reach an annual inflow of 35

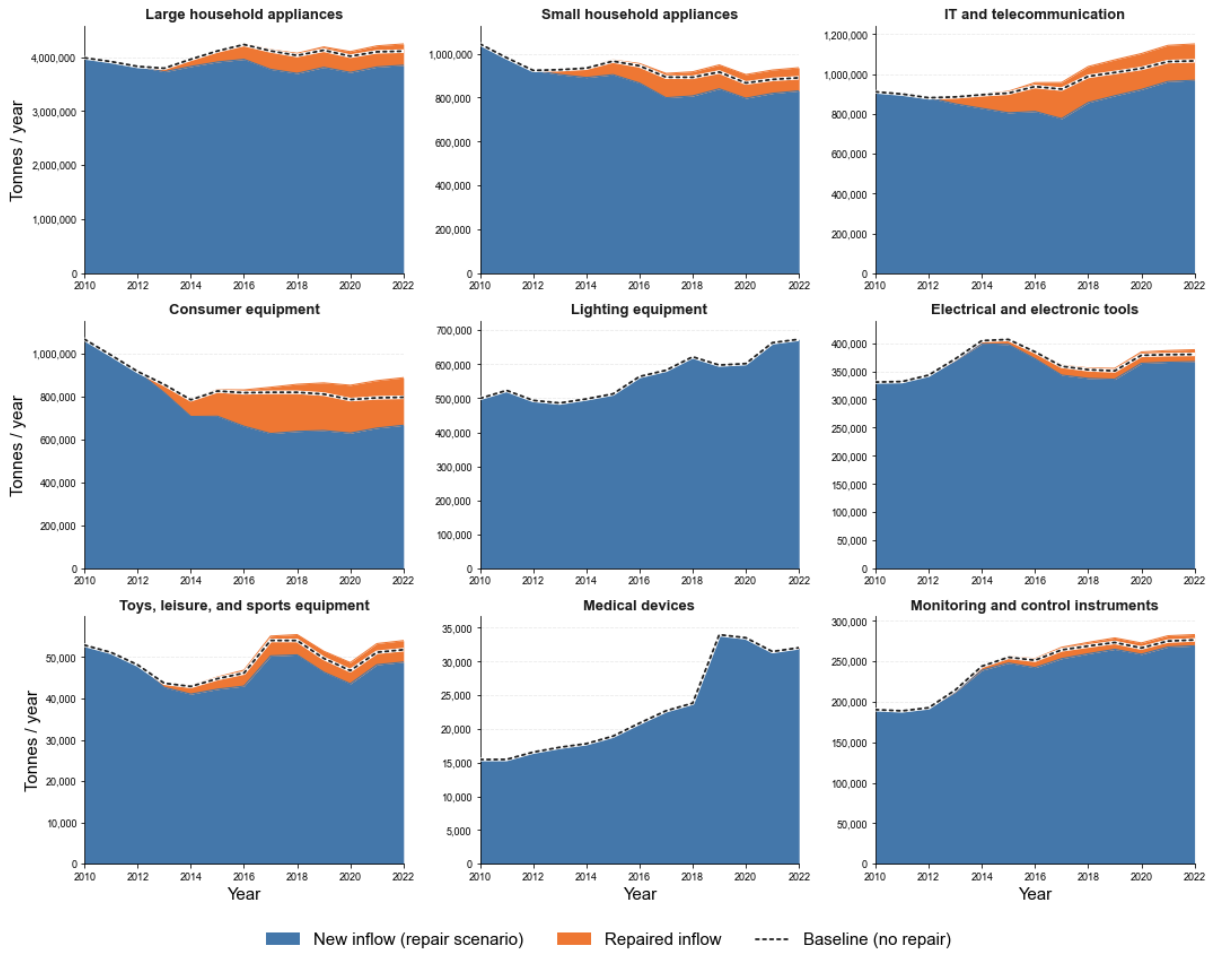


Figure 7: Total new product inflows by EU-10 WEEE category under the baseline and repair scenarios (2010–2022), excluding automatic dispensers

thousand tonnes per year between 2010 and 2022. This difference illustrates the heterogeneity of EEE products, as substantial variation in weight, size, and purchasing patterns results in large differences in the quantities placed on the market. These differences are not driven by repair scenarios but do affect the repair scenario. Here you see that the products in large household appliances only reduce the total inflow by around 8% in 2017, but this relatively small reduction is responsible for 42% of the total material reduction in 2017. In contrast, you see that with a high repair rate, repair is able to reduce the inflow of new consumer equipment by 16%, but this accounts for only 18% of the total reduction.

Disaggregation also makes it possible to see how this effect can vary within the EU-10 categories. Medical devices consist of only two UNU-keys, one for consumer medical devices and the other for professional medical devices. The repair scenario assigns the repair rate only to consumer devices, but the figures above show that the vast majority of medical equipment consists of professional devices, and the impact of repair is therefore not visible.

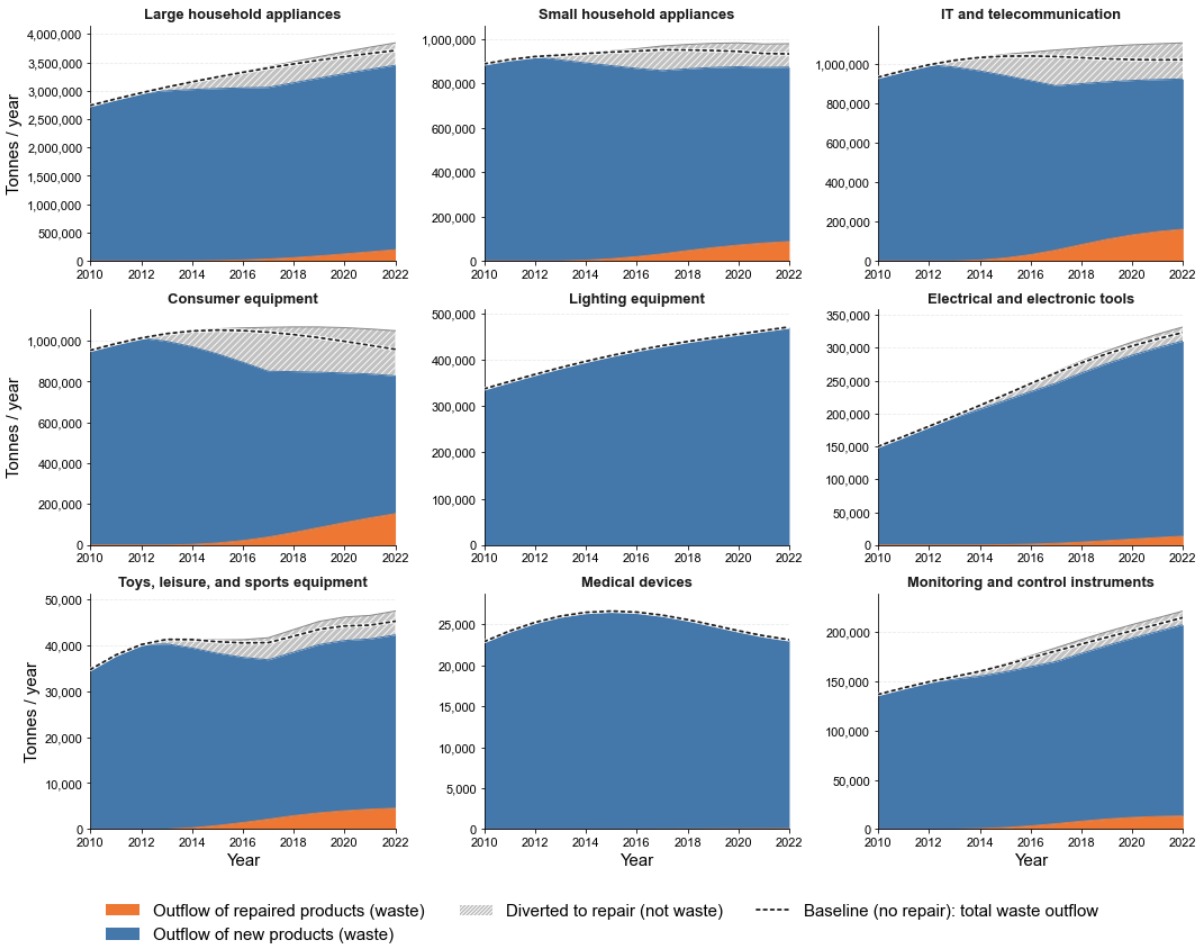


Figure 8: Total outflows by EU-10 WEEE category under the baseline and repair scenarios (2010–2022), excluding automatic dispensers

4.1.2 Monetary equivalent of the material reduction

The previous paragraph showed that the repair scenario in 2017 reduced the inflow of new products and outflow of WEEE by 10.1% and 10.9%, respectively. However, when the monetary flows are translated into monetary values, the story changes. By applying prices to the material inflows (see 5.4.2.2), it is possible to calculate the monetary reduction associated with the material inflow reduction. This reveals that the scenario reduces the monetary inflow by 14.1%.

The explanation for this can be seen in Figure 10, which presents the percentage reduction for both monetary inflows and material inflows for each UNU-key. This shows how this reduction differs when viewed from a monetary versus a physical perspective. Here we see that the translation from kilograms to euros creates big differences in inflow reductions. The increase in the repair of mobile phones (UNU-key: 303) only replaces around 11800 tonnes of new mobile phones, which corresponds to a physical reduction of 0.03%. However, from the monetary perspective, it has the biggest impact with a 3.03% reduction of total inflows of new EEE. This result is not a surprise, as

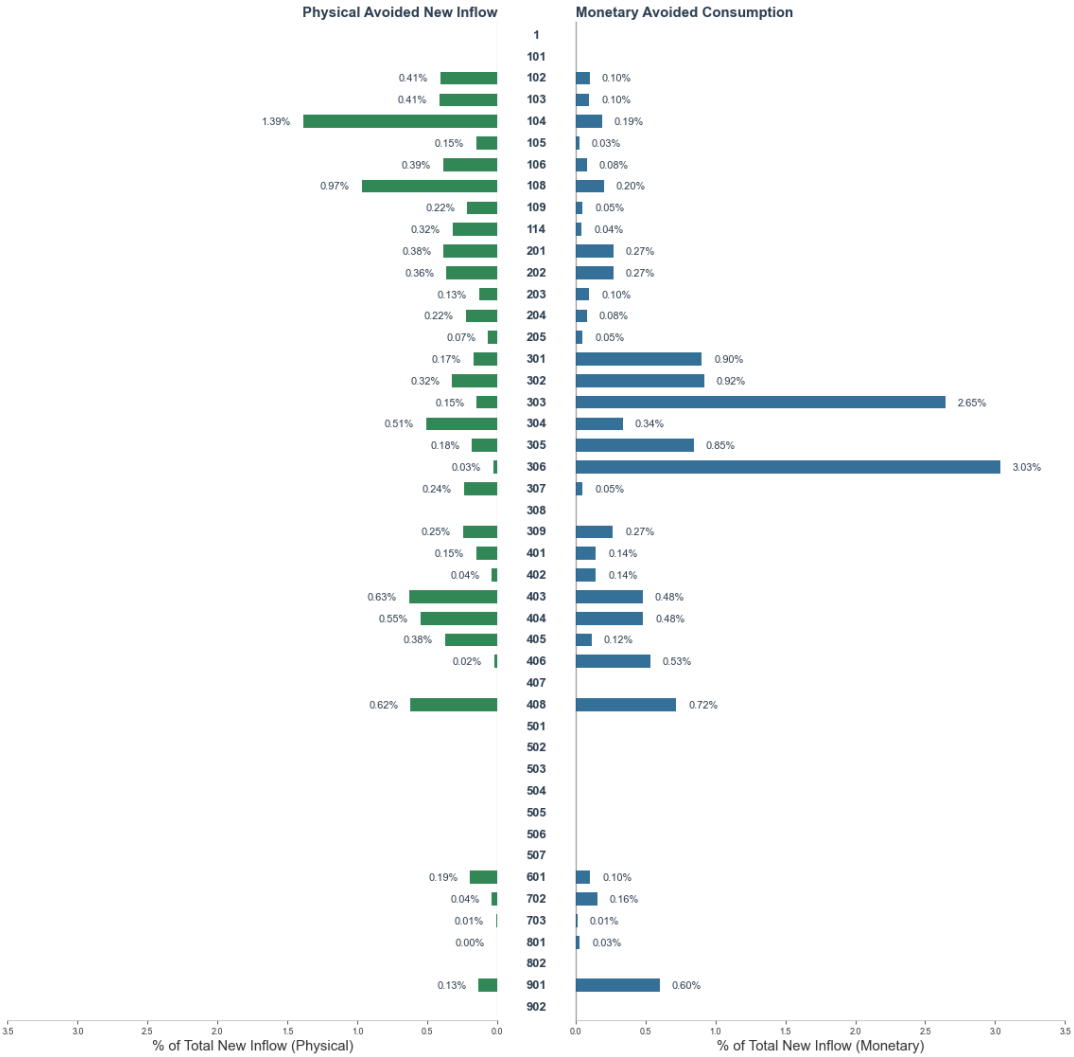


Figure 9: Physical avoided new inflow and monetary avoided consumption per UNU-key as a percentage of total new inflows under the repair scenario (2017)

mobile phones are valuable products that are relatively light, resulting in a price of almost € 2,300/kg. The opposite is happening with very heavy products such as washing machines (UNU-key: 104), which are much heavier than most other EEE categories, and as a result, they have a price of less than € 3/kg. For this reason, the monetary impact of washing machines is quite low, resulting in a change in impact from 1.39% to 0.19%.

4.2 Economy-wide impacts from the CGE model

This section will describe the effects of the preference shock of the CGE model. This is based on the reduction in consumer expenditure on EEE of 14.1% obtained by the dMFA. Based on this reduction, the efficiency of the consumption of households of EEE and ROS is changed to adjust the household expenditure share of EEE downward by 14.1%. Based on our assumption that all household savings from the reduction in EEE expenditure go towards repair, the expenditure share of ROS is increased accordingly. These adjustments will serve as the exogenous shock to the CGE model to capture the dynamic effect of the observed preference change.

Following the introduction of this shock, the model solves for a new equilibrium in which all sectors, households, and government adjust their behaviour in response to the changed relative prices and expenditure patterns. This implies that although the initial shock reduces EEE demand by 14.1% and redirects the full amount to ROS, these final demand changes for both sectors differ from these values in the new equilibrium, due to the behavioural dynamics of the model.

The results of this new equilibrium are presented in three parts. First, the impact of the repair scenario on socioeconomic indicators such as GDP, wages, and income is discussed. This is followed by a decomposition analysis of the repair intervention's impact to understand the drivers behind the changes in final demand. Last, the impacts on GHG emissions associated with the repair scenario are discussed. A complete overview of the CGE results for both the baseline and repair scenarios is provided in Supplementary information S3. One final disclaimer must be given. Since the EEE sector itself is relatively small within the broader economy, and the intervention does not represent a drastic reduction in inflows, the macroeconomic effects may be relatively minor. Some effects are so small that they would not normally be reported. However, since the goal of this thesis is to develop a proof of concept, this is considered acceptable to be able to demonstrate the dynamics of the model.

4.2.1 Macroeconomic effects of the repair scenario

Following the implementation of the preference shock and the subsequent macroeconomic dynamics, the final demand of households for EEE products declines, while the demand for repair services increases (Table 5). Looking at the ELS composite, the household consumption of EEE decreases by 14.05%, which corresponds to an increase in household consumption of the ROS share by almost 4.95%. This seems like a modest increase, but given that EEE repair services represent less than 4% of the total ROS sector output (Eurostat, 2023), this 4.95% increase represents a very significant growth in the repair sector of EEE.

These changes in demand also have an effect on the total value of output of the EEE sector and the ROS sector. In Europe, the domestic output of the EEE sector decreases by 2.05%, and the import of

EEE from ROW is reduced by 0.05%. On the other hand, the output of the repair services sector in Europe increases by 3.06%. Although a decreasing domestic demand for EEE could have increased exports, we see a decrease in exports by 1.94%. This, however, is not caused by the changed preferences, but by the increase in labour and capital costs in Europe, which makes the industry in Europe less competitive.

Table 5: Percentage changes in household consumption for ELS, EEE, and ROS in the EUR region

Sector	**Baseline** (Million USD)	**Repair scenario** (Million USD)	**%change**
EEE	189300	162708	-14.05%
ROS	544174	571097	+4.95%
Other sectors	9800186	9803577	+0.03%
Total	10533660	10537382	+0.03%

These are not the only changes, because they also drive additional effects as repair services are more capital- and labour-intensive than the production of EEE. As a result, the shift in demand from the EEE sector to repair services will result in increased demand for labour and capital. Because this analysis assumes full employment and labour supply is fixed, the additional demand can only be accommodated by increasing wages, which rise by 0.08% (Figure 11). Since households are the suppliers of labour, higher wages will result in an increase in household income. Since other sources of household income, in the forms of capital returns and government transfers, rise by only 0.02%, the nominal income increases by just under 0.04% overall. The nominal incomes represent the total income of households in monetary terms, but this does not account for inflation. As wages and capital increase, the cost of production will subsequently also increase as firms depend on labour and capital to produce goods. Together, this results in an increase in prices of more than 0.04% to cover the increase in cost of production. Since the increase in consumer prices exceeds the increase

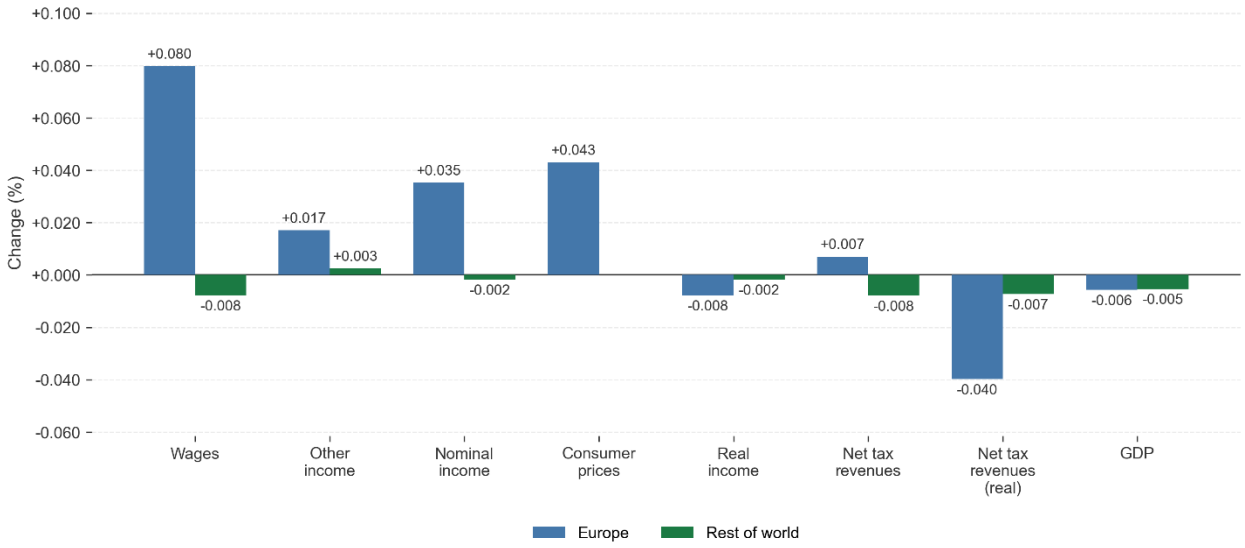


Figure 10: Relative price and income changes associated with preference change compared to baseline

in nominal income, the real income of households drops by 0.01%. The decline in real income leaves households with less purchasing power, which reduces their demand for goods because this is constrained by household income. Households are not the only ones affected by these prices, as the net increase in tax revenue (0.01%) is not able to cover this inflation, resulting in a reduction of government income of 0.04%. Given all these changes, the GDP in the EUR region is declining by 0.01% in response to the preference change.

The decline in real income for households and government, and GDP, are also visible in ROW, but are not driven by inflation. Because consumer prices in the ROW are fixed as the numeraire to solve the model (Hosoe et al., 2010), there is no inflation in this region. However, as European households consume less EEE, their imports of EEE from ROW also go down, and as a result, total output of EEE in ROW decreases. This is not compensated by an increase in imports of repair services, as services are generally not much traded internationally. Consequently, overall demand for labour in ROW declines, resulting in a marginal decrease in wages of 0.01% and a drop in net tax revenue of 0.01%. Together, this reduces the real income of both households and the government by less than 0.01%. As a consequence, the GDP in ROW declines by 0.01%, matching the GDP reduction of the EUR region.

4.2.2 Decomposition of final demand

All these changes in income and prices also affect the supply and demand for goods. Households adjust their spending to maximise the utility obtained from consumption, while firms switch inputs to maximise profits. To understand how the changes in preferences, prices, and income affect the quantity consumed, the change in the quantity of final consumption is decomposed into its underlying drivers as explained in Section 3.4.4. Table 6 presents the results of the decomposition, showing how each of the three effects contributes to the total change in the quantity of household consumption per sector. This involves the first-order impact of the preference change on household consumption of EEE and ROS, the substitution effects caused by changes in relative prices, and the income effects caused by changes in household income. The figures are reported in quantities, deflated using sector-specific baseline prices. They are therefore not directly comparable with the expenditure values in Table 5, which are reported in terms of household expenditure.

Table 6: Decomposition of changes in household final demand by sector under the repair scenario (2017)

Sector	Preference change		Substitution		Income		Total	
	Million USD	%	Million USD	%	Million USD	%	Million USD	%
AFF	0	0.00%	10,2	0.01%	-14,0	-0.01%	-3,8	0.00%
MIN	0	0.00%	0,3	0.01%	-0,2	-0.01%	0,1	0.01%
OIP	0	0.00%	12,8	0.02%	-5,3	-0.01%	7,5	0.01%
CHP	0	0.00%	6,5	0.00%	-19,0	-0.01%	-12,5	-0.01%
MET	0	0.00%	0,7	0.00%	-1,9	-0.01%	-1,2	0.00%
EEE	-20435,4	-14.10%	51,2	0.04%	-9,7	-0.01%	-20393,9	-14.07%
ROS	24082,5	4.90%	-103,5	-0.02%	-40,2	-0.01%	23938,8	4.88%
MEQ	0	0.00%	8,8	0.00%	-27,6	-0.01%	-18,7	-0.01%
OMA	0	0.00%	35,7	0.00%	-98,9	-0.01%	-63,2	0.00%
CNS	0	0.00%	-0,8	0.00%	-5,6	-0.01%	-6,4	-0.01%
TRA	0	0.00%	10,2	0.00%	-32,8	-0.01%	-22,5	-0.01%
SER	0	0.00%	-85,2	0.00%	-464,4	-0.01%	-549,6	-0.01%
COA	0	0.00%	0,2	0.02%	-0,1	-0.01%	0,1	0.01%
COI	0	0.00%	0,0	0.02%	0,0	-0.01%	0,0	0.01%

GAS	0	0.00%	5,9	0.02%	-2,3	-0.01%	3,7	0.01%
POW	0	0.00%	-0,5	0.00%	-10,3	-0.01%	-10,8	-0.01%

When isolating the impact of the preference change, we see that household expenditure initially drops by 20,435.4 million USD, which matches the 14.1% reduction calculated by the dMFA model by assumptions. This reduction in EEE expenditure caused by the preference change is accompanied by an increase of 24082,5 million USD in household ROS expenditure, and results in an increase in ROS of 4.9%. At first sight, the increase for ROS does not match the decrease for EEE, which would suggest that the assumption of full redirection of expenditure has failed. This is not the case, as these values are reported in quantities deflated using sector-specific baseline prices. These two sectors have different price levels in the baseline, and therefore households need to consume a greater quantity of repair services to replace the same value of EEE products. Once the quantities are valued at baseline prices, the reduction in EEE and the increase in ROS are equal in absolute terms, consistent with the assumption set out in Section 3.4.2.2. Because the preference change only applied to the EEE and ROS, none of the remaining sectors is affected by the preference change.

The changes in demand go beyond the preference change, as they will affect the prices of products differently, which creates substitution effects. The substitution effect captures how consumption responds to the new relative prices created by the preference shock. Because repair services are more labour- and capital-intensive, and the prices of labour and capital rise, repair becomes relatively more expensive while EEE becomes relatively cheaper. Consumers respond by shifting their expenses slightly back toward EEE, and as a result, the initial EEE reduction is offset by 51.2 million USD, while consumption of repair services falls by 103.5 million USD. Unlike the preference change, the substitution effect does affect other sectors, albeit only marginally.

Demand is also affected by how much households earn, since income constrains what households are able to spend. This is captured by the income effect, which shows the change in consumption resulting from the change in income. In Section 4.2.1, it was already shown that the real income of households in EUR declines, and as a result, households consume less of both EEE and ROS, with 9,7, and -40,2 million USD, respectively. As a result of the income effect, the combined quantity consumed within the ELS composite is now less compared to the baseline.

Taken together, these effects show that the CGE model produces an equilibrium in which the net change in demand is not identical to the change originally imposed through the dMFA, although the divergence is very small (0.03%). While the preference change alone reproduces the dMFA changes for EEE and ROS exactly, it also creates substitution and income effects that influence the outcomes of the model. The change in preferences thus generates dynamic impacts that go beyond the EEE, which the dMFA cannot capture, since only the CGE incorporates the behavioural responses of households and firms. A possible solution for this could be to run both models iteratively until the outcomes converge, though this falls beyond the scope of this thesis.

4.2.3 Impact on GHG emissions

Linking the dMFA to the GREEN-R model also allows us to analyse environmental impacts associated with the repair scenario, beyond the material flows. Here, I will discuss the final results of the economy-wide environmental impacts associated with the changes in production and repair of EEE, caused by the preference change. These results reflect only the emissions embodied in the production and repair of EEE alone, since energy consumption during the use phase has not been modelled.

In Figure 11, the environmental impacts of the repair scenario are presented from both a production-based and a consumption-based perspective. The production-based emissions reflect the territorial emissions in the EU associated with the production of domestic industries. This allows us to see the direct changes in the EEE and ROS sectors in both the EU and ROW compared to other sectors. The consumption-based emissions reflect the emissions associated with the final demand, which include emissions from industries outside the EU. This is split into direct and indirect emissions, where the direct emissions represent the emissions directly emitted by consumers, such as when driving their car. The indirect emissions, on the other hand, represent the emissions that occur through the supply chain during the manufacturing, transportation, and disposal of household-consumed products. Only the indirect emissions are affected by the repair scenario, since the direct emissions are not modelled as responding to the preference change.

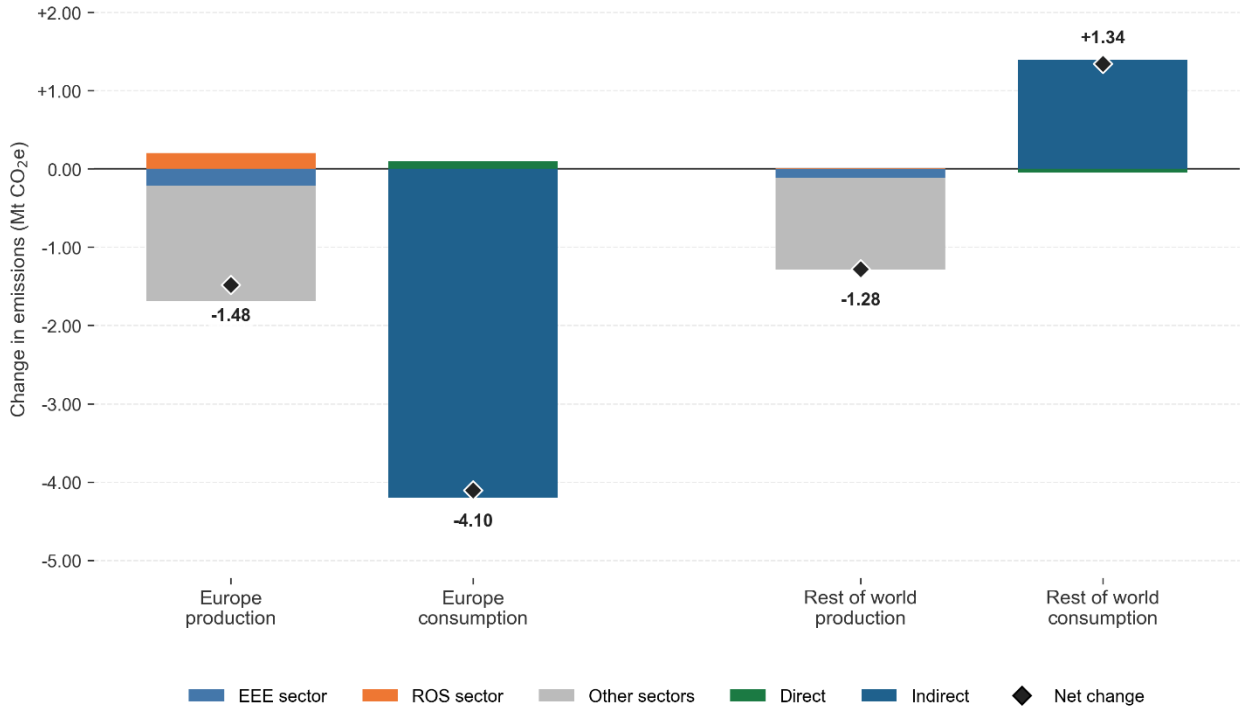


Figure 11: Production-based and consumption-based GHG emission changes under the repair scenario, by region (Mt CO_2-eq)

Production-based emissions decrease across all sectors in both regions, with the exception of the ROS sector. This aligns with the narrative of the repair scenario, since the scenario drives an increase in output for repair services in Europe, and an increase in output leads to an increase in emissions. Because these repair services are almost entirely sourced through domestic output, the corresponding increase in ROS GHG emissions in EUR is 0.20 Mt, whereas in ROW there is no significant change in ROW emissions. Despite these increases, total change in GHG emissions remains negative overall, at −1.48 Mt for EUR and −1.28 Mt for ROW.

Consumption-based emissions tell a different story. Rather than a net decrease for both regions, the GHG emissions in EUR are decreasing by 4.10 Mt, while in ROW they increase by 1.34 Mt. There can be various drivers in the changes in emissions, and to understand the impact of these various drivers, we need to decompose the changes in indirect emissions, as explained in Section 3.4.4. The results of this decomposition are presented in Figure 12, showing how each driver contributes to the total change in the indirect household emissions. This reveals that the various drivers have a varying impact on the indirect emissions, but the main impact is associated with the preference change from EEE to ROS in EUR. You see that the reduction in consumption of EEE is responsible for a -9.15 Mt reduction in GHG, while the new increased consumption for ROS is increasing the GHG emissions by 4.26 Mt. This results in a net reduction of 4.89 Mt in the indirect emissions associated with household consumption of new and repaired EEE.

Because the intervention is not in ROW, there is no impact associated with the changes in EEE and ROS demand in ROW. However, as seen in the previous section, the ROS and EEE sectors are not the only ones affected by changes in demand. The real income of households falls in both regions, which reduces demand for products. This affects the emissions in both regions, together producing a global reduction of 0.93 Mt.

The other drivers of emission change are unrelated to final demand and instead concern the changes in how sector produce their goods, caused by the dynamic impacts induced by the preference shock. The change in emission intensity captures the emissions arising from the use of fossil energy sources, namely coal, gas, and oil. We see that a change in emission intensity is responsible for increasing emissions by 0.27 Mt for EUR and 0.52 Mt for ROW. The other effect is driven by the change in technology structure, which captures the composition of intermediate inputs of all sectors, given a proportional emission related to each sector's output. This has a larger effect than the change in emission intensity, as it is responsible for increasing the emissions for both EUR and ROW by 0.78 Mt and 1.43 Mt, respectively. These changes in emission intensity and technology structure show that, in response to the increasing cost of labour and capital due to the repair scenario, firms decided to increase the intermediate consumption from emissions-intensive sectors and increase their fossil fuel use. They show how the macroeconomic dynamics caused by the preference change also affect GHG emissions. This helps us explain why consumption-based emissions grow in ROW, but are not offset by an increase in repair.

These changes in emission intensity and technology structure show that, in response to the rising cost of labour and capital under the repair scenario, firms overall increase their intermediate

consumption from emissions-intensive sectors and their use of fossil fuels. This demonstrates that the macroeconomic dynamics induced by the preference change also affect GHG emissions. It also helps to explain why consumption-based emissions grow only in ROW, because in that region the emissions driven by the emission intensity and technology structure are not offset by a reduction of EEE consumption.

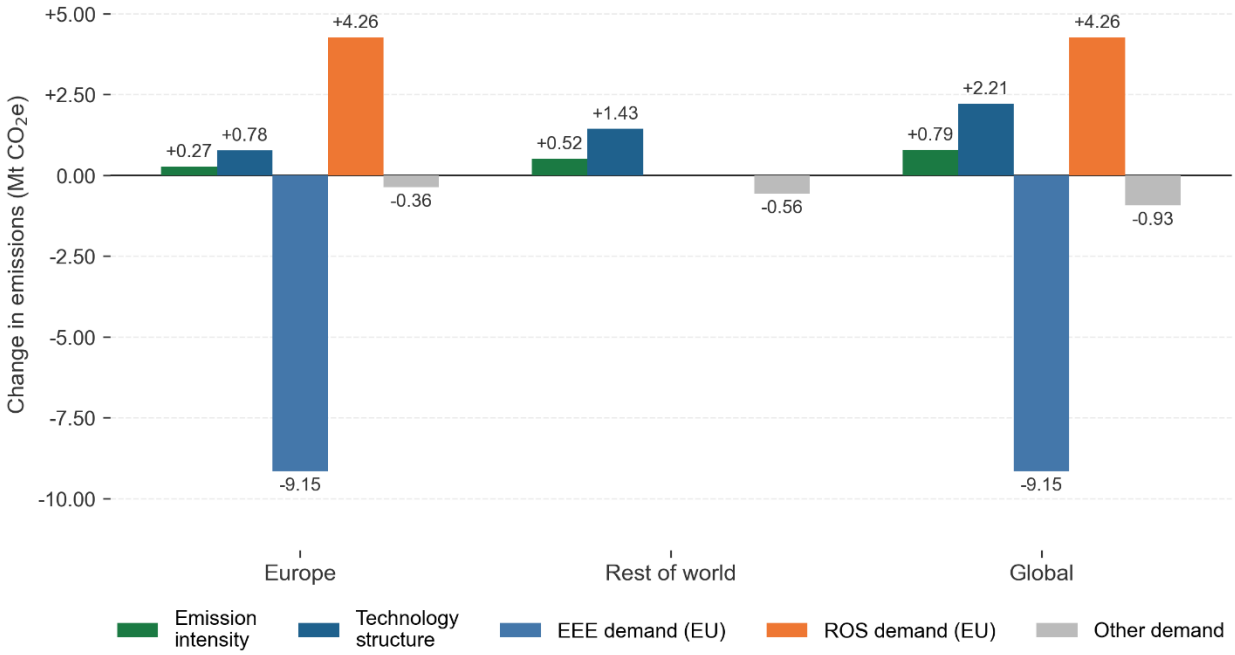


Figure 12: Decomposition of changes in indirect GHG emissions under the repair scenario by driver and region (Mt CO_2-eq)

5 Discussion

The results of the previous chapter are now discussed in three parts. The first part concerns what these results mean for the case of increased repair in the EU, covering the economy-wide dynamics of the repair scenario and what the increase in repair reveals about the material, economic and social dimensions of the CE strategy. The second and third parts concern the linkage approach rather than the case of EEE, setting out the benefits of the linkage approach and comparing these with what a standalone approach offers, before reviewing the limitations associated with the linkage method. One final remark concerns Section 5.1, regarding the insights generated for the EEE case. Given the simplifications adopted in this proof of concept, these findings demonstrate the impacts a repair scenario can produce across the dimensions of the CE transition, but should not be read as precise estimates.

5.1 Interpreting the impact of the repair scenario

The analysis in this study focuses on the impact of increasing household repair of EEE. Comparing a repair scenario, in which a product-specific repair rate applies from 2012 onwards, with a baseline scenario without additional repair shows that increased repair reduces both the amount of WEEE generated by society and the consumption of new EEE. The volume of repaired product is nevertheless larger than the flows it displaces, given the shorter lifetime of a repaired product relative to a new one. A repair rate should therefore not be understood as a direct measure of material savings, as it depends on the gained lifetime of repair and the number of reuse cycles possible. Repair is thus effective in reducing resource consumption, though it is better understood as delaying material consumption than as a full replacement of material consumption.

Implementing this scenario in the CGE model shows that increasing the repair of EEE has impacts beyond the material dimension and creates economy-wide dynamics that require attention. The increased demand for repair services initially appears favourable for households, since it raises wages by 0.08%. However, rising wages also drive inflation, resulting in a decrease in real income of households in the EU. Consequently, the repair scenario produces a decline in GDP of 0.01% in both the EU and the rest of the world. However, not all economic effects are negative. Since repair services are inherently local, the repair scenario reduces the EU's dependence on other regions, providing greater resilience in the supply of EEE and the critical raw materials in these products.

As explained in section 4.2.2, these changes in income and prices also generate substitution and income effects in the consumption decisions of economic agents. The net result of both effects is that a small share of household expenditure is redirected towards new EEE at the expense of repair services (0.03%), since rising wages make labour-intensive repair services relatively more expensive than new EEE. As described in section 4.2.3, these dynamics also affect GHG emissions. The repair scenario generates direct GHG savings through the preference shift away from new EEE, but these are partially offset as firms respond to changes in relative prices by increasing intermediate consumption from emissions-intensive sectors and their use of fossil fuels. The net result is nonetheless positive, with both production-based and consumption-based emissions declining in

the EU. Despite both effects being considerably smaller than the direct preference change, the small increase in new EEE demand and the increase in intermediate consumption from emissions-intensive sectors show that these dynamics need to be accounted for to assess the full impact of CE strategies.

Overall, the results indicate that the repair scenario reduces material consumption and GHG emissions, raises wages in the EU and strengthens the resilience of the EEE supply chain, while producing adverse economic effects through inflation, lower household income and a small decline in GDP. These adverse economic effects may impose real costs on households, but it would be too early to conclude if these effects produce a negative impact regarding the social dimensions of the CE. The CGE framework only captures changes in GDP, prices and income, but it neglects other dimensions of the CE transition, including employment impacts across groups, income distribution and subjective well-being (Fevereiro et al., 2025). This is also visible in the linkage approach developed here, given the following three examples.

First, the scenario reduces material consumption by 10.1% and lowers the GHG emissions associated with the consumption and repair of EEE by 4.89 Mt, at a cost of only 0.01% in GDP, while broadly maintaining the service delivered by the EEE stock in use. Households therefore obtain comparable service from using EEE, but at a lower environmental cost. A reduction in these environmental costs will have a positive effect on societal health and well-being, but this is not captured in the CGE model.

Second, the CGE model used in this thesis also assumes full employment with a fixed supply of labour, so the increase in demand for labour can only be accommodated through higher wages. In regions where unemployment exists, part of this demand would instead be met through higher employment, provided the relevant skills are available. This would both create employment and weaken the inflation generated by rising wages.

Third, households are modelled as a single representative agent, whereas in reality they range from low-income to high-income households with different sources of income. Since wages rise faster than consumer prices, households that depend on labour rather than capital would see their income improve. Depending on how income is distributed across households, the scenario may therefore have a positive distributional effect that the aggregate result does not show.

Since these dimensions of well-being and social value fall outside what the CGE framework measures, no conclusion can yet be drawn about whether the repair scenario has a negative impact on social equity and human well-being, which constitute the social dimensions of the CE (Kirchherr et al., 2017). Therefore, economic goals such as low inflation and higher GDP offer an incomplete basis for assessing the social dimension of the repair scenario.

5.2 Benefits of the linkage approach

The results of the linkage approach presented in the previous chapter show that linking a dMFA with a CGE produces insights that neither model could generate alone. At the micro level, the dMFA revealed that repair reduces material inflows and waste generation, but that the magnitude of this

reduction differs substantially across product categories, reflecting the heterogeneity of EEE regarding size, lifetimes, weight, function, and material composition (Magalini et al., 2014). With a standalone dMFA, the analysis would stop at these results, but through the linkage method developed in this study, it is possible to identify the dynamic economic effects associated with these CE strategies. The results of the CGE show that increased repair not only affects material flows but also generates macroeconomic effects beyond a reduction in EEE expenditure. These include positive societal outcomes for households, such as rising wages, but also less foreseeable effects, such as inflation, since other sectors continue to depend on the same labour factor. The results further show how these socioeconomic effects differ per region: whereas the income reduction in EUR is driven by inflation, the income losses in the ROW are driven by falling labour demand, revealing impacts beyond the border of the implementation of the CE scenario. The CGE further incorporates environmental indicators, demonstrating how the linkage extends the results of the dMFA by also capturing environmental impacts.

These new insights are not only provided by the CGE, but the link with dMFA also provides a material foundation that a single CGE model does not include. By incorporating the output values of a dMFA into the CGE model, the generated results of the CGE become more meaningful, since they are now based on the material flows underlying them. This provides a stronger material foundation for CE scenarios implemented in a CGE. Using a macroeconomic model alone, these insights would not be available. Masui (2005), for example, applies an arbitrary 10% increase in repair to assess the resulting macroeconomic changes, but provides no information on how this relates to an actual material reduction. This provides a poor understanding of the amount of material that is actually reduced by this CE strategy. The same limitation applies to IO-based studies, where final demand is adjusted to represent increased repair (de Boer et al., 2021; Wiebe et al., 2019, 2023) without accounting for the underlying material foundation related to CE intervention for specific products. Another strength of the result at the micro-level is that it is possible to incorporate the stock and flow dynamics. The results of the dMFA show that the decrease in total material demand for EEE is smaller than the amount of EEE that is repaired and reused. This shows that repairing and reusing a product does not function as a one-on-one replacement but should be understood as a delay of new product consumption. Without a dMFA, this kind of stock-flow dynamic would not have been obtained.

The benefits of this dMFA-CGE linking approach also extend compared to the existing MFA-CGE linkage approaches. Where studies such as Nechifor et al. (2020) and Cao et al. (2019) only focused either on a single material or an entire sector, the approach of this study is able to analyse material flows associated with products. Because each product comprises a different material composition, this product-level approach makes it possible to analyse a far larger and more heterogeneous set of materials than the single-material focus. This product-level resolution is also what makes it possible to analyse a CE strategy such as repair, since repair is inherently tied to the product rather than to the material it contains or the sector that produces it.

The dMFA provides the material foundation based on the dynamics at the product level associated with the repair scenario, while the CGE translates these into economy-wide macroeconomic effects that are associated with this scenario. Together, these outcomes demonstrate that the linkage

approach developed in this thesis creates additional insights compared to both the standalone approach and previous MFA-CGE linking methods, by providing a better understanding of the economy-wide dynamics of CE strategies with sufficient product-level resolution.

5.3 Limitations of the linkage approach

As stated above, the linkage approach provides additional insights not possible to have with the standalone models. However, since it is developed as a proof of concept, various assumptions and simplifications have been made, which need to be discussed to provide contrast to these findings. A short overview of all the limitations is presented in Table 8.

5.3.1 Scope constraints and data limitations

The results of this study represent the impacts of increased repair for the EU as a single combined region, which reflects a high level of regional aggregation. While this is acceptable for the purpose of testing the linkage methodology, it limits the relevance of the findings since there are high regional differences in POM, collection rates, and recycling rates of EEE (Pauliks et al., 2026). This shows that the implementation of CE strategies for EEE is much more region-specific in practice, which this study fails to capture. However, since both the material flow and the monetary flow data are already available for each EU27 member state, it would be possible to use this approach for each EU country. However, applying this methodology to a dedicated study focused on a single or multiple EU member states would require additional data collection, including lifetime data for repaired products, collection rates, and repair potential specific to each region. This would provide a stronger empirical foundation for the modelling outcomes and improve the alignment of the results within the regional context of each EU member state.

Another simplification is to focus only on a single CE strategy in the form of LTE through repair, which affects the applicability of this linking method to other CE strategies. Reuse and refurbishment operate through the same mechanism as repair, since both retain the product and its functionality while extending the use phase (Potting et al., 2017). Modelling these strategies in a similar manner should therefore be possible with adjusted parameters. This is not possible for other CE strategies, which require a different implementation. Reduce operates at the manufacturing stage by lowering material inputs per product, which affects production recipes but does not change household final demand. Repurpose alters the function of a product, meaning it no longer contributes to the stock providing the original service. Recycling and recovery act on the materials embedded in the product rather than on the product itself, since both destroy the original product and return its materials as intermediate inputs to other sectors. All these strategies do not affect the household demand for a product, but affect the supply side of a product (Potting et al., 2017), and would therefore require changing parameters affecting the intermediate consumption. Refuse and rethink fall between these cases, since both alter final demand but involve a more fundamental change in how products are used, which would require more than an adjustment of consumption shares.

Another aspect of this modelling approach that should be addressed in later research is the allocation of the preference change in the CGE model. The preference change in the CGE is located

at the final demand and is modelled by replacing a certain amount of household consumption of the EEE sector with consumption of the ROS sector. For two reasons, this has its limitations.

The first reason is that the preference change is driven by MFA inflow data, which does not distinguish between different types of end-users of EEE. This means that the consumption of EEE by businesses and government is not reflected in the preference change applied to the CGE model, which implies that the macroeconomic effects reported in this study are likely to underestimate the true economy-wide impact of the repair scenario. Given that the primary aim of this study was to demonstrate a proof of concept, this was not deemed problematic. However, a next step in the development of this methodology should also focus on the business-to-business flows of EEE products and the government consumption of EEE, by investigating how the inflows of the dMFA relate to the flows from investment to capital formation in the SAM and final demand of the government. A potential direction for this would be to allocate the monetary inflows across different end-user categories based on the output share of the EEE sector across the different final demand categories in the SAM.

The second reason is that the micro-level inflow data of the dMFA is not fully consistent with the sector classifications of the SAM. As stated in Section 3.4.1.1, the underlying data of the UNU-keys do not perfectly align with the GTAP sectors associated with EEE and ROS. For example, the production origin for some UNU-keys is not or only partially linked to the EEE sector, while others do not have any link to the ROS sector. The solution for this study was to exclude certain UNU-keys or have them not be affected by the repair scenario. In reality, a preference change for repair of EEE would not make these distinctions, which means that the shock applied to the EEE sector is probably an overestimation of the impact, as some of the impacts would be spread out across other sectors. Therefore, future research should explore more elaborate methods to address the misalignment between the micro- and macro-data, rather than relying on the assumptions adopted by this study.

Table 7: Simplifications adopted in the linkage approach

Simplification	Description
ROS as proxy for repair services	Repair of EEE accounts for around 4% of the ROS sector, but the linkage does not separate it from the ROS sector, so repair is assumed to share the production recipe of the ROS sector.
Professional repair only	All repair is assumed to be undertaken by professionals, rather than by households themselves, such as DIY.
Household final demand only	Changes in inflows are allocated solely to household final demand, so government consumption and investment by firms remain unaffected by the scenario.
Single EEE-sector	All UNU-keys are allocated to the EEE sector, whereas the underlying data show that UNU-keys also correspond to other or multiple sectors beyond the EEE sector.
Repair located in a single sector	All repair is assumed to take place within the ROS sector, whereas in practice it also involves repair activities from other sectors.
Repair rates	A single repair rate is applied per EU-10 EEE category, neglecting variation between UNU-keys and regions.
Lifetimes	The lifetime of every repaired UNU-key is set at 50% of the original lifetime with a single reuse cycle, neglecting product-specific repair characteristics.

Cost-neutral expenditure shift	The increase in repair expenditure is set equal to the reduction in expenditure on new EEE, so the price of repair is not accounted for.
Single year linkage	The linkage is implemented for a single year rather than across the full scenario period.
Perfect substitution	A repaired product is assumed to deliver the same service as a new one, differing only in remaining lifetime.
One-directional soft link	Material flows are soft-linked to the CGE model without incorporating dynamic effects of the CGE model feedback, so the final output of the dMFA does not converge to the dynamic changes of the CGE output.
Material inputs of repair	The dMFA does not account for the inflows required for repair, such as spare parts.
High aggregation	The CGE model is aggregated into two regions and sixteen sectors, whereas greater sectoral and regional detail is feasible for GREEN-R.
Expert-based elasticity	The elasticity of substitution between EEE and ROS in the CES composite rests on expert estimation by PBL rather than on empirical observation.

5.3.2 Unaccounted dynamics in the linkage approach

Despite adding the macroeconomic dynamic to the changes in material flows, the linking approach still misses some important dynamics associated with the CE strategy of repair. The ELS composite assumes that the money not spent on new EEE is fully redirected to repair services at the same price level. However, this is an assumption which may not reflect reality, as in some cases, repair is the more economically viable option compared to replacing the product (Brusselaers et al., 2019). By assuming that these are equal, this methodology misses certain rebound effects related to an increase and shift in consumption, driven by lowering prices (Zink & Geyer, 2017).

Another rebound that is missing is related to the energy consumption during the use phase of EEE products. The approach in this study assumes that the direct emissions of households in the CGE are not affected by the longer use of older EEE. In reality, however, extending the life of older EEE through repair means that more energy-intensive products remain in use longer, whereas replacing them with newer models would have resulted in lower energy consumption through improved energy efficiency (Castro et al., 2022). The consequence of this is that the direct emissions of households related to energy consumption should have increased under this repair scenario.

The final dynamic that is not accounted for is the material used for the repair of EEE, as the dMFA does not incorporate the material inputs required for repair itself, such as spare parts. This means that the material inflow reduction of the MFA only represents the material flows associated with new products and therefore may overestimate the material reductions associated with the repair scenario. For the CGE model, this would not matter, as the increase in ROS consumption also increases the intermediate input for this sector, so the macroeconomic dynamics do incorporate these intermediate inputs associated with repair.

5.3.3 Temporal misalignment between the two models

There is also a tension between how the dynamics between the two models are influencing each other. In the linkage approach developed in this thesis, the dMFA functions as the background model, capturing changes in material stock and flow dynamics from 1980 to 2022 based on the repair scenario involving an increased repair parameter. However, the CGE creates macroeconomic dynamics that are not incorporated by the dMFA model.

To illustrate, the CGE results show that the first-order impact of the repair scenario in 2017 is accompanied by additional effects driven by substitution and income dynamics. The substitution effect increases the household consumption of EEE relative to repair services, since inflation makes new EEE relatively cheaper than before. The income effect drives a decrease in overall household demand due to a reduction in real household income. Taking these effects into account, the CGE results show that the quantity of EEE consumed falls by 14.07% rather than the 14.10% derived from the dMFA, while the increase in repair services consumption changes from 4.90% to 4.88%. Together, the consumption of the ELS composite drops by 0.01%. These differences are small, but they illustrate that the equilibrium outcome of the CGE diverges from the outcomes produced by dMFA.

This is particularly relevant, since the increase in repair begins in 2012, which means the changes in household consumption of EEE and ROS and the accompanying macroeconomic effects are already occurring before 2017. The dMFA assumes that the development of stocks remains unchanged, which under the repair scenario requires an increase in total inflows. The CGE equilibrium, however, returns a consumption of new EEE slightly above the reduction derived from the dMFA, alongside a small decline in overall consumption within the ELS composite. This produces a minor misalignment between the development of stocks of the two models in the years leading up to 2017.

To address this misalignment, future research should consider linking the dMFA to a recursive CGE model as other MFA-CGE approaches have done (Aguilar Hernandez et al., 2023; Cao et al., 2019; Nechifor et al., 2020), which would make it possible to make the annual dynamics of stocks and flows more consistent with the evolving macroeconomic impacts due to the increase in repair, by iterating the two models until their outputs converge. However, it should be noted that this would mean that the two models are solved iteratively rather than sequentially, which moves it in the direction of a hard-linking approach, which comes with new challenges.

5.3.4 Scenario design

The final limitation of this approach concerns the way in which the repair scenario is implemented. The repair scenario used in the dMFA represents a what-if scenario, designed to assess whether a CE strategy of increased repair is able to reduce the inflow of new EEE products. This type of scenario is common in the field of industrial ecology, but when linking such a scenario to a macroeconomic model, it creates various tensions. A what-if scenario such as the one used in this study assumes that consumers change their behaviour without specifying the drivers of this change. However, through the collaboration with PBL, it became apparent that changes in final demand are generally not imposed exogenously in the field of economics, since this would mean dictating consumer

preferences rather than modelling how consumers respond to changing market conditions driven by concrete policies.

CGE models are therefore better suited to assessing the impacts of concrete CE policy instruments, such as the material levy modelled by Dellink and Kandelaars (2000) or the reduced tax rate on repair services modelled by Brusselaers et al. (2022). Both approaches show how demand is endogenously responding to a policy rather than assuming a predetermined shift in preferences. To bridge this gap, future research should focus on developing scenarios that are more grounded in concrete policy instruments rather than a what-if preference shift, which would make the implementation of the scenario more aligned with the common CGE modelling approaches, and subsequently also more relevant and better suited for the use of policymakers.

6 Conclusion

The central question this thesis aims to answer is: *To what extent can linking an MFA model with a CGE model improve the assessment of product-specific circular economy strategies?* To provide an answer to this question, this thesis addressed three sub-questions across its various chapters.

The literature review addressed SQ1 and revealed that linking MFA with a CGE is not a new development, as previous studies demonstrate that soft-linking a dMFA to a CGE model provides valuable insights by having a stronger material foundation for the CGE models. However, none of these studies achieved the product-level resolution required for assessing CE strategies applied to specific products. To address this gap, this thesis developed a product-oriented dMFA and soft-linked it to a CGE model to be able to assess CE strategies implemented at the product level.

The development of this proof-of-concept methodology addressed SQ2 by identifying and resolving three challenges. First, it showed that the price data used to translate physical flows into monetary values should be at basic price valuation, and that production and trade data meet this requirement, making the approach transferable to other product groups such as furniture or clothing. Second, it showed how the product-level inflows of the dMFA can be allocated to the household final demand of the SAM, and how the misalignment between the UNU-key product categories and the GTAP sector classifications can be addressed through simplifying assumptions. Third, it demonstrated how a nested composite can be used to model the consumer choice between new EEE and repair, and how efficiency augmenters make it possible to implement a demand shift derived directly from the dMFA inputs without breaking the calibration of the CGE model. Resolving these challenges produced a working linking method, capable of analysing the impact of increased EEE repair in the EU.

The results of this analysis produced insights that addressed SQ3 by showing that the linkage grounds CGE scenarios in a material foundation based on stock and flow dynamics, which provides a firmer basis for the preference shock applied to the model. It also demonstrated that the linkage made it possible to identify the dynamic macroeconomic effects associated with changes in material flows at the product level, including income and substitution effects. Furthermore, it makes it possible to identify the economy-wide changes in GHG emissions associated with the changes in material consumption.

Taken together, these findings provide a valuable answer to the main research question. Soft-linking a dMFA to a CGE provides a bridge between the dynamics of material metabolism at the product level and the economy-wide responses of the economic system, generating insights that neither model could produce in isolation. In that sense, the approach represents a meaningful improvement over standalone modelling approaches, which makes it a relevant approach for future CE research in the field of Industrial Ecology, because it enhances our understanding of the relationship between materials and macroeconomic dynamics. Furthermore, the approach developed in this thesis provides a relevant test case to develop a future micro-macro modelling approach for CE modelling.

6.1 Recommendations for further research

This linking approach developed in this thesis also has limitations, and these provide concrete directions for the further development of micro-macro modelling approaches for CE strategies. In the first place, future research should address the scope constraints and data limitations regarding the case used in this thesis, by focussing on a single or several EU member states, investigating how the inflows of the dMFA relate to the flows from investment to capital formation in the SAM, and exploring more elaborate methods to resolve the misaligned between the micro- and macro-data, rather than relying on the assumptions adopted by this study. The scope could also be extended to a broader set of CE strategies. The current method is developed for a single CE strategy, which makes it less directly applicable to strategies such as recycling and reducing, since these operate in a different manner. Extending the micro-macro linkage to different CE strategies would therefore be a logical next step, as this provides a more complete understanding of the impacts of a CE transition.

The method also excludes some dynamics, such as the material usage input of repair, changes in energy usage of in-use EEE, and the cost of repair. All provide relevant dynamics affecting the various dimensions of CE, but it is recommended to focus on the last one, as it is a more central element of the linkage approach. The outcomes of the CGE model also show the equilibrium reflects a different situation from that of the dMFA. To address this misalignment, future research should consider linking the dMFA to a recursive dynamic CGE model, and establishing how the dMFA flows can be adjusted to reflect the dynamic effects the equilibrium produces.

Beyond the methodology itself, a further direction concerns what the linkage can offer policymakers. The results show that assessing a CE strategy through economic indicators alone gives an incomplete picture, since a scenario that reduces material consumption and emissions still registers only as a marginal loss of GDP together with inflation. This neglects the positive externalities associated with these environmental improvements, which may generate additional benefits for societal health and well-being. Furthermore, these economic outcomes reflect assumptions embedded in the model, such as full employment and a single representative household, which conceal potential gains in employment and in the distribution of income across households. Therefore, the traditional focus of policymakers on economic goals such as low inflation and higher GDP offers a limited perspective on whether a CE strategy contributes to societal well-being.

This may also require changes within the field of Industrial Ecology. Similar to this study, it is common practice to develop what-if scenarios in order to identify the impacts of a given intervention. However, this approach conflicts with macroeconomic perspectives, as it dictates consumer preferences rather than modelling how consumers respond to changing market conditions driven by policies. Therefore, developing scenarios grounded in concrete policy instruments, rather than in what-if assumptions, would make it more consistent with common CGE modelling practice. This also makes them more useful to policymakers, since they are interested in how such a shift towards repair might be achieved rather than the impacts associated with a change in preference itself.

The final recommendation is therefore to engage with policymakers through the co-development of model linkages such as the proof of concept presented in this thesis. First, this would ground CE

scenarios in concrete instruments such as Ecodesign requirements, reduced VAT on repair services, or repair vouchers, which would align the approach with common CGE modelling practice and make the results of a linkage methodology more relevant for policymaking. Second, it would broaden the understanding of what CE strategies can deliver for social-wellbeing, beyond the traditional economic goals against which they are currently assessed.

7 References

Acemoglu, D., & Restrepo, P. (2019). Artificial Intelligence, Automation, and Work: Daron Acemoglu and Pascual Restrepo. In A. Agrawal, J. Gans, & A. Goldfarb (Eds), *The Economics of Artificial Intelligence: An Agenda* (p. 0). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0008

Aguiar, A., Chepeliev, M., Corong, E., & Mensbrugghe, D. van der. (2022). The Global Trade Analysis Project (GTAP) Data Base: Version 11. *Journal of Global Economic Analysis*, *7*(2). https://doi.org/10.21642/JGEA.070201AF

Aguilar Hernandez, G. A., Taherzadeh, O. A., & Tukker, A. (2023). *Lessons from micro- and macro-modelling linkages: Example of linking LCA/DMFA and CGE model for developing Circular Economy scenarios*. https://hdl.handle.net/1887/3590029

Aguilar-Hernandez, G. A., Dias Rodrigues, J. F., & Tukker, A. (2021). Macroeconomic, social and environmental impacts of a circular economy up to 2050: A meta-analysis of prospective studies. *Journal of Cleaner Production*, *278*, 123421. https://doi.org/10.1016/j.jclepro.2020.123421

Aguilar-Hernandez, G. A., Sigüenza-Sanchez, C. P., Donati, F., Rodrigues, J. F. D., & Tukker, A. (2018). Assessing circularity interventions: A review of EEIOA-based studies. *Journal of Economic Structures*, *7*(1), 14. https://doi.org/10.1186/s40008-018-0113-3

Al Haj Eid, M., Dandis, A. O., & Cathro, V. (2025). The Social Dimension of the Circular Economy: A Review Towards a Comprehensive Narrative. *Sustainable Development*, *33*(6), 8025–8040. https://doi.org/10.1002/sd.70054

Baars, J., Rajaeifar, M. A., & Heidrich, O. (2022). Quo vadis MFA? Integrated material flow analysis to support material efficiency. *Journal of Industrial Ecology*, *26*(4), 1487–1503. https://doi.org/10.1111/jiec.13288

Babatunde, K. A., Begum, R. A., & Said, F. F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, *78*, 61–71. https://doi.org/10.1016/j.rser.2017.04.064

Baldé, C. P., Kuehr, R., Yamamoto, T., McDonald, R., D'Angelo, E., Althaf, S., Garam Bel, Deubzer, O., Fernandez-Cubillo, E., Forti, V., Gray, V., Herat, S., Honda, S., Iattoni, G., Khetriwal, D. S., Luda di Cortemiglia, V., Lobuntsova, Y., Nnorom, I., Pralat, N., & Wagner, M. (2024). *The Global E-waste Monitor, 2024*. International Telecommunication Union (ITU) and United Nations Institute for Training and Research (UNITAR). https://www.itu.int/en/ITU-D/Environment/Documents/Publications/2025/d-gen-e_waste.01-2024-pdf-e.pdf

Bastein, T., Roelofs, E., Rietveld, E., & Hoogendoorn, A. (2013). *Opportunities for a circular economy in the Netherlands*. TNO. https://www.tno.nl/media/8551/tno-circular-economy-for-ienm.pdf

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

Blomsma, F., & Brennan, G. (2017). The Emergence of Circular Economy: A New Framing Around Prolonging Resource Productivity. *Journal of Industrial Ecology*, *21*(3), 603–614. https://doi.org/10.1111/jiec.12603

Boldoczki, S., Thorenz, A., & Tuma, A. (2021). Does increased circularity lead to environmental sustainability?: The case of washing machine reuse in Germany. *Journal of Industrial Ecology*, *25*(4), 864–876. https://doi.org/10.1111/jiec.13104

Brunner, P. H., & Rechberger, H. (2016). *Handbook of Material Flow Analysis: For Environmental, Resource, and Waste Engineers, Second Edition* (2nd edn). CRC Press. https://doi.org/10.1201/9781315313450

Brusselaers, J., Bracquene, E., Peeters, J., & Dams, Y. (2019). Economic consequences of consumer repair strategies for electrical household devices. *Journal of Enterprise Information Management*, *33*(4), 747–767. https://doi.org/10.1108/JEIM-12-2018-0283

Brusselaers, J., Breemersch, K., Geerken, T., Christis, M., Lahcen, B., & Dams, Y. (2022). Macroeconomic and environmental consequences of circular economy measures in a small open economy. *The Annals of Regional Science*, *68*(2), 283–306. https://doi.org/10.1007/s00168-021-01079-6

Burfisher, M. E. (Ed.). (2017). Introduction to Computable General Equilibrium Models. In *Introduction to Computable General Equilibrium Models* (2nd edn, pp. 8–23). Cambridge University Press. https://doi.org/10.1017/9781316450741.002

Burfisher, M. E. (2021). *Introduction to Computable General Equilibrium Models* (3rd edn). Cambridge University Press. https://doi.org/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 & Technology*, *53*(1), 224–233. https://doi.org/10.1021/acs.est.8b03633

Castro, C. G., Trevisan, A. H., Pigosso, D. C. A., & Mascarenhas, J. (2022). The rebound effect of circular economy: Definitions, mechanisms and a research agenda. *Journal of Cleaner Production*, *345*, 131136. https://doi.org/10.1016/j.jclepro.2022.131136

Chen, W.-Q., & Graedel, T. E. (2012). Anthropogenic Cycles of the Elements: A Critical Review. *Environmental Science & Technology*, *46*(16), 8574–8586. https://doi.org/10.1021/es3010333

de Boer, B. F., Rietveld, E., Rodrigues, J. F. D., & Tukker, A. (2021). Global environmental and socio-economic impacts of a transition to a circular economy in metal and electrical products: A Dutch case study. *Journal of Industrial Ecology*, *25*(5), 1264–1271. https://doi.org/10.1111/jiec.13133

Dellink, R. B., & Kandelaars, P. P. A. A. H. (2000). An empirical analysis of dematerialisation: Application to metal policies in The Netherlands. *Ecological Economics*, *33*(2), 205–218. https://doi.org/10.1016/S0921-8009(99)00138-X

Donati, F., Aguilar-Hernandez, G. A., Sigüenza-Sánchez, C. P., de Koning, A., Rodrigues, J. F. D., & Tukker, A. (2020). Modeling the circular economy in environmentally extended input-output tables: Methods, software and case study. *Resources, Conservation and Recycling*, *152*, 104508. https://doi.org/10.1016/j.resconrec.2019.104508

Ellen MacArthur Foundation. (2013). *Towards the circular economy Vol. 1: An economic and business rationale for an accelerated transition* (No. 1). https://www.ellenmacarthurfoundation.org/towards-the-circular-economy-vol-1-an-economic-and-business-rationale-for-an

European Commission. (n.d.-a). *Critical Raw Materials Act*. Retrieved 11 June 2026, from https://single-market-economy.ec.europa.eu/sectors/raw-materials/areas-specific-interest/critical-raw-materials/critical-raw-materials-act_en

European Commission. (n.d.-b). *Directive on repair of goods—European Commission*. Retrieved 12 June 2026, from https://commission.europa.eu/law/law-topic/consumer-protection-law/directive-repair-goods_en

European Commission. (n.d.-c). *Waste from Electrical and Electronic Equipment (WEEE)—Environment*. Retrieved 12 June 2026, from https://environment.ec.europa.eu/topics/waste-and-recycling/waste-electrical-and-electronic-equipment-weee_en

European Commission (Ed.). (2008a). *Eurostat manual of supply, use and input-output tables* (2008 edition). Publications Office. https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-07-013

European Commission (Ed.). (2008b). *NACE Rev. 2: Statistical classification of economic activities in the European Community*. Publications Office. https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-07-015

European Commission (Ed.). (2023). *European business statistics user's manual for PRODCOM* (2023 edition). Publications Office of the European Union. https://doi.org/10.2785/39767

European Commission. (2026). *User manual on international trade in goods statistics – 2026 edition* (2026 edition). Publications Office of the European Union. https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/w/ks-01-26-012-en-n

Eurostat. (2023). *Supply table at basic prices incl. Transformation into purchasers' prices* [Data set]. Eurostat. https://doi.org/10.2908/NAIO_10_CP15

Fevereiro, J. B. R. T., Genovese, A., Purvis, B., Codina, O. V., & Passarella, M. V. (2025). Macroeconomic models for assessing the transition towards a circular economy: A systematic review. *Ecological Economics*, *236*, 108669. https://doi.org/10.1016/j.ecolecon.2025.108669

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production*, *143*, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Gerst, M. D., & Graedel, T. E. (2008). In-Use Stocks of Metals: Status and Implications. *Environmental Science & Technology*, *42*(19), 7038–7045. https://doi.org/10.1021/es800420p

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production, Towards Post Fossil Carbon Societies: Regenerative and*

Preventative Eco-Industrial Development, *114*, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007

Graedel, T. E. (2019). Material Flow Analysis from Origin to Evolution. *Environmental Science & Technology*, *53*(21), 12188–12196. https://doi.org/10.1021/acs.est.9b03413

Graedel, T. E., van Beers, D., Bertram, M., Fuse, K., Gordon, R. B., Gritsinin, A., Kapur, A., Klee, R. J., Lifset, R. J., Memon, L., Rechberger, H., Spatari, S., & Vexler, D. (2004). Multilevel Cycle of Anthropogenic Copper. *Environmental Science & Technology*, *38*(4), 1242–1252. https://doi.org/10.1021/es030433c

Grames, J., Zoboli, O., Laner, D., Rechberger, H., Zessner, M., Sánchez-Romero, M., & Prskawetz, A. (2019). Understanding feedbacks between economic decisions and the phosphorus resource cycle: A general equilibrium model including material flows. *Resources Policy*, *61*, 311–347. https://doi.org/10.1016/j.resourpol.2019.02.010

Hosoe, N., Gasawa, K., & Hashimoto, H. (2010). *Textbook of Computable General Equilibrium Modelling*. Palgrave Macmillan UK. https://doi.org/10.1057/9780230281653

IRENA. (n.d.). *Geopolitics of the Energy Transition: Critical Materials*. International Renewable Energy Agency (IRENA). Retrieved 11 June 2026, from https://www.irena.org/Digital-Report/Geopolitics-of-the-Energy-Transition-Critical-Materials#page-0

Islam, M. T., Huda, N., Baumber, A., Shumon, R., Zaman, A., Ali, F., Hossain, R., & Sahajwalla, V. (2021). A global review of consumer behavior towards e-waste and implications for the circular economy. *Journal of Cleaner Production*, *316*, 128297. https://doi.org/10.1016/j.jclepro.2021.128297

Jackson, M., Lederwasch, A., & Giurco, D. (2014). Transitions in Theory and Practice: Managing Metals in the Circular Economy. *Resources*, *3*(3), 516–543. https://doi.org/10.3390/resources3030516

Jiang, B. (2026). How Geopolitical Risks Reshape Global Supply Chains: Evidence from the Pandemic, Ukraine Crisis, and Red Sea Crisis. *Journal of Innovation and Development*, *14*(2), 454–457. https://doi.org/10.54097/em5ka710

Kirchherr, J., & Jones, M. P. (2026). Is circularity going to shrink the global economy? Theoretically, yes. *Journal of Industrial Ecology*. https://doi.org/10.1007/s44498-026-00084-2

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, *127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Krych, K., Müller, D. B., & Pettersen, J. B. (2025). The “nature” and “nurture” of product lifetimes in dynamic stock modeling. *Journal of Industrial Ecology*, *29*(1), 6–18. https://doi.org/10.1111/jiec.13586

Lysaght, O., Forti, V., Garam, B., Bottausci, S., Schubert, M., Yamamoto, T., Shyla, H., Blepp, M., Cenni, F., de Linde, S., Escobar Ocampo, D., Iattoni, G., Khwamsawat, K., Kuehr, R., Korajčević, Š., Ngumba, L., Magpantay, E., Martínez, L. H., Menton, N., … Balde,

K. (2026). *E-waste Statistics: Guidelines on Classifications, Reporting and Indicators, Third Edition*. https://doi.org/10.5281/ZENODO.18328494

Magalini, F., Wang, F., Huisman, J., Kuehr, R., Balde, K., Hestin, M., Lecerf, L., Sayman, U., & Akpulat, O. (2014). *Study on collection rates of waste electrical and electronic equipment (WEEE): Possible measures to be initiated by the Commission as required by Article 7(4), 7(5), 7(6) and 7(7) of Directive 2012/19/EU*. European Commission. https://ec.europa.eu/environment/pdf/waste/weee/Final_Report_Art7_publication.pdf

Mainar-Causapé, A., Ferrari, E., & McDonald, S. (2018). *Social Accounting Matrices: Basic aspects and main steps for estimation*. file:///C:/Users/Sam/Downloads/jrc_sams_manual-2018%20(2).pdf

Maldini, I., Klepp, I. G., & Laitala, K. (2025). The environmental impact of product lifetime extension: A literature review and research agenda. *Sustainable Production and Consumption*, *56*, 561–578. https://doi.org/10.1016/j.spc.2025.04.020

Masui, T. (2005). Policy evaluations under environmental constraints using a computable general equilibrium model. *European Journal of Operational Research, Advances in Complex Systems Modeling*, *166*(3), 843–855. https://doi.org/10.1016/j.ejor.2004.07.002

McDonald, S., & Thierfelder, K. (2004). *Deriving a Global Social Accounting Matrix from GTAP Versions 5 and 6 Data* (GTAP Technical Paper No. 22). GTAP Technical Paper No. 22. http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=1645

Miller, Ronald. E., & Blair, Peter. D. (2009). *Input-Output Analysis 3rd Edition*. Cambridge University Press & Assessment. https://www.cambridge.org/universitypress/subjects/economics/econometrics-statistics-and-mathematical-economics/input-output-analysis-foundations-and-extensions-3rd-edition

Modaresi, R., & Müller, D. B. (2012). The Role of Automobiles for the Future of Aluminum Recycling. *Environmental Science & Technology*, *46*(16), 8587–8594. https://doi.org/10.1021/es300648w

Müller, E., Hilty, L. M., Widmer, R., Schluep, M., & Faulstich, M. (2014). Modeling Metal Stocks and Flows: A Review of Dynamic Material Flow Analysis Methods. *Environmental Science & Technology*, *48*(4), 2102–2113. https://doi.org/10.1021/es403506a

Nechifor, V., Calzadilla, A., Bleischwitz, R., Winning, M., Tian, X., & Usubiaga, A. (2020). Steel in a circular economy: Global implications of a green shift in China. *World Development*, *127*, 104775. https://doi.org/10.1016/j.worlddev.2019.104775

Nikas, A., Doukas, H., & Papandreou, A. (2019). A Detailed Overview and Consistent Classification of Climate-Economy Models. In H. Doukas, A. Flamos, & J. Lieu (Eds), *Understanding Risks and Uncertainties in Energy and Climate Policy: Multidisciplinary Methods and Tools for a Low Carbon Society* (pp. 1–54). Springer International Publishing. https://doi.org/10.1007/978-3-030-03152-7_1

Nygaard, A. (2023). The Geopolitical Risk and Strategic Uncertainty of Green Growth after the Ukraine Invasion: How the Circular Economy Can Decrease the Market Power of and Resource Dependency on Critical Minerals. *Circular Economy and Sustainability*, *3*(2), 1099–1126. https://doi.org/10.1007/s43615-022-00181-x

Olijslagers, S., & Brink, C. (2024). *Documentation Model Green-R*.

Padilla-Rivera, A., Russo-Garrido, S., & Merveille, N. (2020). Addressing the Social Aspects of a Circular Economy: A Systematic Literature Review. *Sustainability*, *12*(19), 7912. https://doi.org/10.3390/su12197912

Parajuly, K., & Wenzel, H. (2017). Potential for circular economy in household WEEE management. *Journal of Cleaner Production*, *151*, 272–285. https://doi.org/10.1016/j.jclepro.2017.03.045

Pauliks, N., Fishman, T., Istrate, R., Steubing, B., & Tukker, A. (2026). Assessing historic material losses in European waste from electrical and electronic equipment. *Resources, Conservation and Recycling*, *234*, 109034. https://doi.org/10.1016/j.resconrec.2026.109034

Pauliuk, S., Fishman, T., Heeren, N., Berrill, P., Tu, Q., Wolfram, P., & Hertwich, E. G. (2021). Linking service provision to material cycles: A new framework for studying the resource efficiency–climate change (RECC) nexus. *Journal of Industrial Ecology*, *25*(2), 260–273. https://doi.org/10.1111/jiec.13023

Pauliuk, S., & Müller, D. B. (2014). The role of in-use stocks in the social metabolism and in climate change mitigation. *Global Environmental Change*, *24*, 132–142. https://doi.org/10.1016/j.gloenvcha.2013.11.006

Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2017). *Circular economy: Measuring innovation in the product chain*. https://www.pbl.nl/uploads/default/downloads/pbl-2016-circular-economy-measuring-innovation-in-product-chains-2544.pdf

Redding, S. J., & Weinstein, D. E. (2020). Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences. *The Quarterly Journal of Economics*, *135*(1), 503–560. https://doi.org/10.1093/qje/qjz031

Rockström, J., Gupta, J., Qin, D., Lade, S. J., Abrams, J. F., Andersen, L. S., Armstrong McKay, D. I., Bai, X., Bala, G., Bunn, S. E., Ciobanu, D., DeClerck, F., Ebi, K., Gifford, L., Gordon, C., Hasan, S., Kanie, N., Lenton, T. M., Loriani, S., … Zhang, X. (2023). Safe and just Earth system boundaries. *Nature*, *619*(7968), 102–111. https://doi.org/10.1038/s41586-023-06083-8

Shiquan, D., & Deyi, X. (2023). The security of critical mineral supply chains. *Mineral Economics*, *36*(3), 401–412. https://doi.org/10.1007/s13563-022-00340-4

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 1259855. https://doi.org/10.1126/science.1259855

Svensson-Hoglund, S., Richter, J. L., Maitre-Ekern, E., Russell, J. D., Pihlajarinne, T., & Dalhammar, C. (2021). Barriers, enablers and market governance: A review of the policy landscape for repair of consumer electronics in the EU and the U.S. *Journal of Cleaner Production*, *288*, 125488. https://doi.org/10.1016/j.jclepro.2020.125488

Tukker, A., & Rueda-Cantuche, J. M. (2024). *Modelling circular economy impacts in the context of a transition to a fair and sustainable economy. The need to combine bottom-up and top-down MFA, LCA and GE Models*. JRC Publications Repository. https://publications.jrc.ec.europa.eu/repository/handle/JRC139498

United Nations Environment Programme. (2024). *Global Resources Outlook 2024 - Bend the trend: Pathways to a Liveable Planet as Resource Use Spikes*. International Resource Panel. https://wedocs.unep.org/handle/20.500.11822/44901

United Nations, European Commission, International Monetary Fund, Organisation for Economic Co-operation and Development, & World Bank (Eds). (2009). *System of national accounts 2008*. United Nations. https://unstats.un.org/unsd/nationalaccount/docs/sna2008.pdf

Van Straalen, V. M., Roskam, A. J., & Baldé, C. P. (2016). *Waste over Time [computer software]* [Computer software]. http://github.com/Statistics-Netherlands/ewaste

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

Wiebe, K. S., Harsdorff, M., Montt, G., Simas, M. S., & Wood, R. (2019). Global Circular Economy Scenario in a Multiregional Input–Output Framework. *Environmental Science & Technology*, *53*(11), 6362–6373. https://doi.org/10.1021/acs.est.9b01208

Wiebe, K. S., Norstebø, V. S., Aponte, F. R., Simas, M. S., Andersen, T., & Perez-Valdes, G. A. (2023). Circular Economy and the triple bottom line in Norway. *Circular Economy and Sustainability*, *3*(1), 1–33. https://doi.org/10.1007/s43615-021-00138-6

Winning, M., Calzadilla, A., Bleischwitz, R., & Nechifor, V. (2017). Towards a circular economy: Insights based on the development of the global ENGAGE-materials model and evidence for the iron and steel industry. *International Economics and Economic Policy*, *14*(3), 383–407. https://doi.org/10.1007/s10368-017-0385-3

Zanon-Zotin, M., Fortes, P., Corbier, D., Deetman, S., Edelenbosch, O., van Engelenburg, M., Hauenstein, C., Hertwich, E., Jiang, M., von Köckritz, L., Magalar, L., Pauliuk, S., Straub, L., Vélez-Henao, J., & van Vuuren, D. (2026). Circular economy modelling for climate change mitigation: A review of empirical evidence and modelling approaches. *Resources, Conservation and Recycling*, *234*, 109053. https://doi.org/10.1016/j.resconrec.2026.109053

Ziesmer, J., Jin, D., Thube, S. D., & Henning, C. (2023). A Dynamic Baseline Calibration Procedure for CGE models. *Computational Economics*, *61*(4), 1331–1368. https://doi.org/10.1007/s10614-022-10248-4

Zink, T., & Geyer, R. (2017). Circular Economy Rebound. *Journal of Industrial Ecology*, *21*(3), 593–602. https://doi.org/10.1111/jiec.12545

8 Appendices

8.1 A1 Correspondence between UNU-keys and the NACE sectors

To map the UNU-keys onto the corresponding NACE Rev. 2 sectors, I used the underlying product data used by Pauliks et al. (2026), which connect each UNU-key to multiple HS codes. These HS codes are part of the classifications on economic statistics of the UN, which provide code classifications for products, services, and sectors. Based on correspondences between HS2017, CPC21, and ISIC4, it was possible to map each HS code to one or, in some cases, multiple ISIC4 sectors, which fully align with the NACE Rev. 2 sectors. Based on this, a correspondence table has been made to map each UNU-key to each NACE sector.

Table 8: Correspondence table between UNU-keys and NACE Rev. 2 sectors

UNU-keys	NACE Rev. 2
1	25, 26
101	28
102	27, 28
103	27
104	27, 28
105	27, 28
106	27
108	27
109	27
111	28
112	28
113	28
114	27
201	26, 27, 28
202	27
203	27
204	27, 28
205	27, 32
301	26, 28
302	26
303	26
304	26, 28
305	26
306	26
307	26, 28
308	26
309	26, 27

401	26
402	26
403	26, 32
404	26
405	26
406	26
407	26
408	26
501	27
503	27
504	27
506	27
507	27
601	27, 28
602	28
701	32
702	26
703	26, 30
801	26
802	26, 32
901	26, 27
902	26
1001	28
1002	28

8.2 A2 Aggregation NACE sectors

This table gives the GREEN-R sector aggregation used in this thesis. The first two columns list the GTAP sector name and code. The third column gives the code of the sector into which each GTAP sector is aggregated. Table 3 describes these sectors.

Table 9: Sector Aggregation GREEN-R

Sector name GTAP	Sector code GTAP	Aggregated sector
Paddy rice	pdr	AFF
Wheat	wht	AFF
Cereal grains nec	gro	AFF
Vegetables, fruit, nuts	v_f	AFF
Oil seeds	osd	AFF
Sugar cane, sugar beet	c_b	AFF
Plant-based fibers	pfb	AFF
Crops nec	ocr	AFF

Bovine cattle, sheep and goats	ctl	AFF
Animal products nec	oap	AFF
Raw milk	rmk	AFF
Wool, silk-worm cocoons	wol	AFF
Forestry	frs	AFF
Fishing	fsh	AFF
Coal	Coal	COA
Oil	Oil	COI
Gas	Gas	GAS
Petroleum, coal products	Oil_pcts	OIP
Electricity: Transmission and Distribution	TnD	POW
Nuclear base load	NuclearBL	POW
Coal base load	CoalBL	POW
Gas base load	GasBL	POW
Wind base load	WindBL	POW
Hydro base load	HydroBL	POW
Oil base load	OilBL	POW
Other base load	OtherBL	POW
Gas peak load	GasP	POW
Hydro peak load	HydroP	POW
Oil peak load	OilP	POW
Solar peak load	SolarP	POW
Minerals nec	oxt	MIN
Chemical products	chm	CHP
Basic pharmaceutical products	bph	CHP
Rubber and plastic products	rpp	CHP
Mineral products nec	nmm	CHP
Ferrous metals	i_s	MET
Metals nec	nfm	MET
Bovine meat products	cmt	OMA
Meat products nec	omt	OMA
Vegetable oils and fats	vol	OMA
Dairy products	mil	OMA
Processed rice	pcr	OMA
Sugar	sgr	OMA
Food products nec	ofd	OMA
Beverages and tobacco products	b_t	OMA
Textiles	tex	OMA
Wearing apparel	wap	OMA
Leather products	lea	OMA
Wood products	lum	OMA

Paper products, publishing	ppp	CHP
Metal products	fmp	MET
Computer, electronic and optic	ele	EEE
Electrical equipment	eeq	EEE
Machinery and equipment nec	ome	MEQ
Motor vehicles and parts	mvh	MEQ
Transport equipment nec	otn	MEQ
Manufactures nec	omf	OMA
Water	wtr	SER
Construction	cns	CNS
Trade	trd	SER
Accommodation, Food and services	afs	SER
Transport nec	otp	TRA
Water transport	wtp	TRA
Air transport	atp	TRA
Warehousing and support activities	whs	SER
Communication	cmn	SER
Financial services nec	ofi	SER
Insurance	ins	SER
Real estate activities	rsa	SER
Business services nec	obs	SER
Recreational and other service	ros	ROS
Public Administration and defense	osg	SER
Education	edu	SER
Human health and social work	hht	SER
Dwellings	dwe	SER

8.3 A3 Data processing and code documentation

All data processing and model code is available at https://github.com/Sam-Rasing/MFA_CGE_Linkage. The repository contains the three coding pipelines described in Chapter 3, together with a README documenting the inputs, outputs and processing steps of each:

- **01_Calculating_Monetary_POM** covers the methodology described in section 3.4.2, specifically equations 13 and 14. The output is a price per kilogram for each UNU-key, aggregated for the EU in 2017.
- **02_Linking_MFA_to_CGE** covers the dMFA methodology described in section 3.2 and the impact calculation based on equation 15 in section 3.4.2. The output covers material stocks and flows from 1980 to 2022, and the monetary impact used in the CGE model for 2017.

- **03_GTAP_sector_mapping** covers the method for aligning UNU-keys to GTAP sectors described in section 3.4.1.1. The output determines which UNU-keys are excluded from the analysis.