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Commentary

Balance issues in input–output analysis: A comment on physical inhomogeneity, aggregation bias, and coproduction

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ABSTRACT

Recently, Merciai and Heijungs (2014) demonstrated that monetary input–output (IO) analysis can lead to system descriptions that do not conserve mass when the assumption of homogeneous prices is violated. They warn that this violation of basic balance laws can lead to biased estimates of environmental impacts, and they therefore recommend performing IO analysis in a physically accounted framework.

We take a broader scope on this issue and present price inhomogeneity as a special case of product mix inhomogeneity. We demonstrate that even a fully physically accounted IO analysis or lifecycle assessment will violate balance laws if it suffers from inhomogeneous aggregation. The core issue is not whether a system is described using monetary or physical units, but rather whether product groups are too aggregated to allow for the concurrent respect of energy, mass, financial and elemental balances.

We further analyze the link between the violation of physical balances and the introduction of biases. We find that imbalances are neither a necessary nor a sufficient condition for the presence of systematic errors in environmental pressure estimates.

We suggest two ways to leverage the additional explanatory power of multi-unit inventory tables to reduce instances of imbalances and aggregation biases.

1. Introduction

Both lifecycle assessment (LCA) and environmentally extended input–output analysis (EEIO) relate environmental impacts to the production and consumption of products (Leontief, 1970; Guinée, 2002; Heijungs and Suh, 2002; Suh et al., 2004). These methods routinely rely on both physical and economic data to describe exchanges of products and services, and interactions with the environment (Leontief, 1970; Nakamura and Kondo, 2002; Guinée et al., 2004; Suh et al., 2004; Hawkins et al., 2007; Ardente and Cellura, 2012; Wood et al., 2014). Monetary records of stocks and flows are common in these models, notably because of their greater data availability from statistical offices (e.g., United Nations et al., 2009). The use of monetary units is known to require special care, however: Practitioners must use a consistent valuation scheme, such as purchaser's price, producer's price, or basic price (United Nations, 1999; European Commission, 2008); they must work at constant prices over time, correcting for (general and sector-specific) inflations or deflations (Miller and Blair, 2009); and they must use product prices that are homogeneous throughout the system description (Suh, 2004; Weisz and Duchin, 2006).

Further analyzing this last challenge, Merciai and Heijungs (2014) (hence forth MH) investigate in a recent article in *Ecological Economics* whether the product and emission flows calculated by a monetary EEIO can satisfy the law of conservation of mass[1] when prices of products differ between purchasers. They present an example in which such a violation of the price-homogeneitiy assumption in the EEIO analysis of an arbitrary[2] final demand leads to a system description that is not mass balanced.

MH then draw two main conclusions. First, because of the imbalances that they identify, they find that an EEIO "is always preferable to be performed in a complete physically accounted framework". Second, they warn against potentially biased environmental pressure estimates

[1] As pointed out by MH, their analysis of the effect of price inhomogeneity could equally well have been performed with another physical balance, such as energy balance.

[2] This distinction is important: Retrospective analyses applied to the *historically observed* final demand for the year of inventory will always lead to a globally balanced system descriptions, even in the presence of inhomogeneously aggregated product groups (Olsen, 1993).

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because monetary EEIO "can fail in respecting basic balance laws". In this comment, we strive to contextualize these two claims.

We first present *price inhomogeneity* as a special case of *product-mix inhomogeneity*, which results from the aggregation of products that are dissimilar and are used in different ratios in separate industries (Section 2). Inhomogeneous prices are the only form of inhomogeneity in the example by MH, but we extend their example with additional physical layers to demonstrate how inhomogeneous aggregations can introduce imbalances even in physically accounted EEIO or LCA system descriptions. We demonstrate that it is not the choice of physical or monetary unit but rather the level of homogeneity of product groups that determines the concurrent conservation of mass, energy, and the various chemical elements in calculated lifecycle flows.[3]

We then analyze how physical and economic imbalances in LCA and EEIO relate to systematic deviations, or biases, in environmental pressure estimates (Section 3). We demonstrate that aggregation can sometimes cause biases without causing imbalances. Conversely, we find that coproduction models (allocation in LCA and constructs in EEIO) can introduce imbalances without being associated with biased environmental pressure estimates. We therefore find that physical imbalances in calculated system descriptions are not reliable indicators for the presence of systematic overestimations or underestimations of lifecycle impacts.

Based on this analysis, we then suggest two practical strategies to reduce the imbalances and biases resulting from different levels of data aggregation (Section 4).

2. Physical or Price Inhomogeneities and Imbalances

2.1. Single-, Mixed-, and Multi-unit Product Descriptions

Many of the major tools used in industrial ecology were developed so as to require only minimal data on product characteristics. A monetary input–output analysis (IO) records financial flows that either follow a product-based or an industry-based classification; products are then little more than a classification scheme for value flows (Lenzen, 2001; European Commission, 2008), and none of their intrinsic characteristics are formally needed to conduct the analysis. Similarly, material flow analyses (MFAs) typically track flows of mass between processes, and product categories are often little more than classification schemes for these mass flows (Baccini and Bader, 1996). In LCA, each product is typically assimilated to a single function within the system, the functional unit (Guinée, 2002), and knowledge of its other characteristics are not formally required.

In such inventories, each product is thus recorded in terms of only one of its physical or economic dimensions. If all flows of a system description are recorded with the same unit (single-unit description), the conservation of this unit can be assessed, as is the case for mass balance in MFA (Fischer-Kowalski et al., 2011) or financial balance in monetary IO (United Nations, 1999). Conversely, if each flow is described with a different unit (mixed-unit inventory), the system is not fully described in terms of any of its dimensions and typically cannot be assessed for balance without the acquisition of additional data.[4] For example, an exchange of fuel solely recorded in MJ cannot be directly included in a mass balance assessment, whereas a flow of fuel solely recorded in kilograms (kg) cannot be directly included in an energy balance.

To allow for the assessment of multiple balances concurrently and to answer a broader range of questions, multilayered, multi-unit system descriptions are becoming increasingly popular (Schmidt et al., 2010; Merciai et al., 2013; Ecoinvent Centre, 2013; Pauliuk, 2013; Pauliuk et al., 2015a). Such descriptions encompass more information and describe each flow or stock concurrently in terms of its multiple physical and monetary extensive properties. The same flow of fuel would thus be recorded in terms of kg in the mass layer, in terms of MJ in the energy layer, in terms of € in the value layer, etc.

The ratio between any two such layers gives rise to an intensive property that explicitly describes the products. For example, a system with flows recorded in mass, energy and carbon layers would automatically give rise to product descriptions in terms of energy densities and carbon concentrations. In the EEIO system presented by MH, the ratio between the value layer (€) and the physical layer (kg and MJ) necessarily gives rise to one intensive product description: prices (expressed either as €·kg^{-1} or as €·MJ^{-1}).

Throughout this article, when an intensive property is defined by the ratio between two properties for which a conservation law exists (e.g., energy density, defined by the ratio of mass and energy), we refer to it as a *conservative*, *intensive* property.

2.2. Price Inhomogeneity as Special Case of Product Group Inhomogeneity

Multi-unit product descriptions then bring to light a fundamental assumption of system descriptions in industrial ecology: product groups are always assumed to be *homogeneous* across the whole system and in terms of all properties investigated. Whether in MFA (e.g., Modaresi et al., 2014), in LCA (Clift et al., 2000; European Commission, 2010),[5] or in EEIO (Leontief, 1936; Viet, 1994; Weisz and Duchin, 2006), any intensive property of a product group is always assumed to be independent of where in the system this product group is observed. A product group (e.g., batteries) would prove inhomogeneous in terms of lead-content if this "same" product had a high lead concentration in one part of the system (e.g. car manufacturing) and a low lead concentration in another (e.g. laptop manufacturing). Clearly, such an inhomogeneous product group would result from the aggregation of multiple subgroups (e.g. lead-acid batteries and Li-ion batteries); it would crudely designate under the same name two different mixes of these subgroups in these two industries.

It is important to note that a product group can be considered homogeneous even if the products that it aggregates are not identical to one another. In LCA and EEIO, complete uniformity within a mix is not required for homogeneity, as long as the mix is invariant across all processes or economic sectors that use the mix. For example, the product group "passenger vehicles" may aggregate cars with differing aluminum concentrations, and therefore a certain distribution will exist around the average aluminum concentration for this group. The product group will nonetheless be considered homogeneous in terms of aluminum concentration if this concentration is invariant across industries, that is, if the different sectors (transport industry, tourism industry, final consumers) purchase car mixes that have an equal average aluminum concentration.[6]

Any average intensive property arising from the ratio between two unit layers, whether economic or physical, is always assumed homogeneous across the whole system: prices, carbon concentrations, gravimetric energy density, etc. Product prices, arising from the ratio between a physical and a monetary unit layer, are thus one among many intensive properties that are assumed homogeneous (Viet, 1994; Suh, 2004; Weisz and Duchin, 2006). We extend the example by MH to

[3] Throughout this article, for the sake of simplicity, nuclear reaction processes are excluded from the system boundaries, and the different chemical elements are thus conserved. Similarly, banks are also excluded from the LCA or EEIO descriptions; creation and destruction of money by the different processes within the system boundary is therefore also forbidden.

[4] The mixed-unit, physical layer of MH constitutes an exception. It is possible to calculate a mass balance from this layer because the only flows not recorded in kilograms (kg) have no mass, and therefore the mass flows in the system are fully captured.

[5] "As delivered by homogeneous markets".

[6] In cases where an aggregation does not introduce inhomogeneities, we would rather speak of *aggregation uncertainty*. Such aggregations do not cause biases (see Section 3.1), but they reduce the specificity of the system description and typically increase the dispersion of the distribution around average technical coefficients (Lenzen, 2000, 2001).

show how product group inhomogeneities in terms of any conservative, intensive property can lead to physical or economic imbalances.

2.3. Inhomogeneous Product Groups Cause Imbalances Even in Physically Accounted IO

Let us mirror the example of MH such that a practitioner directly records all flows in a physical, mixed-units inventory (Fig. 1, top, gray and black), in which all flows with a material dimension are recorded in terms of their mass (Fig. 1, top, black) and their carbon contents (Fig. 1, bottom). These descriptions give rise to a new intensive property, instead of prices, to describe products: their carbon concentrations (Fig. 1, middle).

Fig. 1 thus presents a purely physical, mass-balanced, carbon-balanced system description. As made explicit by the carbon concentration table, however, the agricultural product group displays carbon concentrations that differ between consumers, which identifies it as an inhomogeneous product group. The carbon density of agricultural products in the energy sector is more than twice that of agricultural products consumed by final demand. Such a situation could arise, for example, if an inventory's resolution proved too coarse to distinguish between the sales of food to final consumers and of biofuel to the energy sector; "agricultural products" does not have the same meaning across the system description.

If this system description is used to evaluate an arbitrary final demand (e.g., 5 kg of agricultural product, 3 kg of manufactured products, and 1 MJ of energy), the calculated product flows and emissions will seemingly lead to the creation and destruction of carbon (Fig. 2). Following the analysis of MH, using average carbon-density to derive the carbon layer from the mixed-unit layer will lead to imbalances within the processes purchasing agricultural products (Fig. 2, middle), and using per-transaction concentrations will lead to imbalances in the process producing agricultural products (Fig. 2, bottom).

Since it does not contain any monetary information, the example in Fig. 2 is general enough to illustrate the consequences of inhomogeneous product groups not only in EEIO but also in LCA. For instance, in the ecoinvent database (Ecoinvent Centre, 2010), a product "steel, electric, un- and low-alloyed, at plant" may be expected to aggregate many specific steel alloys in a certain ratio. Imbalances in some of the alloying elements are to be expected if this aggregate product group is used as an input to a process that requires a different ratio of these various alloys. Inhomogeneity would also be expected within the product group "iron–nickel–chromium alloy", allowing for different ratios between the three alloyed metals, whereas other product groups explicitly define a tolerable range of inhomogeneity, such as "cement, blast furnace slag 70–100%" (Ecoinvent Centre, 2013).

Contrary to MH, we therefore find that a complete, balanced, and physically accounted framework will in general not lead to balanced

Mixed-unit (gray and black) and mass (black) IO Flows

		Agriculture	Manufacture	Energy	Demand	*Total mass*
Agriculture	kg	0.0	1.0	2.0	4.0	*7.0*
Manufacture	kg	2.0	0.0	3.0	3.0	*8.0*
Energy	MJ	2.0	2.0	0.0	1.0	-
Resource 1	kg	8.0				
Resource 2	kg		9.0			
Emission 1	kg	-3.0	-2.0			
Emission 2	kg			-5.0		
Total mass	*kg*	*7.0*	*8.0*	*0.0*		✓

Carbon Concentration

		Agriculture	Manufacture	Energy	Demand	*Mean*
Agriculture	kg C per kg	n/a	0.75	0.75	0.26	*0.47*
Manufacture	kg C per kg	0.20	n/a	0.20	0.20	*0.20*
Energy	kg C per MJ	0.00	0.00	n/a	0.00	*0.0*
Resource 1	kg C per kg	0.36				*0.36*
Resource 2	kg C per kg		0.095			*0.095*
Emission 1	kg C per kg	0.0	0.0			*0.0*
Emission 2	kg C per kg			0.42		*0.42*

Carbon IO flows

(kg C)	Agriculture	Manufacture	Energy	Demand	*Total*
Agriculture	0.0	0.75	1.5	1.0	*3.3*
Manufacture	0.40	0.0	0.60	0.60	*1.6*
Energy	0.0	0.0	0.0	0.0	*0.0*
Resource 1	2.9				
Resource 2		0.85			
Emission 1	0.0	0.0			
Emission 2			-2.1		
Total	*3.3*	*1.6*	*0.0*		✓

Fig. 1. Input–output system recorded in physical mixed-units (top, black and gray for kg and MJ, respectively), with a balanced mass layer (top, black) and a balanced carbon layer (bottom), but presenting inhomogeneous carbon concentrations in agricultural product descriptions (red, center). Symbol: ✓ indicates a balanced layer; n/a = not applicable (zero carbon divided by zero mass).

Mixed-unit (black and gray) and mass (black) IO Flows

		Agriculture	Manufacture	Energy	Demand	*Total mass*
Agriculture	kg	0.0	1.1	2.2	5.0	*8.3*
Manufacture	kg	2.4	0.0	3.3	3.0	*8.7*
Energy	MJ	2.4	2.2	0.0	1.0	*0.0*
Resource 1	kg	9.5				
Resource 2	kg		9.8			
Emission 1	kg	-3.6	-2.2			
Emission 2	kg			-5.5		
Total mass	*kg*	*8.3*	*8.7*	*0.0*		✓

Carbon IO Flows, calculated with average carbon contents

(kg C)	Agriculture	Manufacture	Energy	Demand	*Total*
Agriculture	0.0	0.51	1.0	2.3	*3.9*
Manufacture	0.47	0.0	0.67	0.60	*1.7*
Energy	0.0	0.0	0.0	0.0	*0.0*
Resource 1	3.4				
Resource 2		0.93			
Emission 1	0.0	0.0			
Emission 2			-2.3		
Total	*3.9*	*1.4*	*-0.6*		✗
Case 1 Imbalance:	0.0	-0.3	-0.6		**-0.9**

Carbon IO Flows, calculated with per-transaction carbon contents

(kg C)	Agriculture	Manufacture	Energy	Demand	*Total*
Agriculture	0.0	0.81	1.7	1.3	*3.8*
Manufacture	0.47	0.0	0.67	0.60	*1.7*
Energy	0.0	0.0	0.0	0.0	*0.0*
Resource 1	3.4				
Resource 2		0.93			
Emission 1	0.0	0.0			
Emission 2			-2.3		
Total	*3.9*	*1.7*	*0.0*		✗
Case 2 Imbalance:	0.1	0.0	0.0		**0.1**

Fig. 2. New input–output flows calculated for an arbitrary, mixed-unit final demand (top, Demand column, black and gray), showing how mass-balance is respected (top, black) but carbon balance is not, both when using average carbon densities (middle) and per-transaction carbon densities (bottom). Symbol: ✓ and ✗ respectively indicate balanced and imbalanced descriptions.

EEIO or LCA representations in the face of aggregated product groups; the basic physical laws will likely not be respected across the different layers. Inhomogeneous product groups are thus a problem regardless of the unit of analysis, and inhomogeneous prices are but the monetary aspect of this problem.

Of course, if a study is only interested in one type of physical balance (e.g. only conservation of mass), it is certainly beneficial to directly record the survey in terms of the unit of interest. If multiple extensive properties are to be concurrently balanced, however, this can only be achieved with product groups that are sufficiently disaggregated such that they are homogeneous across all sectors of the system description, in terms of all properties of interest, regardless of the unit of measurement.

2.4. Comparison of Physical and Financial Balances

In the above section, we treated carbon flows and carbon-concentration inhomogeneities in the same way that MH treated monetary flows and price inhomogeneities; imbalances arose in the same manner.[7] This similarity between physical and monetary layers in LCA and EEIO has two reasons.

First, inhomogeneities in carbon concentrations and prices can be traced to the same source: the classification of products in aggregate groups. Regrouping two products with different carbon concentrations in the same product group can lead to carbon concentration inhomogeneities. Treating two products with different prices as belonging to the same product group can lead to price inhomogeneities. In other words, just as product groups are artifacts of our classification and boundary choices (United Nations, 2008), so are *inhomogeneous* product groups. In the example of electricity sold at different prices to households and to aluminum refineries, there is no fundamental reason why these two electricity packages necessarily need to be considered as "the

[7] Furthermore, some symmetry is apparent in how physical and financial imbalances arise. Just as deriving a physical layer from the calculated monetary flows lead to mass imbalances in the EEIO system of MH, deriving a monetary layer from calculated physical flows would have lead to financial imbalances, in both cases because of price inhomogeneities (see supporting information (SI), Section 1).

same" product. They could just as well be classified as two different products sold at different prices.[8] Considering them as belonging to the same (inhomogeneous) product group constitutes a classification and aggregation choice.

Second, carbon and value are both subject to balances in LCA and EEIO. If no nuclear reaction is present in the system, carbon is always preserved. It is thus expected that the carbon content of a product equals the net inputs of carbon to its production through product flows and exchanges with nature (Weidema and Schmidt, 2010); any other description would contradict basic physical laws. Similarly, the value of a product must equal the net value of all product requirements (costs) plus all value added (European Commission, 2010); that is, the net profits plus the value of factors of production such as inputs from nature, labor, and capital (Duchin, 2009). Any other description would violate accounting rules. Carbon and financial balances are thus two similar quality checks, in different layers, that ensure a valid process description.

These balances then force a correspondence between product characteristics and the description of their production processes in LCA and EEIO. If carbon flows are balanced, a given set of inputs and outputs will always yield a product with the same carbon content. In other words, two products with different carbon contents cannot be produced with exactly the same input and waste structure; some variation in their production functions must account for the difference. Similarly, if value is preserved through a production process, a technical recipe that includes all payments for products and factors of production can only yield a product with a given value. If two products differ in prices, something in their production function must explain this difference; perhaps their production processes had different product requirements, or a different profit margin was taken, etc.

To summarize, in a complete, balanced LCA or EEIO inventory, the characteristics of a product cannot vary independently from this product's production function. This serves as the foundation for the second part of our analysis: the connection between imbalances and biased lifecycle results.

3. Imbalances and Biases

MH postulate a direct link between the violation of physical balances in LCA or EEIO analyses and environmental pressure estimates that are biased. A systematic error or a systematic deviation, often termed *bias*, constitutes a systematic deviation from the "true value of the measurand". Although this true value can never be fully known, a bias can be estimated by a) comparing a set of measurements with a reference value that is believed to be closer to the true value (e.g., a standard) or b) the analysis of the "systematic effect" of specific parameters, such as friction or temperature changes, on the accuracy of measurement values (JCGM, 2008). For example, the miscalibration in a measurement instrument may cause a systematic overestimation in experimental results, which are then biased and require a correction. This definition of systematic deviation is applicable not only to measurements but also to estimations with models (Drosg, 2007). A prominent example for a systematic error in environmental systems analysis is the truncation error in LCA. Because LCA system descriptions typically omit parts of the value chains in the product system, this systematic "truncation effect" makes it more likely that emissions to nature are underestimated rather than overestimated. This leads to a systematic underestimation bias that can be estimated and corrected through hybridization with EEIO (Lenzen, 2002; Suh and Huppes, 2002; Norris, 2002; Majeau-Bettez et al., 2011).

The idea that a bias involves a systematic *direction* of the deviations and requires a *correction* is central to its definition. Moreover, the identification of a bias necessarily and crucially implies an identification of its *sign*: a positive bias for a systematic overestimation, or else a negative bias for a systematic underestimation. This contrasts with the concept of uncertainty, which, by definition, is unsigned (Drosg, 2007) and cannot be "corrected" by simply adjusting the value of the best estimate. Thus, once a bias has been identified, "results should be corrected until it cannot be said whether the measured value is too large or too small", i.e., until the suspected bias is removed and only uncertainty remains (Drosg, 2007). In other words, one cannot identify a bias without identifying the direction in which results systematically deviate.

In this section, we examine whether the presence of an imbalance in an inventory can directly point to the direction of a systematic deviation in calculated estimation of environmental impacts. We do not find a simple, direct link. An apparent 'destruction of mass' in an imbalanced process description may equally well denote an *underestimation* of direct emissions and other outputs, which are associated with environmental impacts, or an *overestimation* of inputs, which are also associated with impacts through their production chain. A mismatch between inputs and outputs does not a priori point to a systematic direction of deviations in environmental impact estimates. Furthermore, environmental impacts are rarely mediated directly by 'mass' or individual elements (C, H, O), but rather by chemical species that stoichiometrically combine multiple elements (e.g., methane, carbon monoxide, carbon dioxide). No single balance could therefore be used in isolation to identify a bias in lifecycle environmental impacts; multiple imbalances would need to point in a consistent direction to show a systematic deviation.

The link between imbalances in system descriptions and the identification of systematic deviations in LCA and EEIO results may prove more complex than anticipated. As illustrated in Fig. 3, and as further detailed in the following subsections, imbalances and systematic deviations sometimes have a common cause, but aggregation biases may also arise in fully balanced systems, and imbalances may be present without indicating clear biases in environmental pressure estimates.

3.1. Inhomogeneous Product Groups can Cause Both Imbalances and Aggregation Bias

The rich literature on *aggregation bias* has explored how inhomogeneous aggregations have a systematic effect on EEIO analysis and can cause systematic errors in analysis results (Morimoto, 1970; Olsen, 1993, 2000; Lahr and Stevens, 2002).

Given that physically or economically different products must have different production recipes (Section 2.4), the production function for

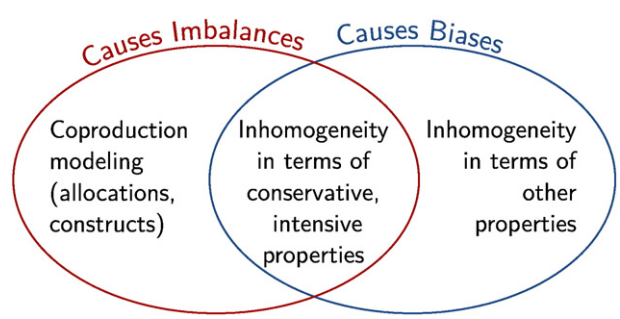

Fig. 3. Partial link between imbalances in system description and systematic deviations (biases) in environmental pressure estimates.

[8] In fact, electricity contracts with the aluminum industry often differ in significant ways. Contrary to contracts with other consumers, for example, electricity supply to the aluminum industry is often not guaranteed during periods of peak consumption. Reducing an electricity product to its mere energy content — a single physical property among many — can thus make abstraction of real, functional differences (voltage, reliability, location, etc.) that explain differences in prices. Such real-world differences can then only be preserved by creating separate product groups (e.g., electricity, high voltage, no peak load and electricity; low-voltage, residential area, uninterrupted) that are more homogeneous across physical and economic layers. Furthermore, because EEIO analyses are normally performed using 'basic prices' (correcting for subsidies, taxes, differences in transport and trade margins, etc.), many factors that can cause prices to differ for households and industries are already taken into account (Miller and Blair, 2009).

a product group that aggregates different commodities can always be represented as the aggregation of multiple distinct production recipes in a given ratio. For example, the input structure associated with the manufacture of the product group "batteries" is the weighted sum of many technical recipes: a recipe for Li-ion batteries, a recipe for lead-acid batteries, etc.

This aggregation of different production functions is not problematic as long as their products are always consumed together in the ratio that defined the aggregation. If every industry consumed the same ratio of lead-acid and Li-ion batteries, their aggregation would not influence the results (see Fisher, 1958; Olsen, 1993 on perfect aggregation). However, if an aggregated product group is inhomogeneous (i.e., its constituents differ and are consumed in different ratios by different industries), then its aggregated production recipe is also inhomogeneous. The battery manufacture upstream of laptop production differs from the battery manufacture upstream of car production, as laptops typically require Li-ion batteries whereas cars predominantly rely on lead-acid batteries. Using a single, aggregated battery production process would therefore lead to systematic deviations in these lifecycles: emissions from lead mining in the lifecycle of laptops and emissions from lithium mining in the lifecycle of passenger cars would both be systematically overestimated. This phenomenon has been thoroughly documented and is known as *aggregation bias* (Morimoto, 1970; Olsen, 1993, 2000; Lahr and Stevens, 2002).

The systematic effect of heterogeneous aggregation in introducing errors in final results has traditionally been studied by comparing the results obtained from a full-resolution EEIO table with those obtained from aggregated versions of this same table (e.g., Lenzen et al., 2004). Alternatively, the biases associated with a given study can be estimated retrospectively by comparing its results with that of a more disaggregated, improved system description.

In the case of inhomogeneous aggregation, it is therefore possible to formulate the notion of an aggregation *bias* because higher resolution and granularity are strongly expected to lead to a more accurate representation of the real system; this more detailed representation leads to 'truer' lifecycle results against which the errors of a more aggregated description could be assessed (Olsen, 1993). The comparison directly gives the likely sign (direction) of the bias, along with an estimate of its magnitude.

Product groups that prove inhomogeneous in terms of conservative, intensive properties thus cause not only imbalances between property layers (Section 2.3) but also necessarily imply inhomogeneous input structures, which are known to cause the misrepresentation of specific value chains and biases in lifecycle results (Fig. 3, center).

3.2. Aggregation Bias can Occur Even in Fully Balanced Descriptions

Not all inhomogeneities are defined in terms of conservative, intensive properties, however. A product group inhomogeneity in terms of any other property will also lead to aggregation biases but will *not* cause imbalances (Fig. 3, right). In other words, a product group could be perfectly uniform in terms of prices, energy density, and elemental concentrations, ensuring respect of all balances, and yet aggregate products that differ with respect to some other property, are manufactured differently, and are sold in different ratios to different industries (see Viet, 1994 and Konijn and Steenge, 1995 on homogeneity of productions and input structures). An inhomogeneous product group might aggregate products that are sold in distinct markets or with different traceabilities.

For example, it is well known that the mix of power plants (e.g. coal fired, nuclear, natural gas) delivering electricity at night is different from that providing electricity during the day. Aggregating daytime and nighttime electricity as a single product aggregates these productions and their input structures in a fixed ratio. If every industry and consumer purchased daytime and nighttime electricity in this same ratio, this aggregation would not lead to inhomogeneities, but otherwise it would: an aggregated electricity mix would misrepresent the value chain of industries that purchase daytime and nighttime electricity in different ratios, causing aggregation biases. And yet, because the products (daytime and nighttime electricity) are identical in terms of their physical characteristics, this aggregation bias would not be accompanied by imbalances of the type produced in Fig. 2 or in the example by MH.

Similarly, steam does not ship well over long distances and is typically produced and purchased locally. Representing the production of such a product in an aggregate, national average would likely cause aggregation bias but not necessarily imbalances. Assuming that steam is recorded with a certain temperature/pressure equivalent across the entire system, this aggregation would not lead to physical imbalances. If it so happens that steam is sold at the same price in the different markets, financial balance would also be respected in the national aggregation. However, this balanced aggregation would nonetheless introduce systematic deviations if production methods differed between markets. For example, it would systematically over-estimate the carbon footprint of industries that use steam in areas where it is produced with natural gas, and conversely systematically underestimate the impacts of lifecycles that rely on steam in coal-based markets.

Aggregating away product traceability labels (such as "certified organic," "fair trade," or "made in Canada") may also lead to inhomogeneities. Let us assume that conventional corn and organic corn present identical energy densities and elemental concentrations. Aggregating these two products as "corn" and their production as "corn production" would cause no mass, energy, or elemental imbalances in the system description. And yet, since these productions differ in terms of land use and pesticide use, this aggregation will cause inhomogeneities and systematic deviations if different consumers in the system description require organic and conventional corn in differing ratios.

The presence of imbalances in a system description is therefore not a *necessary* condition for the presence of aggregation bias in LCA or EEIO pressure estimates.

3.3. Modeling Choices can Cause Imbalances Without Causing Biased Results

Inhomogeneous product groups are not the only likely source of imbalances in LCA or EEIO. On the contrary, physical imbalances may also arise because of deliberate modeling assumptions to resolve situations of coproduction: allocation models in LCA and constructs in EEIO.

Very few coproduction situations can be resolved without introducing modeling assumptions. The subdivision of a multifunctional activity into multiple monofunctional activities based on additional data collection (Guinée, 2002) is not possible when its coproduction presents a strong technological link, such as the joint production of chlorine gas and sodium hydroxide (Jung et al., 2012; Azapagic and Clift, 1999). Pseudo-inversion is only mathematically possible when the different coproducts are jointly used in the same ratio as their production ratio (Heijungs and Frischknecht, 1998). As for classical system expansion, it may be incompatible with the objective of the study (Jung et al., 2012). Furthermore, for coproductions that occur more than a few steps upstream of the final demand, it typically requires such a broadening of the functional unit that it reduces the problem to a trivial solution: the total production impacts of all industries are caused by the total final consumption of all products (see examples in SI, Section 2).

For most analyses, there is thus no assumption-free method to deal with coproduction, and LCA or EEIO practitioners have no choice but to resort to modeling in order to generate independent recipes for products that are not truly produced independently (Kop Jansen and ten Raa, 1990; Guinée, 2002; Heijungs and Suh, 2002). Several coproduction modeling families span across LCA and EEIO practice (Suh et al., 2010; Majeau-Bettez et al., 2014). With partition-based models — partition allocation (PA), partition construct (PC), European-system construct (ESC), industry-technology construct (ITC) — the joint requirements of

a coproduction are split proportionately to a joint property of its coproducts. With substitution-based models — product-substitution allocation (PSA), product-substitution construct (PSC), byproduct-technology construct (BTC) — the secondary coproductions are modeled as having avoided some other primary production. With alternate-activity models — alternate-activity allocation (AAA), alternate-activity construct (AAC), commodity-technology construct (CTC) — the requirements of each secondary production are exogenously fixed based on the requirements of some other independent production, which serves as a technological proxy; and the primary production is then ascribed the remainder of the joint requirements (Majeau-Bettez et al., 2014).

Every single of these three modeling families can lead to physical imbalances, even when applied to balanced physical inventories, depending on the characteristics of its coproductions (Majeau-Bettez et al., 2016). Partition-based allocations and constructs almost always cause imbalances across multiple conservative properties; for instance, mass-based partitions typically lead to imbalances in the energy layer, and vice versa for energy-based partitions (Weidema and Schmidt, 2010). Both substitution and alternate-activity models necessarily lead to imbalances in the presence of exclusive secondary products, that is, products that are the primary objective of no industry and are always produced as secondary products. For example, because there is no such thing as a primary production of oil press cake, the coproduction of this product cannot be modeled as having substituted an identical product from primary production, and it is therefore rather modeled as equivalent to a different product, with a potentially different energy density or elemental composition, leading to imbalances.

Consequently, any LCA or EEIO based on a system description that relies on partition allocation or that represents exclusive secondary products would be expected to display some physical imbalances due to coproduction modeling. Does it follow, then, that all such analyses — indeed, almost all LCA ever performed[9] — calculate "biased pressure estimates" because their treatment of coproduction violates basic physical laws? To answer that question, one would need to determine the reference relative to which the biases could be determined. One also would have to identify the sign of the bias and develop correction methods to rectify these systematic deviations in environmental pressure estimates. This identification, however, is impossible in general. There is no consensual, 'more exact' coproduction model that would better reflect an observable reality (Williams et al., 2009): we cannot observe partitioned productions, or productions that would have occurred had they not been substituted (Heijungs and Guinée, 2007), or technological proxies, which are all artifacts of deliberate modeling choices. The different coproduction models are promoted or criticized not based on their 'trueness' (Williams et al., 2009), but rather based on their concordance with different research perspectives (e.g., Ekvall et al., 2005; Weidema et al., 2009; Brander and Wylie, 2011; Wardenaar et al., 2012; Zamagni et al., 2012; Pelletier et al., 2015; Jung et al., 2012), data requirements, practical considerations, and desirable properties for different types of analysis (e.g., Viet, 1994; Kop Jansen and ten Raa, 1990; Almon, 2000; ten Raa and Rueda-Cantuche, 2003; Heijungs and Guinée, 2007; European Commission, 2008). The leading recommendation is to perform sensitivity analyses (Jung et al., 2013) to account for the existence of differing research perspectives and their influence on lifecycle environmental pressure estimates. We would therefore argue that allocations and constructs — and the physical imbalances that they introduce — are not associated with biased results (Fig. 3, left), but rather with a special type of uncertainty. This uncertainty has been categorized as "uncertainty due to choices" (Huijbregts, 1998; Björklund, 2002), "uncertainty due to fixing multi-functionality problems" (Jung et al., 2013), or as "scenario uncertainty" (Lloyd and Ries, 2007). Through a pseudo-statistical approach, this "choice uncertainty" can be propagated along with data uncertainty to lifecycle results (Mendoza Beltran et al., 2015).

In other words, if the goal and scope and the perspective of an LCA call for the choice of a certain method to allocate emissions and requirements (e.g., energy-based partitioning), leading to the respect of certain balances (e.g., conservation of energy) and not others (e.g., mass), we cannot treat this deliberate choice as a 'mistake' that should be 'corrected', nor can we identify a 'more true' estimate against which the direction and magnitude of our deviation could be assessed. We cannot identify a systematic overestimation or underestimation in the environmental pressure estimates that result from this modeling. A clear bias therefore cannot be identified, despite the physical imbalances that this allocation choice implies.

Though mass, energy, elemental, and price imbalances are key to identifying flaws in data compilation, especially in multilayered supply and use tables (SUTs), we find that such imbalances in calculated LCA and EEIO flows may result from deliberate and necessary coproduction modeling choices. Imbalances are thus sometimes associated with biased results (aggregation bias) and sometimes not (allocation, constructs), and they are therefore not a *sufficient* condition for the presence of systematic deviations in lifecycle results.

Since imbalances are neither necessary (Section 3.2) nor sufficient (Section 3.3) conditions for the presence of systematic deviations in environmental pressure estimates, we find that they are neither a clear cause nor a reliable indicator of bias.

4. Partial Practical Solutions

A greater granularity and homogeneity in the definition of product groups and activities, and the respect of physical and financial balances, are all desirable properties to be searched for in our models of the socio-economic metabolism. Given enough time and resources, the ideal solution to the problems posed by inhomogeneous product groups and inhomogeneous productions would obviously be to disaggregate them with additional data (Guinée, 2002; Nakamura et al., 2011). In Fig. 1, for example, dividing both the agricultural product and the agricultural sector with additional data on animal husbandry and grain farming would yield more homogeneous product and industry descriptions.

There is always a practical limit to data acquisition and disaggregation efforts, however. For a given level of data richness, we propose two strategies to reduce both imbalances and systematic deviations caused by inhomogeneous product mixes.

4.1. Disaggregation of Product Groups Based on Their Inhomogeneities

Descriptions of product group inhomogeneities may be sufficient information in and of themselves to disaggregate product groups, and thus resolve these inhomogeneities without additional data collection. This is notably the case with the example put forth by MH.

As discussed in Section 2.2, inhomogeneous product mixes are problematic because they lead to situations where one industry is described as producing one product with properties that differ for each purchaser. If properties differ, these purchasers are really buying different products, and the aggregate industry can be seen not as producing one product but rather as coproducing many products. This points to a potential solution to the problem of inhomogeneous product mixes: record the aggregate industry as coproducing multiple products instead of a single, inhomogeneous one. This transforms a product inhomogeneity problem into a coproduction problem, as recommended by Suh (2004).

In the example of MH, the price matrix indicates that manufactured products are sold at three different prices. We would then need to subdivide this inhomogeneous product group into three subgroups to achieve price homogeneity (subgroups A, B, and C, sold respectively at 0.8, 1.0, and 1.2 € per kg; see prices in Fig. 4). This disaggregation recasts the manufacturing sector as a multi-output sector, coproducing three

[9] Through the complex networks of our technosphere, almost every process is directly or indirectly involved in the lifecycle of every other, which makes it extremely likely that any given lifecycle will include allocated coproductions.

Mass Prices (€ · kg⁻¹)			Mixed-units (black and gray) and Value (black) Flows								
			Supply flows				Use flows				
			Agriculture Industry	Manufacture Industry	Energy Industry	*Total value*	Agriculture Industry	Manufacture Industry	Energy Industry	Final Demand	*Total value*
1.0	Agricultural prod.	€	7.0			*7.0*		1.0	2.0	4.0	*7.0*
0.80	Manufactured prod. A	€		1.6		*1.6*	1.6				*1.6*
1.0	Manufactured prod. B	€		3.0		*3.0*			3.0		*3.0*
1.2	Manufactured prod. C	€		3.6		*3.6*				3.6	*3.6*
-	Energy prod	€			7.5	*7.5*	3.0	3.0		1.5	*7.5*
	Value added	€					2.4	4.2	2.5		
	Resources	kg					8.0	9.0	0.0		
	Emissions	kg					-3.0	-2.0	-5.0		
	Total value	€	*7.0*	*8.2*	*7.5*	✓	*7.0*	*8.2*	*7.5*		✓

(kg)	Mass Flows								
	Supply flows				Use flows				
	Agriculture Industry	Manufacture Industry	Energy Industry	*Total*	Agriculture Industry	Manufacture Industry	Energy Industry	Final Demand	*Total*
Agricultural prod.	7.0			*7.0*		1.0	2.0	4.0	*7.0*
Manufactured prod. A		2.0		*2.0*	2.0				*2.0*
Manufactured prod. B		3.0		*3.0*			3.0		*3.0*
Manufactured prod. C		3.0		*3.0*				3.0	*3.0*
Energy prod			0.0	*0.0*	0.0	0.0		0.0	*0.0*
Value Added					0.0	0.0	0.0		
Resources					8.0	9.0	0.0		
Emissions					-3.0	-2.0	-5.0		
Total	*7.0*	*8.0*	*0.0*	✓	*7.0*	*8.0*	*0.0*		✓

Fig. 4. Supply and Use flows with extensions (value added and free* emissions and resources), recorded in mixed-units (top, gray and black), balanced in terms of monetary flows (top, black) and mass flows (bottom), assembled from the numerical example of MH, with manufactured products disaggregated into three subgroups (A, B, and C) based on per-transaction prices so as to obtain homogeneous prices (top left). Symbol: ✓ indicates a balanced layer. *Note: for the sake of simplicity and to stay close to the original example by MH, we assume, without loss of generality, that emissions and resources that are described in physical units come at no cost for the industry; i.e., value added aggregates all factor costs.

distinct product mixes (see Supply table in Fig. 4). From the original price matrix, we also know that the agriculture and manufacture industries purchase manufactured products at 0.8 €·kg $^{-1}$ (therefore product mix A); the energy industry purchases manufactured product mix B; and final consumers purchase manufactured product mix C (see Use table in Fig. 4).

As prices are now homogeneous, they can be used to convert the monetary flows into physical flows without introducing imbalances. Fig. 4 presents a valid, homogeneous, disaggregated sut.

This approach only constitutes a partial solution, since it gives rise to multifunctional industries. It has nonetheless the advantage of transforming an explicitly inappropriate EEIO system description (Weisz and Duchin, 2006) into a valid, balanced sut, without requiring additional data. This then provides a 'clean' starting point, to which practitioners may apply a wide range of allocation and construct models to generate symmetric EEIO or LCA representations, thereby introducing different assumptions depending on their research questions (Suh et al., 2010; Ecoinvent Centre, 2013; Majeau-Bettez et al., 2014). Some coproduction models may be able to respect most financial and physical balances, depending on the characteristics of the data (Kop Jansen and ten Raa, 1990; Weidema and Schmidt, 2010; Majeau-Bettez et al., 2016).

4.2. Choice of Base Unit to Reduce Aggregation

Although individual property layers make it possible to assess different physical and economic balances, LCA and EEIO calculations are almost always performed in a mixed-unit layer, as none of the physical or economic dimensions can typically represent all the flows of a system with a non-null value. In a pure mass layer, electricity flows cannot be represented (Fig. 4, bottom); in a purely economic layer, non-taxed emissions would not appear (Fig. 4, top, black); in a carbon layer, carbon-free emissions would necessarily be null and therefore lead to no environmental impact (Fig. 1, bottom, Emission 1). Only a mixed-unit layer can represent all flows of a system in a lifecycle calculation, and a choice must therefore be made as to which unit should be used to represent each product or factor of production in this mixed-unit layer. This choice of a 'base unit' offers an opportunity to minimize aggregation biases.

To minimize aggregation biases in lifecycle results, the differences between the production functions that are aggregated must be minimized (Fisher, 1958). If two recipes are most similar when expressed relative to a certain unit, then this unit minimizes the lifecycle biases resulting from their aggregation. For example, if it is known that requirements of agricultural processes typically differ more per kg of product than per MJ of product (because of, e.g., high variability in the water content of these products), then describing agricultural products with an energy unit rather than a mass unit in the lifecycle calculation would reduce aggregation biases in the environmental impact estimates.

Although services (e.g., banking, entertainment, health care) deliver functions that could theoretically be quantified in physical units (removal of grams of tumor, display of m^2·hours of cinema screen), these physical descriptions are so heterogenous that the service sectors are more appropriately (i.e., more homogeneously) accounted with monetary units (Duchin, 2009).

A potential way of reducing aggregation bias would therefore be to calculate lifecycle impacts with a mixed-unit framework (Weisz and Duchin, 2006) in which each technical recipe would be defined in terms of the unit most likely to minimize disparities within its sector. Further research is needed to generate heuristics to guide such choices of base units. The comparison of LCA and EEIO databases at different aggregation levels, extending Majeau-Bettez et al. (2011) across multiple reference units, seems like a promising approach. One can expect that some sectors will be best represented relative to a given physical unit of output — e.g., most homogeneous per kg, per MJ, or per kg-C of product — whereas other sectors will exhibit input structures that are most homogeneous when inventoried relative to a monetary unit of output.

5. Summary and Outlook

If an analysis requires solely the respect of a single physical balance, as is the case for the analysis by MH or for material flow accounting (Fischer-Kowalski et al., 2011), it is evidently beneficial to perform this analysis in the physical unit of interest. However, if we strive for the concurrent respect of multiple balances (conservation of mass, energy, carbon, etc.), banning monetary units from LCA and EEIO analyses will be of no avail (Section 2.3). The absence of physical imbalances in Leontief models depends not on the exclusive use of physical measurements but on the level of resolution and homogeneity of product groups. In this respect, excluding high-resolution monetary statistical data from our analyses would be counterproductive.

Though physical and financial balances are essential quality checks in the compilation of inventories, we found that the presence of imbalances in calculated flows is not a necessary nor a sufficient condition for the presence of biases in lifecycle pressure estimates. Using imbalances to identify biases misses aggregation biases caused by product groups that are inhomogeneous in terms of non-conservative properties (Section 2.3); and it conflicts with modeling choices that resolve situations of coproduction (Section 3.3). Rather, it would be preferable to focus directly on the causes of systematic deviations in EEIO and LCA, notably the inhomogeneous aggregation of product groups and production functions (Section 3), along with the incompleteness of inventories (truncation errors, see Lenzen, 2002; Suh and Huppes, 2002; Norris, 2002; Majeau-Bettez et al., 2011).

Inconsistent use of monetary data constitutes another potential source of systematic deviation. It is crucial that practitioners express all prices in a single valuation scheme. Working at 'basic prices', as is typically done in EEIO (e.g., Lenzen et al., 2013), notably corrects for the influence of taxes, subsidies, and trade margins (United Nations, 1999). This more directly relates the value of products to their production costs, and it reduces price inhomogeneities between small and large consumers.

Some level of data aggregation and inhomogeneity is practically unavoidable, but the ongoing development of multi-unit, multilayered inventories offers new opportunities to refine LCA and EEIO analyses.

When the inhomogeneities in the inventory can be quantified, as in the example by MH, then this information is sufficient to disaggregate the inhomogeneous product groups into homogeneous sub-groups (Section 4.1). This step, which recasts a situation of inhomogeneity into a situation of coproduction, could be automated; with the right software, it could become a reproducible and transparent part of the calculation routine (Pauliuk et al., 2015b).

For situations where inhomogeneities are suspected but not quantified, we suggest to rely on heuristics to guide the choice of the 'base unit' used in the LCA or EEIO calculation, so as to minimize systematic deviations in environmental pressure estimates (Section 4.2). The specific production functions within each aggregated sector of the economy may present a greater similarity when expressed relative to a certain unit (kg, or €, or MJ of products, etc.) By relying on such heuristics, the careful selection of the right unit to express the output of each sector therefore has the potential to reduce aggregation biases at a given level of data resolution.

These research avenues should be part of a concerted effort to consolidate data collection and modeling across the LCA, EEIO and MFA research communities, so as to build a cumulative knowledge base, avoid systematic deviations, and bolster the physical and economic credibility of research on our socioeconomic metabolism and its interaction with the environment.

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Appendix A. Supplementary data

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