Software and data for circular economy assessment

Donati, F.

3 MODELING THE CIRCULAR ECONOMY IN ENVIRONMENTALLY EXTENDED INPUT-OUTPUT TABLES: METHODS, SOFTWARE AND CASE STUDY

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AUTHORS

Franco Donati, Glenn A. Aguilar-Hernandez, Carlos Pablo Siguenza-Sanchez, Arjan de Koning, Joao F. D. Rodrigues, Arnold Tukker

ABSTRACT

A circular economy is an industrial system that is restorative or regenerative by intention or design. During the last decade, the circular economy became an attractive paradigm to increase global welfare while minimizing the environmental impacts of economic activities. Although several studies concerning the potential benefits and drawbacks of policies that implement the new paradigm have been performed, there is currently no standardized theoretical model or software to execute such assessment. In order to fill this gap, in the present paper we show how to perform these analyses using Environmentally Extended Input-Output Analysis. We also describe a Python package (pycirk) for modelling Circular Economy scenarios in the context of the Environmentally Extended Multi-Regional Input-Output database EXIOBASE V3.3, for the year 2011. We exemplify the methods and software through a what-if zero-cost case study on two circular economy strategies (Resource Efficiency and Product Lifetime Extension), four environmental pressures and two socio-economic factors.

KEYWORDS

Circular Economy, Interventions, EEIOA, Software, Policy, Scenarios

3.1 INTRODUCTION

The current global challenges of climate change and resource supply risk (European Commission, 2018) demand concrete strategies and actions to reach a sustainable society (UNEP, 2011). While various proposals for this future societal state exist (Geng et al., 2016; Sacchi-Homrich et al., 2018), in recent times a paradigm that has gained traction is the Circular Economy (CE): an economy that is "... restorative and regenerative by design, and aims to keep products, components, and materials at their highest utility and value at all times." (EMF, 2012). Decision makers supporting these objectives can employ different strategies intervening at multiple levels (Ghisellini et al., 2016): a) macro-level, by changing regional fiscal and economic conditions; b) meso-level, by changing the way supply-chains are organized; c) micro-level, by changing the way we produce and use materials and products. In this process, decision makers are faced with unknowns over potential benefits and undesired effects of their decisions (Faucheux and Froger, 1995). This is due to the complexity and interconnectedness of economy and environment (Knights et al., 2014). In order to shine light on these complex systems, economic-environmental models can be used (Fauré et al., 2017). Computable General Equilibrium (CGE) and Input-Output (IO) models are the most widely employed ones for the assessment of CE (Kronen et al., 2010). The two models have distinct characteristics that make them suitable for different type of analyses (de Koning, 2018). CGE is a macro-economic model broadly used for its dynamic features and endogenous inclusion of price dynamics, investment and tax relations. IO, in its various forms, is a static structural model which provides a high resolution of sectors and structural economic composition. This makes IO a useful tool for the impact assessment of supply-chains (de Koning, 2018). Both models have been used to assess the potential environmental and economic impacts of CE (McCarthy et al., 2018).

Through the use of a national CGE model of 2000 for South Korea, Kang et al. (2006) estimated the effects of increasing waste recycling and pollution management policies. They showed potential losses of 0.2% in GDP as a result of reduction of environmental pressures. In a study by WRAP on CE for Britain (WRAP, 2015), the authors investigated multiple interventions, such as reuse, recycling, servitization, and repairing and remanufacturing.

Their findings showed a reduction of unemployment rate of 0.1-0.2 percentile points by 2030. Wijkman and Skanberg (2015) analyzed CE effects on CO2 emissions, employment and trade balance. Using 2009 WIOD data (Timmer et al., 2015) for 5 EU countries (Finland, France, the Netherlands, Spain and Sweden), they simulated measures for renewable energy transition, and energy and resource efficiency. Their results showed a reduction of 70% CO2, 875000 created jobs, and an improvement of 2% of the trade balance.

Rutherford et al. (EMF, 2015), employed a CGE model based on GTAP-8 aggregated to 5 global macro-regions and 16 sectors. The study focused on technology shifts in private transport, housing and food production. Results showed that CE could deliver 48% CO2 emissions reductions by 2030 and 83% by 2050 across the analyzed sectors. The study also showed that household disposable income in 2050 would be higher by 12 percentile points in comparison with current linear economy projections.

(Tisserant et al., 2017) analyzed the waste treatment and footprints in the circular economy using the IO database EXIOBASE v2 in the Waste-IO (WIO) format. They observed that despite the difference in waste generation among countries, there is a significant potential for closing material cycles in all regions regardless of the level of country's income.

(Winning et al., 2017) developed a multi-regional macro-econometric model (ENGAGE-materials) using EXIOBASE v2 and GTAP-9. Through the model they showed a reduction of 0.02% in total CO2 and an increase of 0.03% in GDP due to the doubling of yearly scrap availability between 2017 and 2030.

More recently, (Wiebe et al., 2019) presented a global CE scenario to 2030 using EEIOA in EXIOBASE. Their study investigated the impact of recycling, higher material efficiency and repair, reuse and recycling. Results show that reduction in raw material extraction used of 10% with a positive but small impact on employment around 2%.

As shown by these studies, there is still limited information on impacts and indirect effects of the application of the circular economy (Rizos et al., 2017). In particular, more technology-based assessments are needed (McCarthy et al., 2018). IO is a suitable model for the creation of this type of "what-if" scenarios through the application of exogenous changes (de Koning, 2018).

One of the advantage of this type of approach is the level of transparency in assumptions (de Koning, 2018). This is especially important for CE impact assessment as the variety of approaches makes it difficult to compare studies (Rizos et al., 2017). Previous studies have tried to categorize types of interventions within CE (EMF, 2012; Aguilar-Hernandez et al., 2018), their fundamental waste management models (Yifang, 2007; Li, 2012) and indicators (Iacovidou et al., 2017). However, there is still a need for current CE assessment methods to become more comparable and robust in order to serve as policy tools (Rizos et al., 2017).

In order to gain insights for policies, IO databases and methods can be used in specialized software. An overview of such tools is available in Annex II. From this analysis, it appeared that no viable free and open-source alternative is available for the construction and the analysis of complex scenarios using detailed IO databases like EXIOBASE (Tukker et al., 2013; Stadler et al., 2018).

Hereby we present a software and systematic methods to build complex CE counterfactual (what-if) scenarios with Environmentally Extended IO (EEIO) tables. We focus on the creation of CE scenarios for two CE strategies: Product Lifetime Extension (PLE) and Resource Efficiency (RE) (Aguilar-Hernandez et al., 2018). Furthermore, instead of the hybrid unit data (Merciai & Schmidt, 2018) in the WIO framework (Nakamura & Kondo, 2009) as suggested by (Aguilar-Hernandez et al., 2018b) we employ the monetary EEIO framework, as the base for the implementation of the strategies. This is because the hybrid data does not contain value added and employment inputs (Merciai & Schmidt, 2018), key indicators used in previous literature about the implementation of CE strategies.

We first present a CE scenario implementation framework for EEIO tables. Secondly, the data and Python package developed for this study are described. At last, we exemplify methods and software in a case study concerning 2 CE strategies: Product Lifetime Extensions (PLE) and Resource Efficiency (RE). The results section presents the findings and is followed by discussions and conclusions. Furthermore, scenario assumptions and modelling choices and complete results are shown in Annex I.

3.2 METHODS

3.2.1 CE policy modelling framework

CE policies are often articulated at different levels of detail, so it is convenient to define a clear modelling framework (Illustrated in figure 1). We begin by asserting that the objective of a CE policy is always the implementation of the circular economy paradigm. In order to achieve this objective different strategies exist. There are various categorizations of CE strategies such as ReSOLVE (EMF, 2015c), (Kirchherr et al., 2017a), and (Bocken et al., 2016). However, in this study we follow the 4-strategy classification of Aguilar-Hernandez et al. (2018) which consists of: Product Lifetime Extension (PLE); Resource Efficiency (RE); Closing Supply Chains (CSC); Residual Waste Management (RWM).

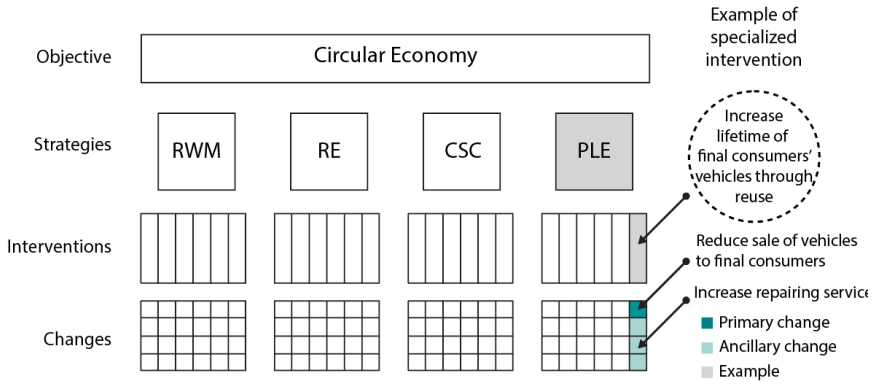


Figure 1: CE policy modelling framework – RWM = Residual Waste Management; RE = Resource Efficiency; CSC: Closing Supply Chains; PLE: Product Lifetime Extensions

In the analyzed literature, the terms strategies and interventions are often used interchangeably. However, we believe that a distinction between these two concepts is needed. We define strategies as sets of policy interventions and improvement options (or simply interventions). For example, PLE can be achieved, among others, by reuse and remanufacturing, or delaying products' replacement (Allwood and Cullen, 2015). In other words, while these two interventions aim at the same objective, the extension of product's life, the way they are implemented is different. We further

distinguish between a general description of interventions and specialized interventions. An intervention (e.g. reuse and remanufacturing) is specialized when it refers to a specific product or application (e.g. increase lifetime through reuse and remanufacturing in final consumers' vehicles). Interventions are modelled through sets of changes that affect the production and consumption systems. We further distinguish between primary and ancillary changes. For instance, if the intervention concerns increasing the lifetime of vehicles the primary change would be a reduction of sale of vehicles resulting from less consumers needing to replace their vehicles. A corresponding ancillary change would be the potential increase in repairing services caused by a higher utilization of the good. We show this conceptual approach in Figure 1.

3.2.2 Environmentally Extended Input-Output (EEIO) analysis

Environmentally Extended Input-Output (EEIO) analysis (Leontief, 1970; Suh, 2009) is based on Input-Output (IO) analysis (Leontief, 1951; Miller and Blair, 2009) and deals with the quantification of environmental pressures that take place along the supply chain of goods and services, by assuming that production structure remains fixed. The basic Leontief demand-driven model can be framed such that a stimulus vector of final demand leads to a set of emissions occurring in each production sector as:

$$\mathbf{r} = \mathrm{diag}(\mathbf{b})(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} \qquad (1)$$

In the preceding expression $\mathbf{r}$ is the column vector of emissions occurring in each production sector (the response variable) and $\mathbf{y}$ is the column vector of final demand of products delivered by each sector (the control variable). The parameters of the model are the column vector $\mathbf{b}$ of environmental intensities (environmental pressure per unit of economic output) and $\mathbf{A}$ is a matrix of technical coefficients (whose entry ij is the volume of inputs from sector i that are required to generate one unit of output of sector j). diag stands for diagonal matrix and $\mathbf{I}$ is the identity matrix.

The technical coefficient matrix is calculated as $\mathbf{A} = \mathbf{Z}\,\mathrm{diag}(\mathbf{x})^{-1}$, where $\mathbf{Z}$ is the matrix of inter-industry transactions and $\mathbf{x}$ is the column vector of total output of each sector, $\mathbf{x} = \mathbf{Z}\,\mathbf{i} + \mathbf{Y}\,\mathbf{i}$, the row sum of $\mathbf{Z}$ and $\mathbf{Y}$, where the latter is a matrix whose columns represent the final demand of different consumption categories (e.g., households, government, investment), and $\mathbf{i}$

is a vector column of ones. For the purpose of this study the stimulus vector entering Eq. 1 is assumed to be row sum of the final demand matrix, $\mathbf{y} = \mathbf{Y}\,\mathbf{i}$. For some environmental pressures (e.g., global warming) there are direct emissions resulting from final consumption activities (e.g., the combustion of fossil fuels by households leads to the emission of greenhouse gases). When that is the case it is necessary to include emissions from final demand to obtain total emissions, r_{tot}, as:

$$r_{tot} = \mathbf{r}'\,\mathbf{i} + b_y\,y \qquad (2)$$

In the previous expression prime (') denotes transpose, b_y is a scalar representing the intensity of final demand environmental pressure (i.e., emissions caused by households per unit of final demand), and y is a scalar of total final demand obtained as $y = \mathbf{y}'\,\mathbf{i}$, i.e., the column sum of the final demand stimulus vector. If more information is available, the intensity of final consumption environmental pressures can in principle be disaggregated by product category.

Note that in the application the system used is multiregional. That is, each entry of $\mathbf{b}$, $\mathbf{A}$ or $\mathbf{Y}$ identify not only a row and/or column economic sector or final demand category but also a region (e.g., EU or Rest of the World).

3.2.3 Baseline and counterfactual scenario

In order to assess the environmental or socio-economic impact of implementing a CE policy we compare the impact that occurs in the baseline and the impact that occurs in a counterfactual scenario in which the changes corresponding to the CE intervention and strategy have been implemented. More formally, the impact of the CE policy is $\Delta\mathbf{r} = \mathbf{r}^* - \mathbf{r}$, where $\mathbf{r}$ is the impact in the baseline scenario, defined in Section 2.1, and $\mathbf{r}^*$ is the impact in the counterfactual scenario, defined as:

$$\mathbf{r}^* = \mathrm{diag}(\mathbf{b}^*)(\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{Y}^*\,\mathbf{i} \qquad (3)$$

If there are final consumption emissions, we can further define $\Delta r_{tot} = r^*_{tot} - \mathrm{r}_{tot}$ where

$$r^*_{tot} = (\mathbf{r}^*)'\,\mathbf{i} + b^*_y\,y^* \qquad (4)$$

A counterfactual scenario (an object adjoined with *) is constructed by adjusting particular elements in the objects that define the baseline EEIO system, $\mathbf{b}$, $\mathbf{A}$, $\mathbf{Y}$ (and possibly b_y and y) with this adjustment being as faithful as possible to the concepts underlying the policy intervention, subject to the limitations of the data and model.

The counterfactual scenario is constructed by adjusting only a (possibly) small set of values of some of the matrix objects than define the EEIO system. All other entries remain identical in both scenarios. With the current methods, we do not perform any automatic rebalancing of the counterfactual scenario, as such the system may become unbalanced when changes are applied to the technical coefficient matrix $\mathbf{A}$ (i.e., total outputs differ from total inputs).

3.2.4 Change coefficients and substitution

The edit of a particular entry ij of an arbitrary $\mathbf{M}$ matrix object from the baseline to the counterfactual scenario, is performed by the software as:

$$M_{ij}^{*} = M_{ij}\,(1 - k_a) \qquad (5)$$

The change coefficient (k_a) expresses the magnitude by which a value in the IO system is modified. It is obtained as the product of a technical change coefficient (k_t) which describes the intervention's maximum potential effect, and of a market penetration coefficient (k_p) describing the size of the given market affected (Wood et al., 2017), $k_a = k_t\, k_p$.

Furthermore, there might exist a substitution relation between edits in different entries. For example, a reduction in the volume of a particular material (e.g., steel) used in a production process might be compensated by an increase of another (e.g., aluminum). This type of relation is modelled as:

$$M_{ij}^{*} = M_{ij} + \alpha(M_{mn}^{*} - M_{mn}) \qquad (6)$$

Here mn are the coordinates of the original change (e.g., reduction in steel) and ij are the coordinates of the substitution (e.g., increase in aluminum). α is a substitution weighting factor accounting for differences in price and physical material properties between products, materials or services.

3.2.5 Modeling CE interventions in EEIO

In this section, we show the suggested assumptions behind modelling CE interventions. These assumptions may vary depending on the specific case, so we encourage a critical reading and application. Firstly, we explain the elements that compose the modelling blueprints. We then present blueprints for modelling CE interventions under PLE and RE. Blueprints are graphic visualizations that indicate where and how changes are applied in the EEIO system in order to simulate CE interventions. They are designed with the conceptual aid of the work of Allwood and Cullen (2012) and the Ellen MacArthur Foundation (EMF, 2015c), which indicate respectively the requirements for the implementation of PLE and RE measures, and business models in the circular economy. The blueprints provide a simplified visual representation of the IO system. This simplification does not include trade. Unless otherwise specified in the assumptions, production of export/import would be subject to the same changes.

The blueprints are composed by the technical coefficient matrix ($\mathbf{A}$), final demand (y), and the environmental extensions $\mathbf{b}$ and b_y respectively. In order to facilitate the identification of points across these tables, we subdivide production and consumption activities into groups of similar economic and technical properties. These are the coordinate groups needed for the blueprints elaborated in this study:

- *Final products (fp):* fully manufactured consumer or capital goods that are not typically a component (e.g. vehicle, building, instrumentation and desktop computers);
- *Components (c):* a manufactured or semi-manufactured product that may be used as an element in production or as subcomponent of final products (e.g. engine, window, spring and metal plates);
- *Primary raw materials (pm):* virgin material resulting from extraction or the refinement of extracted materials (e.g. primary steel);
- *Secondary raw materials (sm):* recycled materials obtained from pre- and post-consumer phase (e.g. Recycled Steel);
- *Services (sr):* activities aiding the supply and maintenance of goods and value (e.g. sharing, renting, selling and repairing).

The blueprints show different symbols which indicate reductive (-), increasing (+) or undefined and case specific (◊) effects of intervention's

changes. In those cases where a substitution between two commodities may apply (equation 9) the blueprint shows a star symbol (*). Following the framework presented in section 2.1, we make a distinction between primary and ancillary changes.

Figure 2 shows how interventions under PLE are modelled at the industry and final demand level. PLE is composed by a set of interventions aimed at prolonging the utility of final products or their components. We divide PLE in two interventions:

- Reuse and remanufacturing: modelled by reducing transactions of new products (or components) and increasing services (e.g. retail trade, maintenance and repairing services). The latter, an ancillary activity, may be applied either at the industrial level or final demand depending on whether specialized intervention assumes services to be internalized by firms or allocated to consumers.
- Delayed product replacement: modelled by reducing transactions of new products (or components) and increasing services in either final demand or for the sectors (depending on the assumptions). Changes in material demand to increase durability may also be needed.

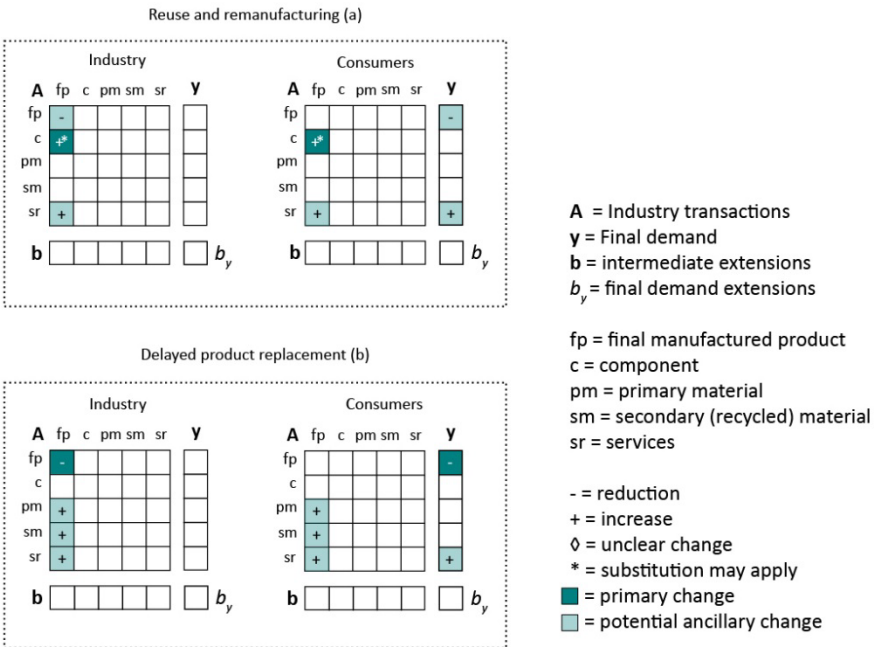


Figure 2: Product Lifetime Extension (PLE) modelling blueprints

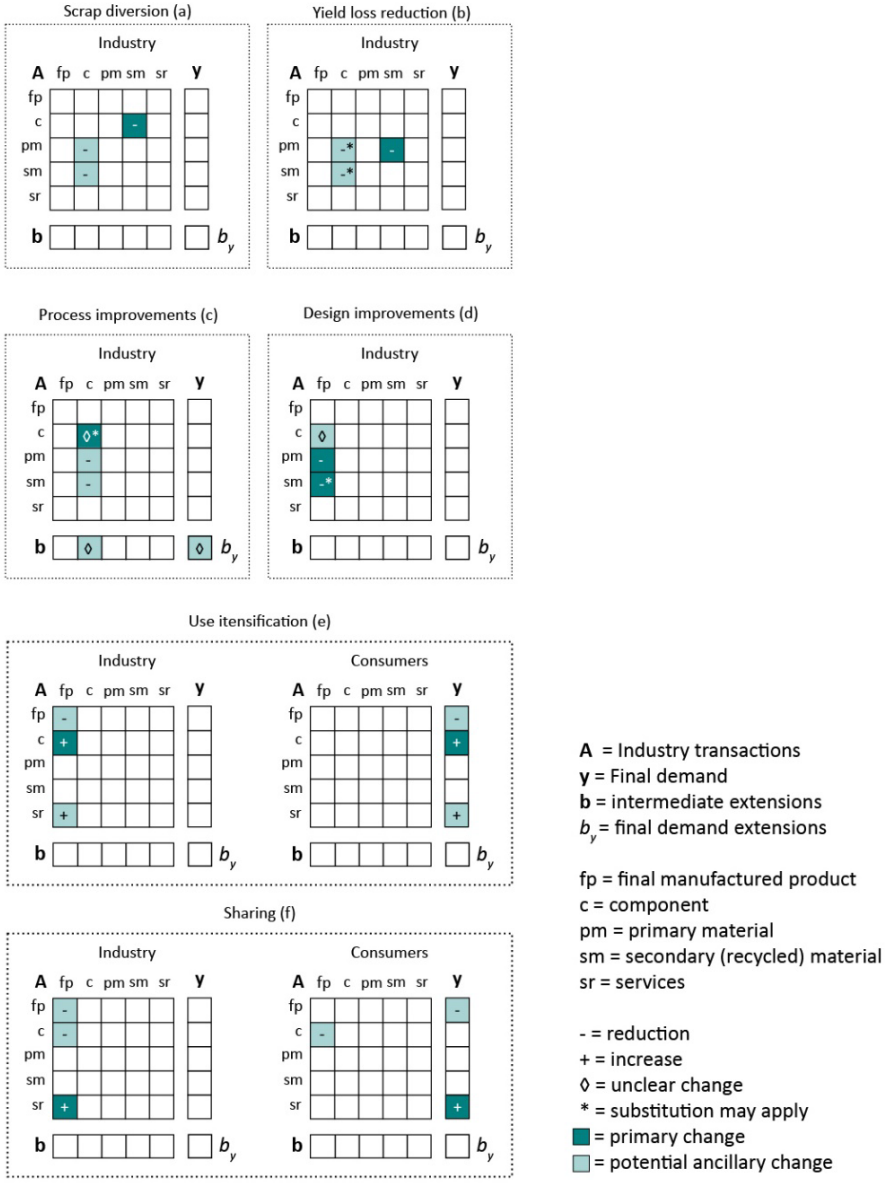


Figure 3: Resource efficiency (RE) modelling blueprints

We define RE as a set of interventions aimed at reducing use of resources and improving performance during their use. In figure 3 we show 8 types of interventions and how they are applied:

- Scrap diversion: This simulates the reduction of swarf due to mechanical processing (e.g. during metal cutting). This is modelled by reducing the scrap going to recycling activities (secondary materials) from a specific manufacturing activity, with it we reduce also the equivalent volume of primary material used. We assume that the output of production remains unchanged. In other studies (Wiebe et al., 2019), this is performed as a market share change in the supply table of the supply-use system. However, here we apply them in the IO so that we are able to distinguish between industries generating scrap.
- Yield loss reduction: this intervention represents the reduction of physical losses at the process level; the simulation method is comparable to scrap diversion, however, it includes possible material substitutions. This is because Yield loss reduction may be obtained by both improving the environmental conditions of processes but also by substituting substances which could help deliver higher yields.
- Process improvements: replacing old technologies with more efficient ones (e.g. introduction of additive manufacturing). In the blueprints we show that the substitution of components may be required, however, it is unclear whether it would have a reductive or increasing effect. As a result of this change, materials may be substituted, however, we assume that process improvements always represent a reduction of materials used. The improvement in the process may also concern emissions intensities both at the industrial level or final consumers. For example, the improvement of the process of combustion in car engines may result in changes in the intensity of emissions during use.
- Design improvements: In this intervention we reduce the amount of materials (primary and secondary) consumed along a manufacturing activity. A change component may also be required depending on the specific case.

- Use intensification: using products or materials more over a period of time would result in higher demand for components and maintenance services while reducing the demand for new goods.
- Sharing: using products among multiple users. Here it is assumed that a firm holds the ownership of the product and allows use among multiple actors. This means that replacement of components and maintenance remains a responsibility of the firm while the sales of final products serving the same purpose are reduced.

3.3 DATA, SOFTWARE AND CASE STUDY SETTINGS

3.3.1 Data

The database used is the multi-regional Supply-Use Tables (SUTs) EXIOBASE V3.3 from 2011 (Tukker et al., 2013; Wood et al., 2015; Stadler et al. 2018). We chose to employ this database for its high level of detail on product categories. Specifically, for its inclusion of primary and secondary raw materials (PRM and SRM) and environmental extensions. These characteristics make EXIOBASE a suitable option for the analysis of CE. EXIOBASE is broadly used in the analysis of policies through the use of symmetric IO tables. IO tables are calculated from SUTs through the use of various transformation methods (Eurostat, 2008). In this work we use the Product-by-Product Industry Technology Assumption (ITA). This method is commonly used by practitioners and thereby a suitable format to facilitate future comparability of studies.

3.3.2 Software

The Python Circular Economy (pycirk) software package was designed for the creation and analysis of CE scenarios, and it builds on previous software for modelling CE (Donati, 2017). This Python3 package can be used by import into a Python interpreter or a command line interface. To initialize modeling users have to specify various parameters: transformation method; directory; aggregation (bi-regional or 49 regions); make secondary (make SRM apparent during transformation from SUTs to IO, see section 3.1). The package reverts to default settings if parameters are not specified. Upon initialization a scenarios.xls file is created in the specified directory. This file

works as an interface to set scenario inputs and assessment parameters through its multiple spreadsheets. The analysis sheet allows to specify assessment indicators while sheets beginning with ”scenario_” represent a scenario. These sheets are set to facilitate the integration with the methods highlighted in sections 2.3 through 2.5. Once the settings are saved, the model is run and results can be calculated for one or all scenarios. Further information on use, architecture and logic flows is available through on the software documentation (Donati, 2019b). Pycirk is made available for any practitioner interested in scenario making or further development of the tool. The software is shipped with a bi-regionally aggregated version of EXIOBASE v3.3 in pickle format. This is done to facilitate study replicability by using a common database and software. The complete multiregional database (48 regions) is also available upon request in the same format. Additional information on changes to the database can be found in Annex II.

3.3.3 Case study settings

With the case study we exemplify the use of pycirk through the analysis of global implications of applying Product lifetime extensions (PLE) and Resource efficiency (RE) CE strategies. The data used is at a bi-regional (EU-ROW) level of aggregation as our interest is in the global effects of the strategies and their significance to the EU28. For this study we also made secondary raw materials explicit in IO, an explanation of how this was done can be found in Annex II. We further elaborated the 2 CE strategies into 8 interventions (figure 2 and 3), for which we identified their specialized applications (i.e. interventions applied to a specific product). These 37 specialized interventions, their assumptions and inputs to the case study are in Annex I.a. The results from the processing of each individual intervention were used to calculate the intervention priority order for the total scenario. This processing order was based on the size of the sum of the relative change (RC) of all the indicators from the baseline. The smaller the total RC the higher the priority in the total scenario. In table 1 we show a summary of the interventions with a cumulative RC < -4%.

In the first specialized intervention “Increase average lifetime of office buildings in constructions 1.5 times”, we reduce the transactions of construction in Final demand (except households) and industry. This indicates that offices last longer and therefore there is a reduced need for

building new ones. We increase by the same relative value services going to constructions to simulate more renovation and maintenance. These services are contained within the construction category.

For “Increase average lifetime of vehicles 2.3 times”, we reduce the sales of “Motor vehicles, trailers and semi-trailers” both in final demand and industry. The category "Sale, maintenance, repair of motor vehicles, motor vehicles parts, motorcycles, motor cycles parts and accessories" is increased by the same relative value in both final demand and in the technical coefficient matrix where the services intersect with motor vehicles.

In “Increase 2.5 times the intensity of use of vehicles due to higher occupancy”, we reduced transactions of cars to final demand. With it, we modelled an equivalent reduction of public transport demand. This is modelled by using the substitution formula (eq. 6) and applying a negative value to the substitution weighting factorα.

At last, “Increase average life time of electrical machineries and apparatus to final consumers 4 times”. In order to simulate a longer life in this specialized intervention, we reduced the transactions of “Electrical machineries and apparatus n.e.c.” to final demand. We increase by the same relative value the services for maintenance and repair "Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods".

Table 1: Specialized Interventions with a cumulative relative change < -4%

Strategy (Intervention)	Specialized intervention	Change type	Product category	Consumption activity	Technical Change (%)	Market pen. (%)	Substitute (SWK) (%)	Citations
Product lifetime extension **(Delayed replacement)**	Increase lifetime of office buildings in constructions 1.5 times	Primary	Construction work	Final Demand except households	-60	32.1		(Allwood and Cullen, 2012, p234; FIEC, 2019)
		Ancillary	Construction work	Construction work	60	22.7		
Product lifetime extension **(Delayed replacement)**	Increase average lifetime of vehicles 2.3 times	Primary	Motor vehicles, trailers and semi-trailers	All final demand categories	-50.7	100		(Allwood and Cullen, 2012, p234; Allwood and Cullen, 2012, p271)
		Ancillary	Sale, maintenance, repair of motor vehicles	Motor vehicles, trailers and semi-trailers	50.7	100		
Resource Efficiency **(Intensify use)**	Increase 2.5 times the intensity of use of vehicles due	Primary	Motor vehicles, trailers and semi-trailers	All final demand categories and all product categories	-60	33		(J. M. Allwood, 2015; Litman, 2019;

Strategy (Intervention)	Specialized intervention	Change type	Product category	Consumption activity	Technical Change (%)	Market pen. (%)	Substitute (SWK) (%)	Citations
	to higher occupancy	Proportional reduction to the above change	Other land transportation services	All final demand categories			-30	Mount, 2016)
		Ancillary	Sale, maintenance, repair of motor vehicles	All final demand categories and all product categories	120	33		
Product lifetime extension **(Delayed replacement)**	Increase average life time of electrical machineries and apparatus to final consumers 4 times	Primary	Electrical machinery and apparatus n.e.c.	All final demand categories	-75	100		(Allwood and Cullen, 2012, p275)
		Ancillary	Retail trade services, except of motor vehicles and motorcycles	All final demand categories	75	100		

3.4 RESULTS

3.4.1 Impact of the strategies

Figure 4 shows the relative change (RC) of Product Lifetime Extension (PLE), Resource Efficiency (RE) and their combination (Total). Starting from the total scenario, environmental indicators are reduced by -10.1% Global Warming Potential 100-years (GWP), -12.5% Raw Material Extraction (RME), -4.3% Land Use (LU) and -14.6% Blue Water Withdrawal (BWW). BWW concerns the withdrawal of surface and ground water by the manufacturing, electricity production and domestic use sector (Eisenmenger et al., 2014). It includes all the water used which may be consumed or returned to the environment (Eisenmenger et al., 2014). LU is strongly dominated by the agricultural sector; therefore, it may see milder effects due to interventions in the product categories we analyzed.

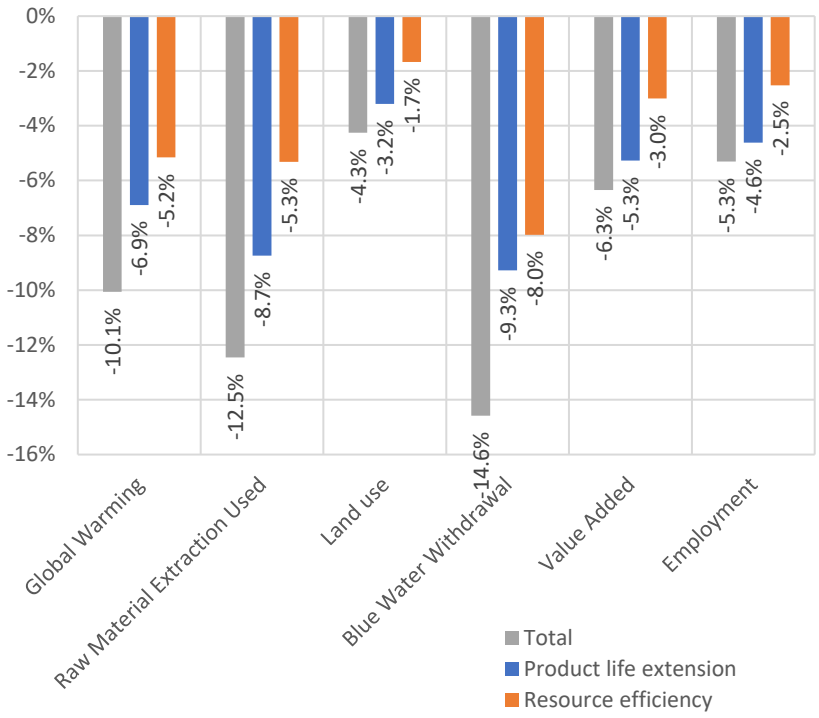
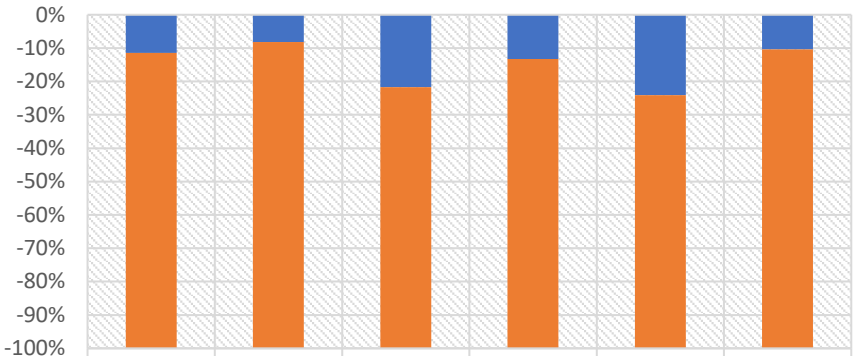


Figure 4: Global potential effects of the CE strategies and their combination

We also see a great reduction of socio-economic indicators, -6.3% Value Added (VA) and -5.3% employment. These results are in contrast with previous macro-economic studies and general aims of the CE, where economic growth is ensured while decoupling environmental impacts. This is in part logical. We focused on Life time extension. Life time extension and a more intensive use of products imply that with less product output (and hence less VA and labor) the same final demand can be satisfied. Society has no wealth loss, needs less labor and hence can provide more free time, but optically produces a lower GDP. Another explanation of this discrepancy is the absence in our model of interventions concerning investment and other dynamic changes (e.g. in price) that were included in other studies. For instance, we did not assume that as a result of a more economically efficient production, a sector may invest more in other activities nor did we include rebound effects. However, it is to be noted that the modelled interventions have a stronger relative reductive effect on almost all environmental indicators than the socio-economic indicators. That suggests that even at parity of economic performance, a circular economy could deliver environmental benefits.

Analyzing the individual strategies, PLE shows the largest contribution to reductions across all indicators: -6.9% GWP; -8.7% RME; -3.2% LU; -9.3% BWW. In terms of socio-economic indicators, PLE showed an important effect in the reductions of employment (-4.6%). RE also indicated a change of employment of -2.5% which might imply an overall difference of 2.1 points between PLE and RE. However, we obtain a -5.3% change in employment when we combine the interventions, a 0.7 point difference. This is due to the sequential processing of the interventions, producing counterfactual values in the matrix of reference at each implemented change. Furthermore, in order to understand the sensitivity of the total scenario to changes in the order of intervention, we tested different processing sequences. By modifying the order of application of the changes, we noticed that employment may vary by ~0.05 points (annex I.g). This indicates that results on employment have a mild sensitive on the way scenario inputs are processed. A similar sensitivity can also be seen in VA. On the other hand, the other impact categories remain between 0.1-0.3 percentile points.

Despite smaller effects due to RE, we still see notable improvements in environmental performance in this strategy: -5.2% GWP, -5.3% RME, -1.7% LU and -8.0% BWW. To be noticed is also the difference in GWP of the two strategies (PLE -6.9%; RE -5.2%) (Annex I.b). So PLE has deeper effects in reduction of GWP, however, a similar difference can also be observed across the other impact categories.



	Global warming GWP100 - kg CO2 eq.	Raw material extraction used - kt	Land use - km2	Water Withdrawal Blue - Total - Mm3	Value Added - M.EUR	Employment - 1000 p.
ROW	-3.850E+12	-8.984E+06	-2.578E+06	-1.151E+05	-2.517E+06	-1.462E+05
EU	-4.954E+11	-7.954E+05	-7.167E+05	-1.756E+04	-7.996E+05	-1.699E+04

Figure 5: Relative and absolute regional change of global effects due to application of CE strategies

Figure 5 shows the regional relative change due to the global application of the total scenario. As it is to be expected, the implementation of CE strategies delivers minor results on environmental reductions at the EU level in comparison with ROW (Rest Of World). In fact, if we analyze the change of environmental impacts in comparison with the regional baseline (Annex I.c), the EU showed GWP -6.4%, RME -7.8%, LU -4.1% and BWW -9.8%; while ROW showed GWP -10.9%, RME -13.1%; LU -4.3% and BWW -15.7%. At the same time, socio-economic indicators may also see a reduction in both regions. The question then remains on how the capital saved is reused by industry and final consumers in each region. Therefore, care should be given when interpreting the results as economic and environmental impacts may vary depending on how the intervention is implemented.

3.4.2 Impact of individual interventions

Finally, the interventions are analyzed (figure 6 and 7). We first analyze the interventions included in PLE, Delayed replacement and Reuse and remanufacturing. Delayed replacement shows major reductions in comparison with the other interventions (-6.06% GWP; -7.86% RME; -3.06% LU; -7.74% BWW, -4.78% VA, -4.21% E). The specialized interventions (annex I.f) mainly responsible for the strength in delayed replacement are the increase in average lifetime of office buildings and longer lifetime of vehicles. Office buildings were increased 1.5 times (J. Allwood & Cullen, 2013) in 32% of the market (FIEC, 2019) and all vehicles increased 2.3 times (J. Allwood & Cullen, 2013) in the entire market. This increase in lifetime is modelled by reducing the size of transactions proportionally. Therefore, longer life means fewer sales of a specific product. Furthermore, repairing and maintenance services are increased proportionally according to the intervention.

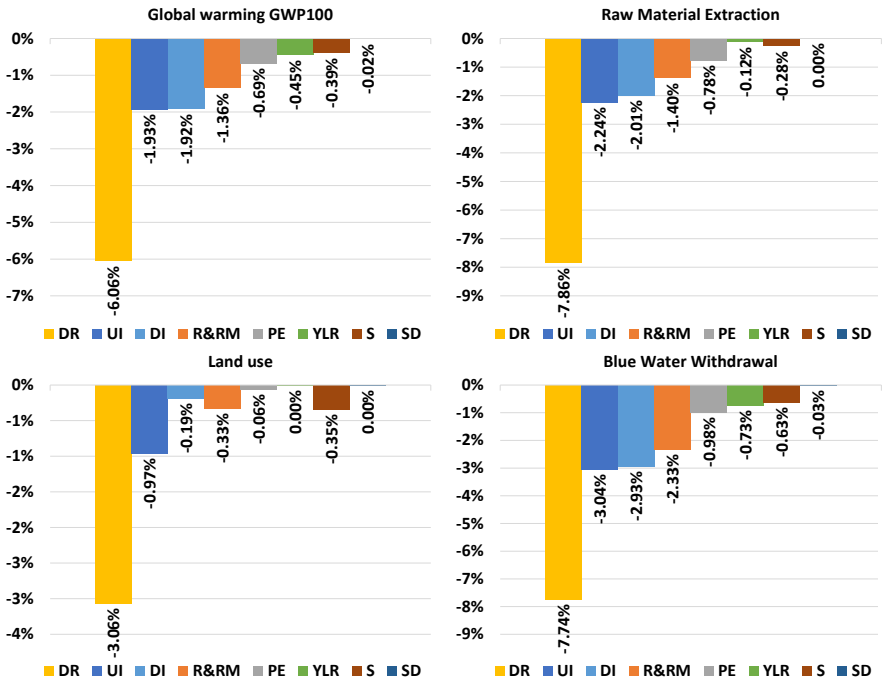


Figure 6: Global relative change in environmental indicators due to the individual Circular Economy Interventions. Labels: DR = Delayed Replacement; UI = Use Intensification; DI = Design Improvements; R&RM = Reuse and Remanufacturing; PE = Process Efficiency; YLR = Yield Loss Reduction; S = Sharing; SD = Scrap Diversion

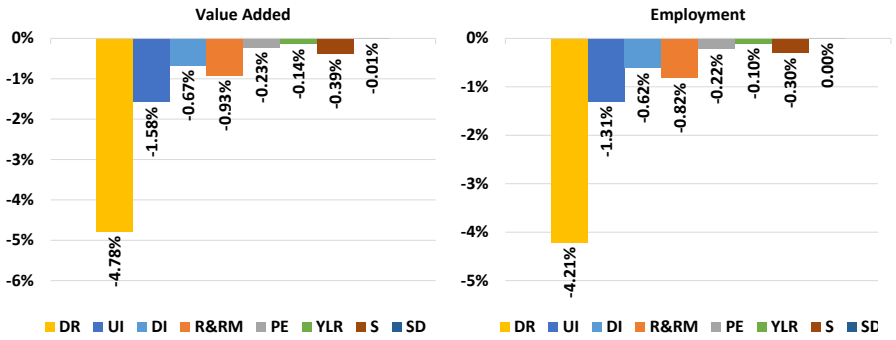


Figure 7: Global relative change in socio-economic indicators due to the individual Circular Economy Interventions. Labels: DR = Delayed Replacement; UI = Use Intensification; DI = Design Improvements; R&RM = Reuse and Remanufacturing; PE = Process Efficiency; YLR = Yield Loss Reduction; S = Sharing; SD = Scrap Diversion

Reuse and remanufacturing on the other hand, while less meaningful than delayed replacement, may still deliver significant environmental benefits (-1.36% GWP; -1.40% RME; -0.33% LU; -2.33% BWW) at a lower burden on employment (-0.93%) and value added (-0.82). However, our input data concerned mostly the reuse and remanufacturing of components for industrial or infrastructural purposes (e.g. refurbishing electricity transmission components), with only a few interventions affecting final consumer goods (e.g. reuse of parts in vehicles and mechanical products). Therefore, while we show environmental impact reduction, this cannot be considered a rule for all cases of reuse as discussed also by (Cooper & Gutowski, 2015) and effects may differ depending on the region (Duchin & Levine, 2019).

Use intensification and Design improvements appear to be the most effective RE interventions under all environmental indicators, followed by Process efficiency. In particular, changes in GWP amounted to: -1.93% Use intensification; -1.92% Design Improvements; -0.69% in Process Efficiency; -0.45% in yield loss reduction; -0.39% Sharing and -0.02% in scrap diversion.

Covering how vehicles, buildings and machineries are used on a daily basis - and their maintenance and reparation - use intensification's environmental benefits also appear to be substantial (-1.93% GWP; -2.24% RME; -0.97% LU; -3.04% BWW). However, these environmental benefits rely on the

assumption that production is avoided due to a more intensive use. Followed by this category, we find design improvements, concerned the reduction of material used during the production of various transport methods (-53%), structural construction components (-29.4%), and mechanical and electrical equipment (-34%). This was modelled by reducing the amount of steel and aluminum during manufacturing (Annex I.a). It is important to note that we did not take into account other types of design improvements concerning better performing components or design for disassembly, which may influence emissions during the use phase as well as enabling availability of scrap at the end of life.

Process improvements concerns only the application of additive manufacturing. We assumed that 28% (Fraunhofer-Gesellschaft, 2018) material savings are obtained by using additive manufacturing for steel and aluminum in the production of parts for the transport sector, precision tools, and mechanical and electrical equipment. Due to lack of data on the potential market penetration, we assumed that this process improvement would affect the entire production.

Yield loss reduction intervention also indicates some environmental benefits (-0.45% GWP; -0.12% RME; -0.73% BWW) except for LU which remained unchanged. Also socio-economic indicators were moderately reduced (-0.14 VA and -0.10 E). This intervention was modelled by assuming that a cumulative 35% of steel and aluminum going to recycling processing from the production of semi-manufactured products is diverted to other uses instead.

The environmental benefits of Sharing appear moderate in comparison with the other interventions (-0.39% GWP; -0.28% RME; -0.35% LU; -0.63% BWW). Also socio-economic indicators see a contraction (-0.39 VA and -0.30 E). Analyzing the specialized intervention we see that this is mainly due to the change in the way we travel - namely increasing occupancy and use of personal vehicles – and sharing machineries across industries. In particular the increase in occupancy of vehicles is most aggressive specialized intervention affecting environmental performance, which however also has the highest impact on socio-economic indicators. This is due to the fact that increasing occupancy of vehicles would negatively affect the demand on public transport.

At last, we see that the implementation of Scrap Diversion shows moderate reductions in environmental factors. This is mostly due to the limited scrap availability. For instance, while scrap diversion of steel and aluminum in the construction sector could be diverted by 90% (J. Allwood & Cullen, 2013), the availability of scrap from this use is only 7% (J. Allwood & Cullen, 2013). This leads us to consider that while this intervention may be a good practice and beneficial for individual manufacturing firms, their benefits on the global scale may be limited.

3.5 DISCUSSION

3.5.1 Methods and framework

One of the aims of this paper was to propose standard EEIO modeling procedures for CE strategies and their interventions. We proposed a total of 10 interventions under two CE strategies. Although the basic CE strategies are in line with those found by Aguilar et al. (2018), we innovated by making a clear distinction between strategies and interventions. We also expanded the approach of Aguilar-Hernandez et al. (2018) by including components, services, and primary and secondary materials. These interventions' blueprints provide a large degree of flexibility in describing the relationships between various elements of IO tables. However, they need to be applied critically because, as shown in the case of sharing, variations may be needed depending on the specific case. Additionally, the blueprints do not discuss how trade should be modelled. Therefore, we are assuming that trade would change relative to the applied changes. This is an assumption that in some case may need to be modified. Furthermore, our modeling choices respond to the premise of creating static representations of a counterfactual economic structure using IO. As such, they do not take into account changes in price dynamics, investments and stocks. Concerning the use a static monetary IO system, we see that it limited our possibilities to model strategies for residual waste management. The use of dynamic models (e.g. CGE or Stock and flow consistent models) and hybrid unit IO data could provide respectively additional insights on monetary dynamics of the CE and the physical transaction and stocks creation in the global economy.

3.5.2 Software and Data

Open-access software and data was of great importance in our study. Our desire was to ensure study replicability and transparency. In our review we found some proprietary software and platforms that allowed for the simulation of interventions. However, they were specific to a few regions and in some cases the software or data was not publicly accessible. In particular, no Python packages were available that allowed for the transformation from SUTs to IO and for scenario modeling. We therefore developed pycirk, a Python package to handle EXIOBASE V3.3 and convert SUTs to IO tables to create scenarios for CE. Pycirk gives the opportunity to implement an indefinite number of changes in any matrix in the IO system. In this way, one can process multiple type interventions at ones, including substitutions. These features are useful in the creation and analysis of scenarios. Currently, pycirk only supports product-by-product industry-technology transformation. Furthermore, pycirk allows for the creation of EXIOBASE IO tables in which secondary raw material transactions are explicitly separated from primary raw materials. This is a unique feature that allows modelers to analyze secondary raw material production and consumption in EXIOBASE IO tables.

3.5.3 Case study

We performed a zero-cost analysis of a counterfactual economy using the EEIOA. Therefore, we presented a world in which CE strategies were already implemented. Investments and fiscal stimuli were not included. This means, that effects of material taxes and subsidies could not be investigated. For this reason, many of the other studies found focused on CGE models. Their advantage is in the ability to represent dynamic aspects of the economy. This comes at the expense of sectoral resolution, something for which EEIO as a structural model is better suited. For this reason many previous studies on CE are difficult to compare to our results.

For the interventions, strategies and goods that we investigated, various assumptions had to be made on the basis of EXIOBASE product category aggregation. For instance, the data collected (Annex I.a) often referred to products for which there was no explicit category in EXIOBASE and were therefore sub-items of an aggregated product category. Where it was possible we disaggregated the values by their relative market size, otherwise

we made an average of the change coefficients to be applied. In order to provide a logical order of intervention processing, their schedule was optimized against the baseline. However, other types of scheduling may output different results (Annex I.g). Moreover, the study was conducted on a bi-regional global level, with EU and ROW as the only two regions, however, results at a country or regional level may differ greatly as also discussed by (Duchin & Levine, 2012) and (Wiebe et al., 2019).

Additionally, we did not take into consideration changes in commodity and service prices resulting from endogenous or exogenous factors. Changes in investment, reinvestment of savings due the increased efficiency and global market trends such as the transition to a renewable energy system and electrification of mobility were not considered. This differs from previous studies we analyzed which often presented analyses of the transition to a new CE state within a time range (EMF, 2015; WRAP, 2015; Wijkman and Skanberg, 2015; (Winning et al., 2017), Wiebe et al., 2019). In particular, the study by WRAP (2015) which concerned reuse, recycling, repair and remanufacturing and servitization in the UK, showed that by 2030 the circular economy could deliver an increase of employment between 31,000 and 517,000 people in the UK alone (0.1-2% from 2015 UK employment). Our results, while of different scope, show that in the EU (EU28) employment may decrease by 5.31%. In the study by Rutherford et al. (2015), provided an aggressive EU agenda on CE to 2050, reductions of 83% in CO2 emissions and an increase of 27% in value added could be seen in the EU (EU27). However, while our study shows a different picture, it is important to stress that we did not take into consideration the transition to a renewable energy system and changes in the food system while they did. Therefore, much more moderate impacts are seen on our results. In the study by Wijkman and Skanberg (2015), only one part could be compared to our work, the resource efficiency scenario. Although, the process efficiency improvement in their scenario (25%) is comparable to ours (28%), their other RE interventions appear more aggressive than in our case. Despite the differences in assumptions, their results show GWP reductions between 3 and 10% depending on the analyzed country, against our 10.1% global reductions. Furthermore, (Winning et al., 2017) showed -0.02% change in GWP due the doubling of scrap availability which appears to confirm our results concerning scrap diversion. Our results on material extraction (-

12.5%) are also above those seen in the work of Wiebe et al. (2019) (-10%). At the same, their results on employment are ~2% while we show -5.3%. The change in employment and value added seems to vary substantially across literature as shown also by McCarthy et al. (2018).

3.5.4 Future work

From a methodological perspective, intervention modeling blueprints should be further expanded and validated. Relationships concerning fiscal stimuli and rebound effects specific to interventions should also be established. The blueprints should be adapted to other types of IO models (e.g. hybrid unit) and to SUTs. The software could be instrumental in this by being expanded to allow changes on different types of data structures, using different types of datasets and transformation methods. This would allow modelers to run sensitivity analysis on their scenarios, something that was not possible to do with the current software. Future studies should also enrich our findings on CE so to provide a representation of CE closer to real world dynamics. In particular, more research is needed on the CE strategies and interventions that could not be investigated in our study. For instance, Closing Supply Chains and its potential interventions. Future work should provide additional insights on CE effects of many other interventions, product categories and their stocks across regions as well as more strongly integrating economic and physical material studies through the use of EEIOA.

3.6 CONCLUSIONS

We presented a framework, a software and a structural study on the Circular Economy (CE). The framework provides an overview of the structure of CE strategies and their implementation in EEIO. Modeling blueprints were used to aid scenario building and to provide a systematic and transparent application of interventions. We also presented pycirk, a free and open-source Python package for modeling policies, and technological and market changes in EEIO starting from the SUTs database EXIOBASE v3.3 for 2011. This is done chiefly to provide practitioners with tools to model CE policies in EEIOA in order to facilitate decision making in the transition to a sustainable society. The possibilities and use of pycirk were exemplified

through a case study on the CE on a bi-regional (EU-ROW) IO system. Using this system, we created scenarios for 2 CE strategies: Product Lifetime Extensions and Resource Efficiency. The results from the case study show that environmental benefits can be obtained through the pursuit of CE strategies. In particular, the combined global effects could amount to a global relative change of -10.1% (GWP100), -12.5% raw material extraction used, -4.2% land use and -14.6% blue water withdrawal. The analysis of the socio-economic indicators showed global reductions of 6.3% in Value Added and 5.3% in Employment globally. However, it is to be noted that fiscal stimuli (subsidies or tax changes), investment and price changes were not included. For this reason, our approach did not follow the premise that a CE delivers equal or better economic performance. Additionally, an apparent change in GDP does not necessarily represent a loss of general wealth so long as the same utility is maintained. Nevertheless, the results from this case study should be used and interpreted with care as our scenarios aimed largely at show-casing the use of the methods and software presented.

SUPPLEMENTARY INFORMATION

Annex I and II: https://doi.org/10.5281/zenodo.7419203

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