# Review of methods to trace material use to final products in dynamic material flow analysis - from industry shipments in physical units to monetary input-output tables (part I)

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# Abstract

To connect services for human well-being with constituting resource use, we require knowledge about the allocation of total material consumption to different ‘end-use products’, i.e. the different product stocks as which material consumption accumulates, because product lifetimes, recycling potential, and contribution to human well-being vary greatly. Previous estimates of materials in end-use products often only cover few years, countries, and product groups. Recently, several methods to distinguish end-use products in dynamic material flow analysis (dMFA) were proposed, which so far lack a systematic comparison.

Herein, we review five approaches for tracing material consumption to end-use products in top-down dMFA and systematize them to discuss their strengths and limitations. We find that widely used data on industry shipments in physical units has low spatio-temporal coverage, limiting their applicability across countries and years. In contrast, monetary input-output tables (MIOTs) are widely available and their coverage of economy-wide industry sectors makes them a valuable data source to approximate material end-uses. We find four distinct MIOT-based approaches: consumption-based, waste-input-output MFA (WIO-MFA), Ghosh absorbing Markov chain, and partial Ghosh methods. We show that when applied to a given MIOT, the methods’ underlying input-output models yield the same results, with exception of the partial Ghosh approach which involves simplifications. The key distinction between approaches is the manipulation of MIOT-data to adjust the system boundaries between MIOTs and dMFA. WIO-MFA produces the most accurate results as it customizes MIOT system boundaries by excluding massless and waste transactions, even so differences to dMFA remain for classifying intermediate and end-use products.

# Introduction

Dynamic Material Flow Analysis (dMFA) is increasingly used for the mass-balanced modelling of socio-economic material stocks and flows, thereby enabling estimations of the biophysical basis of society, including economy-wide, long-term, high process and product resolution stock-flow dynamics (Müller et al. 2014; Lanau et al. 2019; Haberl et al. 2019). Such information offers important insights on sustainability and high-level political goals like the Sustainable Development Goals or the Paris Climate Agreement (Pauliuk und Hertwich 2015; Haberl et al. 2019; Clark und Harley 2020).

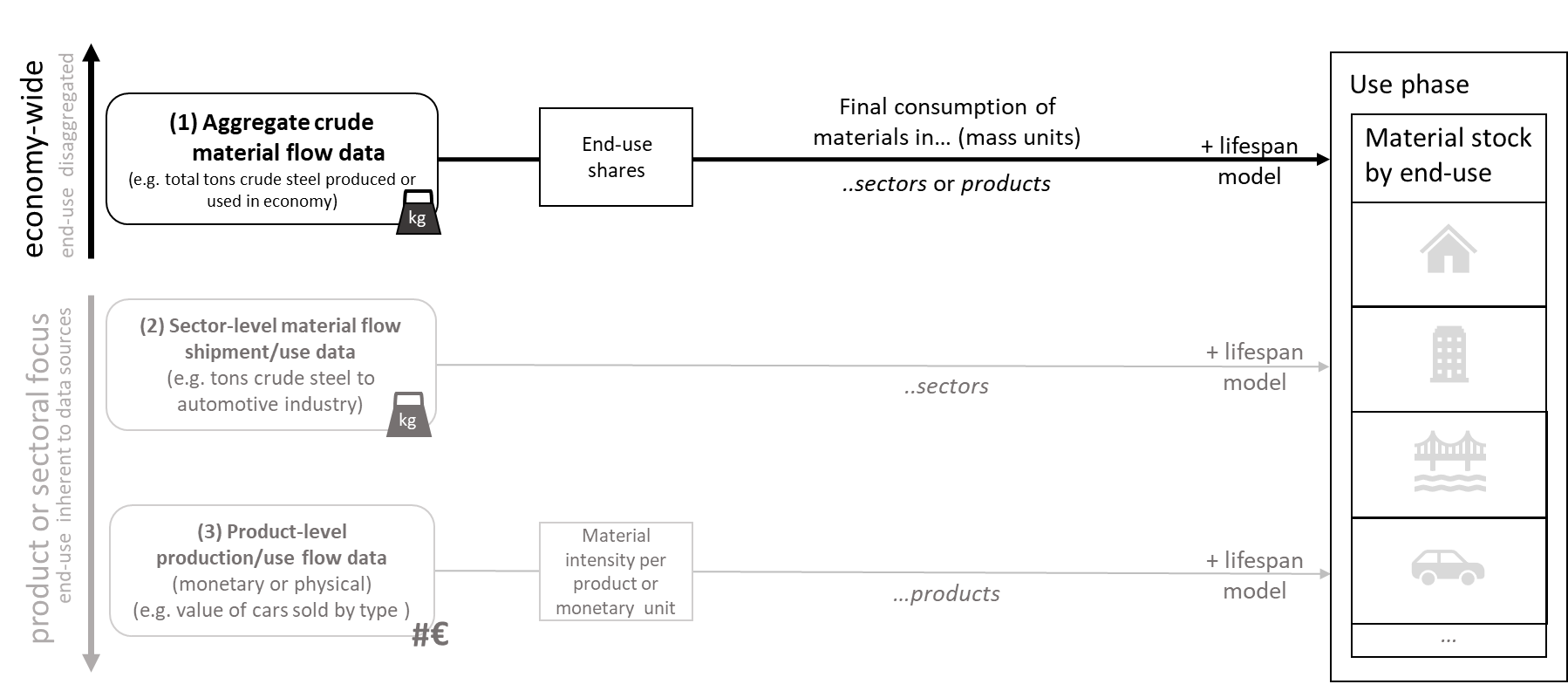
Research using dMFA can be divided into stock-driven (‘bottom-up’) and inflow-driven (‘top-down’) applications, depending on which exogenous data is used to endogenously derive either stocks or flows (Müller et al. 2014; Lanau et al. 2019; Wiedenhofer et al. 2019). We herein focus on inflow-driven ‘top-down’ dMFA that draws on widely available data on material or product consumption, production and trade, and models the accumulation of stocks from those physical flows into use (Wiedenhofer et al. 2019). One drawback of the underlying data is that they either refer to specific products, or report total economy-wide material consumption that does not distinguish products (Müller et al. 2014; Chen und Graedel 2015; Lanau et al. 2019). Improving the resolution and coverage of end-use products in inflow-driven dMFA is therefore an important research frontier.

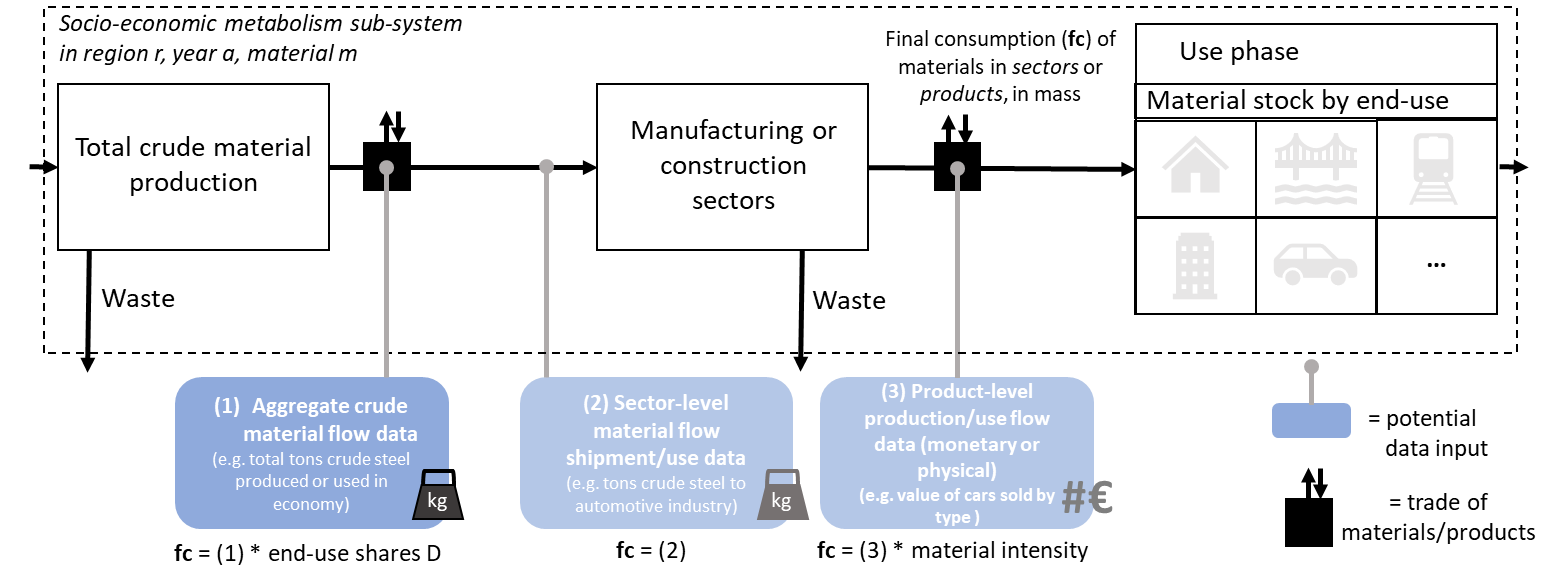
Material end-use products refer to the type of product stocks as which materials accumulate and which are ultimately used to provide functions and services (e.g. living space provided by buildings, mobility enabled by infrastructure and bicycles, cars, trams, etc.; Haberl et al. 2017; Carmona et al. 2017; Tanikawa et al. 2021). Improved end-use product resolution would enable progress on: first, refined modelling of material stock dynamics and end-of-life outflows through more appropriate lifetime assumptions (Chen und Graedel 2015; Miatto et al. 2017); second, better possibilities for validation and integration with independently derived ‘bottom-up’ end-use estimates, as well as information for further analysis, such as energy use, emissions, or circularity; and third, linking stocks and flows with material and energy services, practices and ultimately their contributions to well-being (Haberl et al. 2021).

To model the end-use products that materials accumulate in, inflow-driven dMFA studies draw on various data sources and methodological options (Figure 1). In this article, we focus on the first option, which directly starts with widely available economy-wide data on production, trade and apparent consumption for many materials (Figure 1, option one) . Because this data is compiled in an aggregate manner, material end-uses need to be re-introduced exogenously, using data on ‘end-use shares’ as proxy (Figure 1, identifier one). Ideally, information on ‘end-use shares’ should be on the product rather than sectoral level (Chen and Graedel (2015) and Chen (2017)). Sector and product-specific data (Figure 1, option 2&3) directly provide end-use information when estimating material flows (reviewed in Chen und Graedel (2015)) but are often scarce and/or very labor intensive to compile, rendering the economy-wide, long-term coverage of many materials, end-uses and countries hardly achievable.[[1]](#footnote-1)

Table 1: Approaches for inflow-driven dynamic Material Flow Analysis to differentiate material end-uses by product or sector-level stocks, inspired by Chen und Graedel (2015). Material end-uses are the ‘products’ as which materials accumulate, e.g. the steel accumulated in a bicycle, car, building or infrastructure. Data availability and research scope determine which approach is feasible and useful (Chen und Graedel 2015; Wiedenhofer et al. 2019)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Scope | Option | Data source | Unit | Example | Introduction of end-use information | Result: final consumption of materials in … [units: mass] |
| Economy-wide | 1 | Aggregate crude material flow data | mass | Total tons crude steel produced or used in economy | Introduced via ‘end-use shares’ | Products or sectors |
| Product or sectoral focus | 2 | Sector-level material flows shipment / use data | mass | Tons crude steel to automotive industry | Inherent in data | Sectors |
| 3 | Product-level production / use flow data | Number or value of items | Number or value of cars sold, by type | Inherent in data; mass introduced via material intensities | products |





To derive the required ‘end-use shares’ for economy-wide material flows, several methods and data sources have been utilized. However, so far, these methods have not been systematically compared and due to different terminology, mathematical notations, as well as study scopes, it is difficult to assess their strengths and weaknesses. Additionally, inflow-driven dMFA is increasingly utilized for global-country level modelling and recent studies have begun to re-use published end-use shares from original works (e.g. Klose und Pauliuk 2021; Godoy León et al. 2020; Jarrín Jácome et al. 2021; Wieland et al. 2021). Therefore, it seems relevant to comparatively assess these methods to inform and improve result re-usability, as well as cumulative research efforts for economy-wide, long-term modelling for many materials and across spatio-temporal scales, i.e. national to global. Here, we pose the following research questions:

* RQ1: Which data sources and methods have been used to determine the share of different end-use products in the final consumption of different materials (‘end-use shares’) for inflow-driven dynamic Material Flow Analysis?
* RQ2: What are the specific rationales and methodological requirements for each method and what are their similarities, differences, strengths and weaknesses in terms of consistent system boundaries and end-use resolution, as well as efficient application to many materials, countries and years?

In this study, we conceptually review and compare five distinct methods to derive material end-use shares applicable to economy-wide material flows, drawing on industry shipment data in physical units and monetary Input-Output Tables (MIOTs). We first give an overview of the identified literature and methods and discuss each methods’ data availability, clarity of documentation, system boundaries and potential end-use resolution. We then focus on MIOT-based methods and provide a harmonized description of the procedures, rationales and methodological requirements. In section 3 we conclude on industry shipments vs. MIOTs, and on the different MIOT-based methods, and suggest potential methodological improvements. In part II of this work, we also comparatively apply the five identified methods, including the suggested improvements, to the data-rich case of the USA, as well as to regions of a multi-regional input-output model (Streeck et al. in prep.).

# Reviewing methods to derive end-use shares

To identify all original methods which exogenously derive end-use shares for inflow-driven dMFA, we searched the English-language peer-reviewed literature, going through the comprehensive reviews by Müller et al. (2014) and Lanau et al. (2019), searched google scholar, and drew on in-house expertise together with citation snowballing, with a cut-off in January 2022. We did not aim to systematically cover every single study using these methods. Rather, we want to identify and review pioneering studies and recent prominent applications, to identify the strengths and weaknesses of the state of the art.

Nakamura et al. (2014) found that various terms are used to describe ‘end-use shares’, which suggests that there is no harmonized definition. Terms range from ‘branching ratio’ (Spatari et al. 2005), ‘sector split’ (Müller et al. 2006), ‘distribution of resources among consumption products’ (Duchin und Levine 2010), ‘share of each respective end-use’ (Hatayama et al. 2010), ‘product-to-use matrix’ (Cullen et al. 2012; Wang et al. 2007), ‘allocation matrix’ (Cullen et al. 2012), ‘allocation matrix of materials to final products’ (Nakamura et al. 2014), to ‘split ratio of end-use sectors’ (Cao et al. 2017b). The different terms already point towards different methods and scopes to derive end-use information. Herein, we consistently use the terms ‘end-use shares’, and scrutinize if the reviewed methods can yield information on actual products or product groups, instead of only broad sectors, such as ‘construction’.

We found five original methods to derive material end-use shares, based on two widely used types of data sources (Table 1). Firstly, there are many studies using industry shipment data in physical units, the sample in Table 1 achieving 3-10 end-uses (17 end-uses as exception). Secondly, we find four methods using MIOTs, the underlying studies achieving 3-33 end-uses, some focusing on one specific product type.

Industry shipments are reported by statistical bureaus (e.g. International Steel Statistics Bureau), industry associations (e.g. International Wrought Copper Council), or geological surveys (e.g. USGS mineral commodity summaries; Kelly und Matos 2014). Terminology and definitions vary, from ‘shipments […] to manufacturing and fabrication’ (Dahlström et al. 2004), ‘shipments by end-use‘ (The Aluminum Association 2009), ‘apparent use […] by market‘ (PCA 2016), or ‘supply […] in the end-use markets’ (CDA 2020). Herein, we use the summary term ‘industry shipments’. Pioneering studies using end-use shares derived from industry shipments started in the 1990s, focusing on single materials and countries with good data availability (Melo 1999; Zeltner et al. 1999; Dahlström et al. 2004). Several recent and prominent studies followed that approach and extrapolated end-use shares available for only a few years and single countries, to conduct global, country-level, long-term modelling (Pauliuk et al. 2013; Müller et al. 2006; Glöser et al. 2013; Liu und Müller 2013; Cao et al. 2017b). Details can be found in Table 1, and section 2.1. below.

The second major approach, containing four original methods, utilizes monetary input-output tables (MIOTs) to derive end-use shares (Table 1, and section 2.2. below). MIOTs contain data on monetary flows between economic sectors, which can be used as proxy for physical flows, and are available from national statistics offices (e.g. US BEA 2021). From the identified studies, 12 works used national-level MIOTs to derive end-use shares, thereof 7 for Japan or the USA, which provide the most detailed MIOTs globally. National MIOTs were also linked into several global, multi-regional input-output models (MRIOs), most of those starting in the 1990s (Inomata und Owen 2014; Tukker et al. 2018), some already in the 1970s (Lenzen et al. 2013; Lenzen et al. 2021). To our knowledge, Pauliuk et al. (2017) present the only empirical case using an MRIO with coverage of many countries/regions (25) for dMFA purposes.[[2]](#footnote-2)

Table 2: Overview of selected studies that use industry shipment data in physical units versus input-output tables in monetary units to derive material end-uses or end-use shares for (inflow-driven) dynamic Material Flow Analysis. Only highly cited or recent studies are listed for industry shipment data.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Physical  Industry shipments (prominent examples) | **Publication** | **Material flows** | **Geographical resol.** | **Time** | **End-uses** | **End-use source** | **Actual data on end-uses for:** |
| Zeltner et al. (1999) | Copper | USA | 1900-2100 | 10 | Black und Lyman (1990) | 1975, 1989 |
| Melo (1999) | Aluminum | Germany | 1970-2012 | 7 | Metallgesellschaft and WBMS as cited in Melo 1999 | 1985-1995 |
| Dahlström et al. (2004) | Iron & steel, aluminum | UK | 1958/68-2001 | 6/9 | Alfed, WBMS, ISSB | 1978-2011, 1958-1997, 1970-2000 |
| Spatari et al. (2005) | Copper | North America | 1900-1999 | 10 | various, e.g. U.S. Bureau of Mines (1941), CDA (1980), literature, expert knowledge | unclear |
| Müller et al. (2006) | Iron | USA | 1900-2004 | 4 | AISI (domestic shipment), imports as domestic shares | 1941-1999 |
| Daigo et al. (2007) | Steel | Japan | 1980-2000 | 7 | JISF 1971–2003 | ~1971-2003 |
| Kapur et al. (2008) | Cement | USA | 1900-2005 | 7 | USGS, PCA | unclear |
| Hatayama et al. (2010) | Steel | 42 countries | 1980-2005 | 8 | 40 countries with 1-6 datapoints: JISEA 1980-2005, USA: AISI 1960-2006, Japan: JISF 1971-2000 | min. 1980, max. 2005, ~1960-2006, ~1971-2000 |
| Du und Graedel (2011) | 15 rare earths | Global, total\*\* | 1995-2007 | 17 | USGS, CSRE (2008), JOGMEC (2007), MERI/J (2003), resolution unclear (~China,Japan,USA) | ~2007 |
| Glöser et al. (2013) | Copper | Global, total | 1910-2010 | 17 | ICSG, ICA & Ayres et al. (2003), resolution unclear | 1912-2008, 2006-2010 |
| Pauliuk et al. (2013) | Iron & steel | Global, country-level | 1700-2008 | 4 | USA: AISI (1941-2005), UK: ISSB (1979) & Dahlström et al. (2004), India: SERC | 2004, 1960-65 & 1970-2000, 1995-1999 |
| Liu und Müller (2013) | Aluminum | Global, country-level | 1900-2010 | 7 | 19 countries, various sources, e.g. WBMS, GARC, Alfed | min. 1950, max. 2010 |
| Cao et al. (2017a) | Cement | Global, country-level | 1950-2014 | 3 | Statistics by industry experts, e.g. PCA, Cembureau | min. ~1990, max. 2011 |
| Geyer et al. (2017) | Plastics | Global, total | 1950-2015 | 7 | Various, e.g. PlasticsEurope, ACC, CPMAI, for EU, USA, China, India | 2002-2014 |
| Carmona et al. (2021) | Steel in transport sector | UK | 1960-2015 | 5 | WSA and secondary data made available by Dahlström et al. (2004) and Pauliuk und Hasan (n.a.) | 1978–2011,see Dahlström et al., unclear |

\*\* however, some country-level results in text; ~indicates that the period is not entirely clear from documentation and that primary sources could not be accessed for checking; ACC = American Chemistry Council; Alfed = The Aluminum Federation; AISI = American Iron and Steel Institute; Cembureau = European Cement Association; CDA = Copper Development Association; CPMAI = Chemical and Petrochemicals Manufacturers’ Association India; CSRE = Chinese Society of Rare Earths; GARC = Global Aluminum Recycling Committee; ICA = International Copper Association; ICSG = International Copper Study Group; ISSB = Iron and Steel Statistics Bureau; JISEA = Japan Iron and Steel Exporters’ Association; JISF = The Japan Iron and Steel Federation; JOGMEC = Japan Oil, Gas and Metals National Corporation; MERI/J = Metal Economics Research Institute, Japan; PCA = U.S. Portland Cement Association; SERC = Spark Steel & Economy Research; USGS = United States Geological Survey; WBMS = World Bureau of Metal Statistics; WSA = World Steel Association

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Monetary  Input-Output Tables | **Sub-approach** | **Publication** | **Material flows** | **Geography/resolution** | **Time** | **End-uses** | **Source for IO table** | **Validation?\*** |
| Consumption-based accounting (CBA) | Hashimoto et al. (2007) | Construction minerals | Japan | 1995 | 24 | Japanese 1995 | 2nd method |
| CBA + investment matrix (section 2.2.5) | Dombi (2018) | Total domestic extraction | Hungary | 1995-2015/ 2001-2015 | Exiobasev2 sectors (3 further analyzed) | Exiobasev2 2007, EU KLEMS, Hungarian statistics | Comparison to literature (Dombi et al. 2018) |
| Waste Input-Output Approach to Material Flow Analysis (WIO-MFA)\*\*\*  (Nakamura und Kondo 2002; Nakamura et al. 2007) | Nakamura et al. (2014) | Steel in a car | Exemplary/Japanese data | 100 years | Car (1) | Japanese 2005 | No |
| Pauliuk et al. (2017) | Steel | Global, 25 regions | 2015-2100 | 10 | Exiobase2 2007 | Sensitivity Analysis |
| Yokoi et al. (2018)\*\* | Copper | Japan | 2011 | 16 | Japanese 2011 | No |
| Nakatani et al. (2020) | Plastic containers & packaging | Japan | 2015 | Packaging (1) | Japanese 2000/05/11/15 | No |
| Helbig et al. (2022) | 7 metal elements | Global, global | 1000 years | 11 | Combine ExiobaseV3 2011 & Japanese 2005 | Comparison to USGS 2011 production data |
| WIO-MFA + price extension (section 2.2.5) | Chen und Graedel (2015) | Aluminum | USA | 1963-2007 | motor vehicles (1) | U.S. BEA benchmark 1963-2007 | Other estimation methods |
| Chen (2017) | Aluminum | USA | 1963-2007 | 33 (>100 products) |
| WIO-MFA + investment matrix (section 2.2.5) | Kondo et al. (2012) | 17 materials | Japan | 2000 | 10 (in 17 sectors) | Japanese 2000 | No |
| Yokoi et al. (2022)\*\* | Copper | Japan | 1960-2015 | 16 (in 12 sectors) | Japanese (1960-2015, ~5 yearly) | Comparison to literature |
| Partial Ghosh-Input-Output (IO) | Cao et al. (2017a) | Cement | China | 1970-2013 | 3 | Eora national table 1970-2013 | Statistics in mass 1999/2000 |
| Aryapratama und Pauliuk (2019) | Wood | Indonesia | 1961-2016 | 6 | Indonesian 2010 | No |
| Ghosh-IO Absorbing Markov Chains (AMC) | Duchin und Levine (2010) | Exemplary ‘resource’ | exemplary | exemplary | 3 exemplary | exemplary | - |
| Duchin und Levine (2013) | ‘Ores’ | Global, 3 regions | 1990 | 4 | WTMBT 3 regions | - |

\*of end-use shares, \*\*Yokoi et al. (2018,2022) also apply transaction specific prices (in a price extension), \*\*\*multiple other studies apply WIO-MFA, mostly in static studies looking at a single year, e.g. in substance case studies Nakamura et al. (2009), as methodological development (Nakamura et al. 2011; Ohno et al. 2017b) or to track material flows through supply networks (Chen et al. 2016; Ohno et al. 2016; Jiang et al. 2017; Nuss et al. 2019). Schiller et al. (2017) also use MIOTs to estimate the direct material input (DMI) of stock-building materials going to ‘capital goods’. To the best of our knowledge, the authors understand capital goods as certain types of equipment not falling under buildings, infrastructure or consumer goods. From the documentation in Schiller et al. (2015) it seems that a classical Leontief model (CBA) was used with one particular category of final demand (‘Ausrüstung und sonstige Anlagen‘ = capital goods) to calculate end-uses. However, certain service flows in the interindustry/technology matrix were not considered, which resembles aspects of WIO-MFA. Furthermore, the authors did not distinguish DMI output by MIOT sector but rather estimated DMI in capital goods by using the final demand category ‘capital goods’ as final demand vector, which is somewhat similar to disaggregated investment matrices. As the documentation does not give explicit formulas, we cannot surely allocate the cited work to a specific method. Eora = see Lenzen et al. 2013; EU AMC = Absorbing Markov Chains; KLEMS = see O’Mahony und Timmer 2009; Exiobase = see Stadler et al. 2018; U.S. BEA = United States of America Bureau of Economic Analysis; WTMBT = World Trade Model with Bilateral Trade (Hammer Strømman und Duchin 2006); USGS = United States Geological Survey

## 2.1 Assessing industry shipments as approach and method to derive end-use shares

Industry shipments are at first sight an attractive data source to derive end-use shares and have been applied to various materials, countries and years (Table 1). However, there are number of critical limitations to be considered, starting from practical data scarcity and inaccessibility, as many times substantial fees or memberships have to be paid for (e.g. The Aluminum Association 2009), to poor documentation of data generation, system boundaries and end-use definitions, as well as usually quite low end-use resolution reported. Consequently, when such data is applied, various extrapolations and assumptions are required to compensate for the following limitations:

*Scarce coverage of space and time:* industry shipment data requires use of large-scale extrapolation. Pauliuk et al. (2013) for instance mapped industry shipment data for India (1995-99), the UK (1960-65/1970-2000) and the USA (2004) to three sets of four end-use shares each (transport, construction, machinery, products) and used the derived shares as time-constant for all countries globally. The authors then optimized international end-use shares by selecting those shares resulting in the best scrap market balance.

*Incomplete reporting of material flows:* first, data at times reflects only a share of total economy-wide material use or production. Second, data can either refer to shipments to manufacturing sectors (mostly for highly manufactured materials, e.g. steel to automotive), in which case trade of final products is not included; or to shipments to final markets for which trade is included (mostly for little manufactured materials, e.g. cement to residential buildings). Both points are not always transparently reported, e.g. the inclusion of imports of materials contained in final products (end-uses) can remain unclear (Pauliuk et al. 2013). To nonetheless achieve coverage of economy-wide material flows, end-use shares derived from shipments are often combined with independent estimates of total apparent consumption or gross additions stocks to derive total material end-use.

*Ambiguous system boundaries of end-use categories*, becausecertain categories such as ‘construction’ are very broad and might contain only the materials used for constructing buildings, infrastructure, etc., or additionally can also contain the machinery and tools for construction activities. For example, in the USA this is the case for copper end-use statistics, while it is not specified for aluminum in the publicly available data sources (CDA 2020; The Aluminum Association 2009; Kelly und Matos 2014).

*Incoherent system boundaries across materials*,because definitions of end-uses differ across materials, e.g. material use for ‘containers and packaging’ is reported as own category in U.S. aluminum, but included in the category ‘others’ for iron and steel statistics (Chen und Graedel 2015).

*Potential for misclassification*,because industry shipments toend-uses might actually be intermediate products, which are supplied to other end-use products. Ohno et al. (2017a) give the example of ‘electric and electronics equipment’ being delivered to the ‘automobile industry’ in which case part of the material in the first end-use would be misclassified.

*Non-descriptive and unclear end-use definitions*, where substantial shipments to sectors such as ‘service centers’ or ‘other’ are reported, where the actual end-use of the respective shipments remains unclear (Pauliuk et al. 2013; USGS 2018).

*Low end-use resolution*: the resolution of shipments’ destination (end-use) is often on a more aggregated sectoral rather than product level (Chen und Graedel 2015; Ohno et al. 2017a).[[3]](#footnote-3)

## 2.2 Assessing monetary input-output tables as approach to derive end-use shares (MIOTs)

MIOTs are derived from the system of national accounts, thereby following a national, economy-wide system boundary, and report on the sectoral interdependencies of an economy (United Nations 2009, 2014). They are widely available (e.g. US MIOTs since 1947), they cover all economic sectors, including many sectors of material production, and they show medium to high sector resolution which enables detailed modelling of end-use sectors or even products (Chen und Graedel 2015). However, utilizing MIOTs as proxy for physical flows can come with several assumptions, the most prominent being the assumption of homogenous prices for each sector and product group output, assuming proportionality between monetary and physical flows (Bullard und Herendeen 1975; Weisz und Duchin 2006).[[4]](#footnote-4)

To facilitate the description of the four MIOT-based methods to derive end-use shares in the following sub-sections, Figure 2 gives an overview of a schematic typical MIOT, visually illustrating its structure and contents. In the equations below, non-italic, non-bold lower-case letters (like ‘a’) denote vectors and italic, non-bold lower-case letters (like ‘*c*’) denote scalars or elements of vectors/matrices. Non-italic, bold uppercase letters (like ‘**B**’) stand for matrices. *i* and *j* stand for row and column indices respectively. e stands for appropriate column vector for summation that contains only ones. ^ denotes diagonalization of a vector.

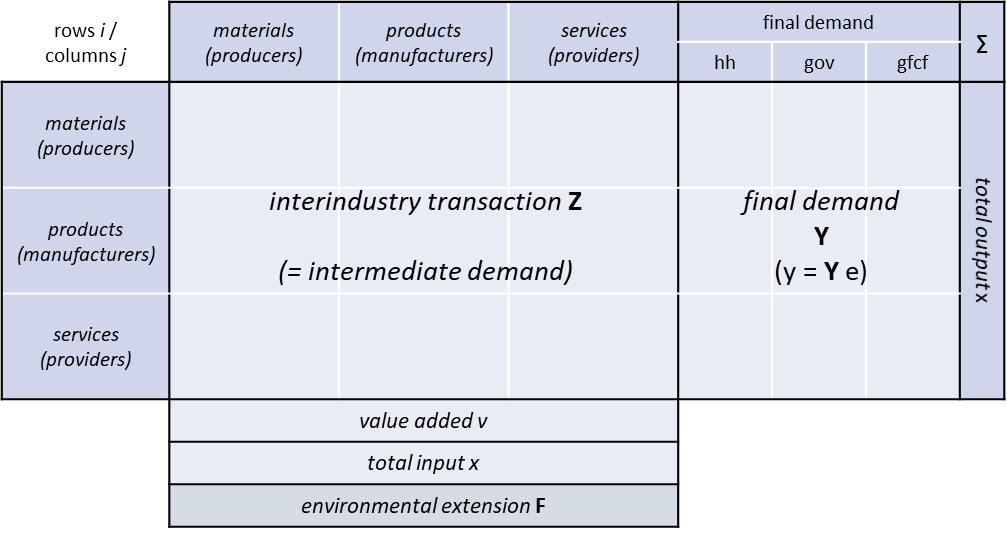


Figure 2: Schematic Input-Output Table (IOT) with exemplary three sectors corresponding to materials, intermediate or consumer products, and services. The labels for the table’s compartments are used in subsequent equations. hh = household consumption, gov = government consumption, gfcf = gross fixed capital formation.

For the transparent comparison of the four methods below, we define the end-use share matrix which satisfies the following conditions: 0 ≤ ≤ 1 , . can come in two different forms: for an element indicates the share of sector output *i* (e.g., a material; row)contained in the deliveries of sector *j* (column) to final demand, *j* therein identified as end-use sector for *i* (the index referring to one of the four identified methods in sections 2.2.1-2.2.4: WIO-MFA, CBA, Ghosh-IO AMC, and Partial Ghosh-IO). For an element states the share of a natural resource or material (e.g., an ore or crude steel) listed in the extension table that is allocated to the deliveries of sector *j* to final demand. In here, we primarily show the calculation of . The two forms of can be transformed into each other, using a matrix of allocation factors of environmental indicators in satellite to sectors *j* (, for details see SI2).

### 2.2.1 The Waste Input-Output Approach to Material Flow Analysis (WIO-MFA)

WIO-MFA was first presented in Nakamura et al. (2007), introducing a mass-balanced material flow analysis perspective into MIOTs. WIO-MFA aims to manipulate monetary transaction data to approximate the flow of materials into downstream supply chain products at their actual mass. For this purpose, WIO-MFA introduces filter matrices which exclude all monetary inputs that do not become part of the ‘physical output’ of a supply chain sector (‘physical output’ of MIOT sectors assumed according to sector label/definition, e.g. automobile production assumed to output automobiles). The mass filter matrix excludes all monetary inputs deemed to be non-physical transactions (i.e. service transactions; see Figure 3), and the yield factor matrix deducts part of the monetary transactions as processing waste, the remainder of which (1-) defines a waste fraction. Both matrices are multiplied element-wise (Hadamard product ) with the technology matrix to exclude non-physical transactions and separate waste flows (Equation 1):

|  |  |
| --- | --- |
|  | Equation 1 |

is furthermore partitioned according to the degree of the sector output’s fabrication. is a matrix with only non-zero elements for those transactions where ‘materials’ *i* become part of ‘products’ *j* (see Figure 3). is a matrix with only non-zero elements for ‘products’ *i* becoming part of other ‘products’ *j*.[[5]](#footnote-5) This partition is crucial to enforce mass-balance across the WIO-MFA model (Nakamura et al. 2007).

From these two matrices, a material composition matrix is calculated (Equation 2). Each coefficient of states the concentration of materials in product output to final demand, i.e. the material input *i* per (monetary) output of produc*t j* leaving the interindustry system towards final demand.

|  |  |
| --- | --- |
|  | Equation 2 |

To obtain , a calculation similar to obtaining the Leontief inverse is conducted, with the difference that the interindustry system is cut off towards upstream material sectors. Thus does not represent supply chain wide requirements, but a material concentration matrix, in which the exogenous direct material input *i* to product *j* () is delivered to the industry system (), which traces product-to-product flows across industry supply chains. coefficients can be in either monetary or hybrid units depending on the original units of the partitioned matrix. WIO-MFA equation 2 is the analogue of a Leontief price model, just that the material concentration table is substituted for the commodity price and exogenous material input for value added (for detailed explanation, see SI2).

To calculate the end-use share matrix , i.e. the output share of material *i* (e.g. cement) as product *j* (e.g. a house) to final demand, material composition is post-multiplied with final demandand divided by total output of material*i* contained in all products *j* (Equation 3, Nakamura et al. 2014).

|  |  |
| --- | --- |
|  | Equation 3 |

Below, we briefly describe selected literature studies that use WIO-MFA for splitting aggregate material flows to end-use categories (see Table 1).

**Nakamura et al. (2014)** developed the MaTrace model, a combination of dynamic MFA and a linear IO-model, to trace material flows through their lifecycle, amongst others, to end-use products. The authors apply the model to trace ferrous materials in Japanese passenger cars and use the WIO-MFA approach together with the Japanese MIOT for the year 2005 to generate an end-use share matrix for refined materials. **Pauliuk et al. (2017)** extended the model by Nakamura et al. (2014) to MaTrace Global which covers steel flows in the global economy in 25 regions. They used the MRIO database Exiobase v2 for the year 2007 in combination with WIO-MFA to calculate the end-use share matrix for all regions. Several other studies used and extended upon the original MaTrace model, including the development of MaTrace-alloy (Nakamura et al. 2017), MaTrace-multi (Helbig et al. 2022), and various case studies (e.g. Takeyama et al. 2016; Klose und Pauliuk 2021; Godoy León et al. 2020; Jarrín Jácome et al. 2021; not all of them use WIO-MFA to derive end-use shares). Nakamura und Kondo (2018) furthermore worked towards a dynamic model for the Waste-Input-Output approach by integrating it with MaTrace-alloy, which also comprises an end-use share matrix.

**Yokoi et al. (2018)** present an approach to distinguish pathways of material flows that accumulate as end-use products in final demand versus in endogenous (interindustry) sectors, and those that are accompanying product flows (e.g. packaging) or are dissipated within the industries, and apply it for WIO-MFA and copper flows in Japan (2011). Additionally, the authors propose a new approach to distinguish materials in different processing forms for WIO-MFA (2.1.4. in Yokoi et al.), which is similar to the Hypothetical Extraction Method that has been proposed for the Leontief model (Dietzenbacher et al. 2019; Hertwich 2021) and with similar outcome to a method already introduced in the original WIO-MFA publication by Nakamura et al. (2007). The approaches to distinguish materials in different processing forms are also important for differentiating end-uses and are further elaborated on in section 3.2. The approach of Yokoi et al. (2018) was furthermore applied by **Nakatani et al. (2020)** who trace the flows of plastic containers and packaging in Japan.[[6]](#footnote-6)

### 2.2.2 Consumption-based accounting (CBA)

CBA is widely used to estimate so-called environmental footprints (Wiedmann et al. 2006; Galli et al. 2012; Wiedmann und Lenzen 2018). In there, environmental burdens from socio-economic activity are allocated to categories of final demand, depicting the ‘embodied’ environmental burdens accumulating along (global) supply chains. To estimate the flow of embodied environmental burdens per sector, i.e. sector *footprint* , an environmental extension (expressing the absolute environmental burden by sector) is divided by total output , and multiplied with the total requirement matrix and the vector of final demand (Equation 4):

|  |  |
| --- | --- |
|  | Equation 4 |

The environmental extension can be constructed either as supply or use-extension (Owen et al. 2017; Wieland et al. 2020). For materials, a supply-extension translates to the supply or extraction of raw materials (e.g. limestone) by different sectors, while a use-extension refers to semi-manufactures that are used further downstream the supply chain (e.g. cement made from limestone used in construction). Depending on extension choice, the footprint has different interpretations: for the supply-extension, element of matrix represents the accumulated amount of natural resource *i* (e.g. limestone or iron ore), while for the use-extension the accumulated amount of material *i* (e.g. cement or steel), that is required for producing the final demand for sector *j*.

From equation 4, the end-use share matrix , can be calculated via Equation 5, with coefficients representing the share of environmental burdenthat is embodied in final demand of sector *j*. , i.e. the share of sector output *i* that is embodied in final demand of sector output *j*, can be calculated via Equation 6. In comparison to WIO-MFA, does not solely contain end-use shares for ‘materials’ but also for all other MIOT sectors (potentially including both ‘products’and ‘services’ in the sense of Figure 3).

|  |  |
| --- | --- |
|  | Equation 5 |
|  | Equation 6 |

For CBA, the end-use shares calculated for sector output *j* include all upstream direct and indirect (raw) material, product and service inputs, also those that might not become physical part of the output to final demand *j.* These are on the one hand monetary transactions that have been assigned physical material via the proportionality assumption of monetary and physical flows, but are most likely not of physical nature (i.e. services), and on the other hand monetary transactions (or fractions of those) that are physical, but refer to waste flows which do not become part of end-use products (e.g. new scrap during manufacturing). Thus, the end-use share for a physical product *j* represents embodied material use, different from the actual material mass of the physical product like for WIO-MFA. In effect, these properties lead to misclassifications of material end-uses.[[7]](#footnote-7),[[8]](#footnote-8)

**Hashimoto et al. (2007)** used CBA with a type of use-extension for a Japanese MIOT for 1995 to allocate the Japanese domestic production of construction minerals (cement, sand and gravel, crushed stone) to 24 material end-uses. The authors compared end-use results with a second estimation method, which they deemed more reliable than CBA. Also **Dombi (2018)** uses CBA with supply-extension to distribute total domestic extraction to end-uses (for details see SI1.1).

### 2.2.3 Ghosh Input-Output Absorbing Markov Chains (Ghosh-IO AMC)

Duchin und Levine (2010) proposed an Input-Output notation to Absorbing Markov Chains (AMC) and introduced a framework to trace the number of times a resource flows through the industrial network (‘resource-specific networks’). Duchin und Levine (2013) furthermore specified this approach to only track those flows going to a single final product (‘resource end-use networks’), which can be used to calculate end-use shares.

The AMCs’ central element is the so called *transition matrix*, i.e. documenting the probability of transitioning between two previously defined states, e.g. the transformation of a resource into an intermediate product. Duchin und Levine (2010) propose that for IOA, the transition coefficients represent the proportion of a resource transitioning to a product. This definition in IOA terms can be understood as the *direct output coefficients matrix* .

Similar to WIO-MFA, Duchin and Levin (2010) introduce supply-chain directionality according to the degree of a product’s fabrication into their model. They achieve this by partitioning the matrix *’s* sectors into resources (which we here call materials *m* to align with WIO-MFA notation) and products *p* (Equation 6) where only the two right-sided quadrants are non-zero. The *direct output coefficients* matrix denotes that materials can become part of intermediate products () and the latter can become part of the same or other intermediate products (), but other directionalities are excluded:

|  |  |
| --- | --- |
|  | Equation 7 |

Besides this directionality, the IO-AMC defines absorbing states which once entered, ‘capture’ associated flows (‘consumption goods’). Duchin und Levine (2010) define these states as matrix (Equation 8) which gives the share of final demand in total gross production of products (*p*). Materials (*m*) are assumed to not directly transition to final demand, but first become part of intermediate products (thus zero). Please note that if transactions in original and are deleted, requires re-calculation before calculating and .

|  |  |
| --- | --- |
|  | Equation 8 |

To trace flows over the whole supply chain, the inverse of is calculated (which is similar to the Ghosh inverse ). Multiplying this inverse with yields the distribution of sector outputs *i* to final demand as product *j* (Equation 9). Like for CBA, includes shares for all sectors defined in the MIOT used.

|  |  |
| --- | --- |
|  | Equation 9 |

**Duchin und Levine (2013)** apply the framework to the world trade model with bilateral trade (Hammer Strømman und Duchin 2006), tracing the use of ‘ores’ to four end-uses. Besides this study, we are not aware of any other application of this framework.

In the distinction of materials, intermediate and consumption products the proposed Ghosh-IO AMC corresponds closely to WIO-MFA. In contrast, like for CBA, Ghosh-IO AMC does not remove waste flows and, depending on the definition of sectors, might also include services (which would translate to a consumption-based footprint perspective).

### 2.2.4 Partial Ghosh Input-Output (IO)

In their work on stocks and flows of cement and wood, Cao et al. (2017a) and Aryapratama und Pauliuk (2019) use procedures that are similar to the first steps of the Ghosh-IO AMC in order to derive end-use shares . However, the authors only make use of a modified version of the *direct output coefficients matrix* , which is why we term their approach *Partial Ghosh-IO*. While in the Ghosh model, is calculated with gross output(see SI), the two studies only use the intermediate output, i.e. summing over the row elements in the interindustry transaction matrix (). Hereafter, this matrix is termed in which the resulting coefficients give the direct allocation of a sectors output to all interindustry sectors (Equation 10). Thus, the summation of elements in rows adds up to one.

|  |  |
| --- | --- |
|  | Equation 10 |

To calculate the distribution over supply chain steps, Cao et al. (2017a) and Aryapratama und Pauliuk (2019) define sectors as either intermediate or end-use: intermediate sectors deliver 100% of their output further downstream the supply chain to other intermediate or end-use sectors; end-use sectors only receive inputs from intermediate sectors, which are assumed to be delivered in full to final demand (the absorbing state in AMC terms). Materials (*m*), like defined in the Ghosh-IO AMC, are part of intermediate products (*p*) in this method. The authors of the respective studies manually traced material flows to several downstream steps in the supply chain until reaching end-use. Here we formalize the procedure using matrix notation: analogous to Equation 7, we first partition into with the individual rows/columns reflecting intermediate (*p*) and end-use products (*c*), respectively. Only flows of intermediates (to intermediate use and end-use) are non-zero (Equation 11):

|  |  |
| --- | --- |
|  | Equation 11 |

Second, we compute the Ghosh-inverse of i.e. where the top right quadrant contains the end-use share matrix, reflecting the flow of intermediates (*p*, for this method including materials *m*) to end-uses (*c*, Equation 12):

|  |  |
| --- | --- |
|  | Equation 12 |

***Cao et al. (2017a)*** apply this approach for the Chinese interindustry transaction matrices for 1970-2013 from the global MRIO Eora (Lenzen et al. 2013). The authors distribute the apparent consumption of cement according to the derived end-use shares along up to two intermediate supply-chain steps, before arriving at end-use, and deduct 1.5% material losses during transportation. Out of a total of 122 sectors in the Eora MIOTs, the authors aggregate 113 sectors to three end-use sectors (agriculture, buildings, infrastructure). For the years 1999 & 2000 the authors compare the derived cement use in buildings with statistics from the China Building Industry Yearbook (NBSC 2002) which shows close fit.

***Aryapratama und Pauliuk (2019)*** use the interindustry matrix of the Indonesian national MIOT for 2010 and distribute the apparent consumption of wood/roundwood, pulp, sawnwood and wood-based panels to six end-use categories (paper & packaging, furniture, buildings, infrastructure, agriculture, others). The category ‘others’ contains all sectors not included in the other five end-use categories. Export of end-use products is only considered for furniture as for other end-uses, monetary export flows reported in the MIOT were small compared to final demand.

Additional to the four methods descibed here, we found dMFA studies that apply extra modifications to MIOTs (i.e. use of investment matrices & transaction specific prices) which are desribed in SI1.1.

# Discussion

## Using industry shipment and monetary input-output data for global end-use shares

If available, end-use shares derived from industry shipments in physical units are superior compared to monetary data as they resemble more closely the biophysical flows modeled in MFA. However, in practice, industry shipment data are scarce in terms of tempo-spatial coverage, usually yield low end-use resolution, and are prone to misclassification of end-use categories and partial system coverage (see section 2.1). For individual countries with good data availability, industry shipments might be well suited to differentiate end-uses. However, to systematically derive end-use shares for economy-wide material use across multiple materials, years, and countries, these data sources seem limited and their potential largely exploited (Table 1).

Therefore, monetary Input-Output Tables (MIOTs) present a promising complement data source due to their global availability, often relatively high resolution of countries and sectors, and their economy-wide coverage. The few studies that compared end-uses derived from MIOTs with other methods for a handful of years and three countries mostly find good agreement (Hashimoto et al. 2007; Chen und Graedel 2015; Chen 2017; Cao et al. 2017a). However, the assumptions that apply to the environmental extension of MIOTs, as described in section 2.2, need to be considered when evaluating results. Additionally, the following drawbacks of MIOTs call for further investigation:

Firstly, the quality and differentiation of derived end-uses relies heavily on the properties of specific MIOTs. The number and classification of differentiable end-uses depends on the number and aggregation of sectors in the MIOTs. While previous work mostly utilized MIOTs for countries with the highest available sector resolution globally (i.e. USA and Japan, see Table 1), such detailed information is hardly available for other countries. For MRIOs, substantial efforts have been invested to improve sectoral resolution especially in the primary extractive industries, which influences the matching of environmental extensions to MIOT sectors and required assumptions, e.g. matching material or energy use which are usually reported with system boundaries different from those of MIOT sectors, with strong influence on results (Inomata und Owen 2014; Owen et al. 2017; Tukker et al. 2018; Wieland et al. 2020). Resolution of end-use sectors can in turn still be quite low. For instance, ‘construction’ is responsible for the lion’s share of global material use, but represents only one sector in many MRIOs, though recent GLORIA at least distinguishes ‘all buildings’ and civil engineering (Lenzen et al. 2013; Krausmann et al. 2017; Stadler et al. 2018; Lenzen et al. 2021). Also when detailed MIOTs allow for product-level resolution, some end-use shares might show large differences to physical accounts (Chen 2017), which merits the question how reliable the interpretation of results for individual MIOT sectors is (Abd Rahman et al. 2021; Lutter et al. 2019).[[9]](#footnote-9) In paper part II, we further empirically investigate these issues (Streeck et al. in prep.).

Secondly, the system boundaries of MIOTs complicate integration of a MFA perspective, i.e. the definition of intermediate demand. Intermediate demand shows the transactions that are input to an industry and become part of the industries output, thus *‘transformed or entirely used up’* (United Nations 2009: 6.224). However, also smaller maintenance, repairs and small tools can be accounted for in intermediate demand (United Nations 2009: 6.225 & 6.226). Therefore, when using MIOTs we cannot be exactly sure which part of the flow remains as material stock within the receiving industry as e.g. small repairs or hand tools, and which part is contained in the industries output. Following above definition one would however expect, that the majority of flows in intermediate demand are transformed and contained in a sectors output. Yokoi et al. (2018) document an attempt to tackle this problem (see section 2.2): by referring to the Japanese MIOT definition of fixed capital assets in final demand (unit price >100,000 Yen and durability of over one year), the authors use the purchaser unit prices for products to identify the transactions not meeting these criteria and label them as accumulating within sectors of intermediate demand.

Besides the differences between the data two sources industry shipments and MIOTs, the methods used to analyze the latter can strongly influence resulting end-use shares, which we investigate in the next section.

## 3.2 Comparison of approaches to MIOTs and their strengths and weaknesses

The four approaches to distinguish material end-use shares from MIOTs presented in section 2.2 are different in two ways: they make use of different input-output (IO) models, and they apply different kinds of data manipulation to original MIOTs, raising the question, how strongly these two elements influence end-use results. Table 2 summarizes differences between approaches and the following text elaborates on these (roman letters in the text below refer to row identifiers in Table 2).

Table 3: MIOT-based methods for deriving the end-use share matrix D and their characteristics. For literature studies that apply the four methods please see Table 1 and section 2.2. Dark orange x = criterion applies, light orange p = criterion can potentially be applied but few studies do (see Table 1).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Attributes/method | **WIO-MFA** | **CBA** | **Ghosh-IO AMC** | **Partial Ghosh-IO** |
| **(I) Use intermediate demand only (Z)** |  |  |  | x |
| **(II) Use intermediate & final demand (Z,Y)** | x | x | x |  |
| **(III) Materials external to industry supply chain wide tracing\*** | x |  | x |  |
| **(IV) Yield filter\*\*** | x |  |  |  |
| **(V) Mass filter (≠ non-physical)\*\*\*** | x |  |  |  |
| **(VI) Exclude ‘materials’ to final demand\*\*\*** |  |  | x | x |
| **(VII) Use vs. supply-extension\*** | p | p | p | p |
| **(VIII) Transaction specific prices\*\*** | p | p | p | p |
| **(IX) Investment matrix\*\*\*** | p | P | p |  |
|  | | | | |
| **Underlying input-output modelǂ** | Leontief price | Leontief quantity | Ghosh quantity + market balance | Ghosh quantity (partially) |
| **Advantages** | Mass-balanced MFA logic excluding waste and service flows | Time-efficient application (no filter matrices required) | Introduction of processing degrees | * Applicable with little IOA knowledge * Products that are intermediate demand in MIOTs can easily be defined as end-use (e.g. packaging) |
| * Simultaneous sector output to both intermediate and final demand * Convenient handling of imports/export in final demand | | |
| **Challenges/disadvantages** | * Assumptions for processing degrees and filters (deleting data) * Complexity as entry threshold for MFA practitioners | Footprints (‘embodied perspective’) = misallocations | * Dependent on definition of ‘products’: footprints (‘embodied perspective’) = misallocations | Only uses information in interindustry transaction matrix  Assumptions on cutting the supply-chain by defining intermediate and end-use products  Imports/export not automatically considered |
| ‘Functionality’ of product outputs that in MFA logic are end-uses (=final demand), but are intermediate demand in MIOTs is lost (e.g. packaging) | | |
| * MIOT system boundaries of intermediate demand challenge application to material flows (section 3.1) * Assumptions on price homogeneity & physical-monetary proportionality (if no transaction specific prices) * Domestic technology assumption for single-region MIOTs | | | |

Comments: can also be considered as change of \*the input-side system boundaries of the industry system (partitioning the A matrix for WIO-MFA and Ghosh-IO AMC, or using different kind of satellites assigned to different MIOT sectors), \*\*the interindustry system boundaries, \*\*\* the output-side system boundaries (either cut off where physical flows end and service flows start, or applying different vectors of final demand); ǂsee supplementary information two for further explanation

The most prominent distinction of the four methods can be drawn between the model group CBA, WIO-MFA and Ghosh-IO AMC, which uses full input-output models corresponding to either the input-output market or industry balance, and the Partial Ghosh-IO which only uses the MIOT interindustry matrix and represents a partial IO-model not fulfilling any IO-balance (see I-II Table 2; SI2). Within the first group, the individual methods of CBA, WIO-MFA and Ghosh-IO AMC in turn, correspond to fundamentally different underlying IO-models: the Leontief quantity (CBA), Leontief price (WIO-MFA) and Ghosh quantity (Ghosh-IO AMC) model (for detailed explanation see SI2). Despite these different models, the three approaches are equivalent in deriving the end-use share matrix , if applied at scale, i.e. to fully quantified MIOT systems, and with no or equivalent manipulation of MIOT data as specified in Table 2 III-IX (for proof see sections 6 and 7 of SI2). Discrepancies between the end-use shares of CBA, WIO-MFA and Ghosh-IO AMC can thus be attributed solely to the differences in manipulation of MIOT data.

In the following we discuss the differences and similarities of all four approaches identified in the literature and the implications that arise from data (non)-manipulation in detail:

**First,** the reviewed methods apply different definitions of material end-uses (or in AMC language: the absorbing state). While for Partial Ghosh-IOthe practitioner defines the absorbing state by selecting products in the interindustry matrix (Cao et al. 2017a; Aryapratama und Pauliuk 2019), all other approaches refer to a certain type of final demand matrix/vector.

For Partial Ghosh-IO, the transition of intermediate products to an absorbing, end-use state is not dependent on values in the matrix of final demand, but selected products in intermediate demand are assumed to directly reflect end-use and 100% of related materials being delivered to this category (see section 2.2). For MIOTs with extremely high product resolution, products might be identifiable as either intermediate or end-use. However, most often products represent a product mix, which is supplied to both intermediate and final demand (e.g. electric machinery as input to the automotive industry and investment in a fixed asset). Thus, if misclassifications occur, the supply-chain is either artificially elongated (misclassified as intermediate use) and all material distributed downstream, or cut off (misclassified as end-use) and all material considered as end-use. Thereby, this approach is particularly sensitive to a practitioner’s decision.[[10]](#footnote-10)

All remaining approaches make use of final demand data to define the share of the absorbing states in total industry output. In MIOTs, final demand consists of different categories, tables distinguishing ‘consumption’ and ‘gross fixed capital formation’ (GFCF, see Figure 2). For GFCF, the " *asset boundary for fixed assets consists of goods and services that are used in production for more than one year“* (United Nations 2009: 10.33) and thus matches with the definition of material stocks in MFA research (Fischer-Kowalski et al. 2011). Consumer durables (e.g. washing machines and small tools) are accounted for in other categories of final demand (e.g. private consumption expenditure). Some goods might be defined as either GFCF or another category of final demand (e.g. a car) depending on whether they are for private or commercial use (United Nations 2009: 10.34, 10.35, 10.41).

Different studies use varying forms of final demand, the use of a particular sort of this data not tied to one particular of the reviewed methods. Most of the reviewed studies use the sum of all final demand accounts from MIOTs as absorbing state, while some only use data on GFCF, sometimes from sources other than MIOTs (Chen und Graedel 2015; Chen 2017). Kondo et al. (2012) and Yokoi et al. (2022) use a breakdown of GFCF into the ‘investment matrix’ (Pauliuk et al. 2015), which not only distinguishes investments into products but also the industry sector where the investment occurs, thus allowing conclusion about which industry uses the end-use products (Table 2 IX, see 2.2.5).[[11]](#footnote-11)

From above definition it seems that only using data on GFCF neglects material stocks accumulating in the categories above referred to as ‘consumption’ (might depend on national GFCF definitions). Overall, we propose that, when determining the end-uses within a region, all final demand accounts referring to use within the respective region and time should be used, i.e. including accounts for both ‘consumption’ and GFCF, while excluding accounts for exports and inventory changes.[[12]](#footnote-12)

**Second,** some approaches calculate embodied materials (footprints), while others aim to track material flows at their actual mass by following MFA principles. Consumption-based accounting (CBA) calculates material footprints by assigning material use to IO-sectors and linking them through monetary intersectoral transactions that are partially also non-physical or waste (e.g. service-flows and processing waste, see section 2.2), to final demand. When accounting for material end-use shares, one is however interested in a final product’s actual mass. Thus, following a mass-balanced MFA perspective like aimed for in WIO-MFA through locating resources/materials outside of the industry system (III), as well as the introduction of mass and yield filters (IV-V), is superior to CBA.[[13]](#footnote-13) This applies in particular, if supply-extensions of raw materials are used instead of use-extensions of engineering materials (VII). The remaining two Ghosh model approaches can calculate either footprints or actual mass, depending on the definition of materials and products (e.g. service transactions included as ‘products’ or not) and application of filter matrices (not mentioned in the original studies).

However, also the methods that aim to track actual mass come with their own challenges in manipulating MIOT data (see Equations 2, 7 and 11). When defining different degrees of fabrication (e.g. materials, intermediate and consumption products) and filter matrices that exclude non-physical and waste flows (WIO-MFA), transactions are deleted, which influences the resulting end-use shares. The definition of filter matrices requires expert knowledge and is to some degree up to assumptions (e.g. when is a transaction non-physical). Specifically, the decision on excluding transactions with service sectors (see compartment in Figure 2), i.e. whether to only filter service sector outputs (non-physical assumption likely) or also service-sector inputs (non-physical assumption precarious), can give wrong results, for example, when large material flows to service sectors like repair are ignored (Streeck et al., 2022). Additionally, filter matrix compilation can be tedious and filters are hardly available in published works, which complicates comparing different studies. Making these filters available through more transparent publication would benefit re-use, open and cumulative science.

**Third,** the MIOT system boundaries present a challenge for tracking material use to particular end-use products. The functionality of products that are end-use products in the sense of MFA but are intermediate products in the definition of MIOTs (e.g. packaging) is lost during calculations (e.g. plastic in computer packaging identified as plastic in a computer). This problem applies to all reviewed approaches except for the Partial Ghosh-IO (end-uses defined by practitioner here; see ‘First’ above).

In theory, the correct end-use can be re-identified via secondary calculations. Nakamura et al. (2007), Dietzenbacher et al. (2019), Hertwich (2021) and Yokoi et al. (2018: section 2.1.4) propose distinct methods to calculate materials in a final product’s subcomponents (e.g. to determine product packaging). However, to our knowledge none of these methods is capable of doing that without facing issues of double counting. Nakamura et al. (2007) propose an approach similar to production layer decomposition (Wieland et al. 2018) for WIO-MFA, in which supply chain layers are decomposed one supply chain step at a time. Dietzenbacher et al. (2019) and Hertwich (2021) propose different variations of the Hypothetical Extraction Method (HEM) to the Leontief model, in which the effect of one product/sector is evaluated by comparing a counterfactual in which this sector is extracted with the unperturbed system. Yokoi et al. (2018) propose an approach similar to HEM for WIO-MFA. However, unless the interindustry matrix is perfectly directional (triangular, which requires many assumptions, Nakamura et al. 2007), all of these approaches lead to double counting if one subsequently wants to decompose into individual sectors/products. Hertwich (2021) corrected for double counts in a downstream step through identifying the amount of environmental burden that is allocated more than once using a decomposition approach inspired by footprint studies that aim to resolve, i.e. avoid, double counts in production-based footprints (Cabernard et al. 2019). However, the decision on how to resolve such double counts can be very case specific and such approaches can be challenging when applied to a larger number of products. In a companion paper (Streeck et al. in prep.), we propose a simple way to re-define selected intermediate products such as packaging as end-use by altering the system boundaries of the MIOT industry system towards the output-side (we call this approach ‘Hypothetical Transfer’).

**Fourth,** most of the studies that used above approaches suffer from the price homogeneity assumption which assumes that all individual products of an aggregate product mix have the same unit price (Weisz und Duchin 2006). This introduces bias when the prices of individual products in the mix largely differ. For aluminum that does not seem to be a large issue in the studies of Chen und Graedel (2015) and 2017 (Chen 2017) as supposed by the good fit of WIO-MFA results with results of other estimation methods. However for materials like steel, which strongly differ in quality and price (e.g. for automotive versus construction steel), this might be more important. Principally there are two ways to tackle above assumption: first by disaggregating the material sectors (e.g. Nakajima et al. 2013; Ohno et al. 2015); and second by using transaction-specific prices (Table 2: VIII) for the output of sector *i* to different sectors *j* like applied by Yokoi et al. (2018, 2022) as the only study we found that applies this approach. The scarcity of price data for different material applications, that additionally matches the product average assumed for MIOT’s sector output product mixes, appear like major limitations.

**Fifth,** thereviewed approaches differ regarding ease of use and required IOA proficiency. Partial Ghosh-IO can be implemented without detailed knowledge of Input-Output Analysis (like done in Cao et al. 2017a; Aryapratama und Pauliuk 2019), however is very sensitive to practitioner decisions (see point ‘First’ above). All other methods require at least basic IOA operations. From these, CBA is the easiest and most efficient method to apply but is problematic for calculating end-uses due to its footprint perspective. WIO-MFA closely follows a physical MFA logic but is comparatively complex, which might represent an entry threshold for the dMFA community not too familiar with IOA. However, this point might partially be resolved by making available WIO-MFA filter matrices and underlying scripts via code platforms like Github.

There are several additional points to consider when applying the different methods, like choosing the MIOT sectors corresponding to ‘materials’, the exact design of filter matrices and so on, which will be discussed in the technical method application in Streeck et al. (2022).

# Conclusions and potential next steps

The use of monetary Input-Output Tables (MIOTs) to derive end-use shares for splitting economy-wide material flows to end-uses appears like a valuable complement to the limited availability of data in physical units. The reviewed methods can be applied to readily available MIOTs covering many materials, countries and years. The widely used method of WIO-MFA theoretically leads to the most accurate end-use shares by applying corrections to align MIOTs with dMFA system boundaries.

However, also for WIO-MFA, non-matching system boundaries between MIOTs and dMFA remain for definitions of intermediate demand (e.g. packaging intermediate in MIOTs while end-use in dMFA), leading to overall biased end-use shares. Additionally, the decisions about filter matrix configurations could be more transparently reported and matrices themselves shared.

The MaTrace model has demonstrated the use of WIO-MFA with data from the MRIO Exiobase to generate end-use shares for steel in 25 countries/regions (Nakamura et al. 2014; Pauliuk et al. 2017). However, the derived results have hardly been compared against physical data or end-use results derived from national-level MIOTs and suffer from presented theoretical drawbacks. Therefore, we see the need to empirically compare end-use results from MRIOs to national MIOTs and physical unit industry shipments, as well as to investigate and improve upon the theoretical drawbacks, which we investigate in a companion paper (Streeck et al. in prep.).

While MIOTs can provide valuable end-use information, this review described some of the drawbacks that come with using monetary proxy data to model physical flows. Therefore, to enable more accurate assessment of material use and efficiency, circular economy, or integrated modeling of monetary and physical capital (Pauliuk et al. 2015), we require a political process that pushes stakeholders to compile detailed information on material end-uses and to make it publicly available (e.g. through mandatory direct compilation and publishing by industry associations), in the best case ultimately enabling the compilation of purely physical IOTs.

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# Supplementary Information 1

SI1 – Additional Text for the main manuscript

SI2 – in-depth theoretical comparison of the four MIOT-based methods to trace materials to final products

SI3 – empirical example to SI2

## S1

### Basic MIOT relationships

|  |  |
| --- | --- |
|  | Equation S1 |

### S1.1 Additional modifications: use of investment matrices & transaction specific prices

There are two potential augmentations to above methods: using transaction-specific prices and investment matrices.

#### Transaction-specific prices

In theory, different prices for material and product inputs to different sectors could be applied. This would be instrumental for relaxing the homogenous price assumption of MIOTs sectoral output (Weisz und Duchin 2006; Jakobs et al. 2021), which is especially relevant for materials with a wide range of qualities and prices (e.g. price for steel going to construction vs. automotive). In practice, however, few studies use such data.

**Yokoi et al. (2018, 2022)** used transaction-specific copper unit prices from the supplementary tables of Japanese MIOTs together with WIO-MFA to estimate copper flows in Japan for 16 end-use product in 2011 and 1960-2015 respectively. Also **Chen und Graedel (2015)** and **Chen (2017)** applied a variation of WIO-MFA (or specifically the UPIOM model; Nakamura et al. 2011), that in theory can use transaction-specific prices. The authors used price data from USGS to convert a monetary material composition matrix (*cij* in $/$) into a mixed-units matrix (*cij* in kg/$) which was multiplied with monetary demand to receive physical material flows to end-uses. However, the authors used a single yearly aluminum price for all transactions to estimate the 1960-2009 use of aluminum in U.S. automobiles and 33 end-use categories respectively, not exploiting the potential of transaction-specific prices.

#### Investment matrices

Some literature studies draw on what Lenzen und Treloar (2004) call ‘capital flow matrix’ and Pauliuk und Müller (2014) call ‘investment matrix’ instead of using aggregated MIOT final demand as ‘absorbing state’. This matrix specifies investments into capital by asset type and industrial sector, instead of only representing annual gross fixed capital formation by sector only (usually not part of MIOTs). Using such investment matrices, one could not only model in which products materials end up, but additionally which industrial sector invests and thus ‘uses’ these assets. This would be valuable information for various purposes (e.g. assessment of industry transformation through digitalization). Such capital investments matrices need to be differentiated for buildup, maintenance and depreciation of assets and often follow monetary principles (e.g. of bookkeeping values of the asset, not necessarily of the physical ‘actual’ lifetimes; Pauliuk und Müller 2014). Clearly, only build-up and maintenance relate to gross additions to stocks, while depreciation would reflect wastage during use and end-of-life outflows from stocks. However, sufficiently detailed investment matrices are extremely scarce which might also be the reason, why few studies seem to make use of them (Pauliuk et al. 2015) .

**Kondo et al. (2012)** used a Japanese MIOT and investment matrix for the year 2000 together with WIO-MFA to identify 10 end-uses of 17 materials, accumulating in 17 industrial sectors. **Yokoi et al. (2022)** traced 16 end-uses of copper in 12 different sectors for 1960-2015 using ~5-yearly Japanese MIOTs and investment matrices with WIO-MFA. Also **Dombi (2018)** use investment matrices from EU KLEMS 2007 (O’Mahony und Timmer 2009) and supply-extension CBA to distribute total domestic extraction as net additions to stock (NAS) to Hungarian Exiobase v2 end-use sectors. From these, the author then estimated coefficients of a Cobb-Douglas production function for NAS of buildings and machinery and used these in a fit-optimizing regression to estimate respective material stocks in the agriculture and transportation sector in 2015.

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1. Option 2 are *sector-level physical flow data* (Figure 1, identifier 2), for which end-use is identified by the destination of the destined manufacturing sector or market (e.g. tons crude steel shipped to automotive). Later, we call these ‘industry shipments’ as data source to inform end-use shares. Option 3 are *product-level flow data* (Figure 1, identifier 3) which directlyreport the sale of specific products in either physical (e.g. number of cars sold) or monetary units (e.g. value of cars sold) for which material use is inferred via material intensities. [↑](#footnote-ref-1)
2. We also identified one study that uses the physical-monetary hybrid unit input-output database Exiobase v3.3 instead of its purely monetary version to allocate an extension of material gross additions to stock (GAS) to industry and final demand sectors (Aguilar‐Hernandez et al. 2021). The extension was constructed via mass-balancing resource use and waste accounts (Merciai und Schmidt 2018). While the extension allows to determine the GAS used in an industry sectors’ products, it cannot directly discern the products that contain GAS in final demand and therefore cannot comprehensively allocate material use to end-use products (final products). Additionally, the construction of the extensions is difficult to repeat, related quality of waste data problematic (Tisserant et al. 2017, and hybrid tables so far only available for a single year. For these reasons we decided to not distinguish this approach as additional methodology to derive end-use shares. [↑](#footnote-ref-2)
3. Some studies take additional steps to improve the quality of industry shipment data or fit additional data to their purpose. For instance, as mentioned above, Pauliuk et al. 2013 optimized limited information on end-use shares against scrap market balances. Spatari et al. 2005 consulted with industry and academic experts. Daigo et al. 2007 and Hatayama et al. 2010 refine end-use resolution by splitting Japanese steel industry shipments for ‘automobiles’, into ‘trucks’ and ‘passenger vehicles’, through the assumption of a 2:1 weight ratio derived from the Japan Automobile Manufacturers Association 2000. They then also split steel industry shipments for 42 countries to the end-use ‘construction’ into ‘civil engineering’ and ‘buildings’, based on the relationship of the two end-uses with population density for Japanese prefectures. [↑](#footnote-ref-3)
4. Furthermore, MIOTs represent a model in which primary data collected through national accounting first needs to be compiled into supply-use tables and/or balanced MIOTs, with a number of underlying assumptions and resulting caveats, e.g. limited sector resolution due to reasons of confidentiality (Eurostat 2008; Miller und Blair 2009; United Nations 2009). Also the import proportionality assumption for trade flows into individual industrial sectors (Schulte et al. 2021), and, in the case of single-regional MIOTs, the domestic technology assumption (Lenzen et al. 2004; Bouwmeester und Oosterhaven 2013) apply. [↑](#footnote-ref-4)
5. In how far ‘service’ sectors can also be classified as ‘products’ is discussed in section 3.2 [↑](#footnote-ref-5)
6. Building upon WIO-MFA, also problems other than end-use shares can be tackled, e.g. by relating the flows of materials in MIOTs to a product unit, similar to the functional unit in Life Cycle Assessment ‘(UPIOM = unit physical input-output by materials; Nakamura et al. 2011), using WIO-MFA for linear optimization of vehicle recycling (Ohno et al. 2017b) and for tracing material flows through supply chain networks (e.g. Chen et al. 2016; Ohno et al. 2016; Nuss et al. 2019). [↑](#footnote-ref-6)
7. An example would be monetary transactions recorded between ‘physical materials’ (e.g. cement) to a non-physical service (e.g. government services), which in turn delivers a service transaction to another physical end-use product (e.g. a house). Through the physical extension in CBA, the service-input ‘government services’ to the ‘house’ would then be associated with a physical ‘cement’ flow and thus add to the footprint of the ‘house’, although the service-transaction does not contain a physical flow in reality [↑](#footnote-ref-7)
8. For CBA, also the endogenization of capital into footprints of final consumption, i.e. the treatment of capital goods not as final demand but as part of production, has been discussed in the literature and applied for materials (Södersten et al. 2018; Miller et al. 2019). For materials this approach was termed ‘capital-augmented material footprints’ (Södersten et al. 2020) and allocates the embodied impacts of capital goods such as machinery and buildings used by the industry sectors to the respective industry output to final consumption. The system boundaries of this approach are not suited to determine material end-uses, as it in addition to standard CBA footprints allocates materials embodied in the endogenized capital goods further downstream to goods for final consumption (i.e. gross fixed capital formation ‘gfcf’ allocated to consumption of households ‘hh’ and government ‘gov’ in Figure 2). [↑](#footnote-ref-8)
9. Additionally, while national MIOTs follow internationally harmonized principles (United Nations 2009), national specificities apply, regarding national statistical efforts and procedures in data gathering and aggregation as well as estimation procedures, nationally specific decisions for sectoral (dis)aggregation (e.g. confidentiality and/or national interests), or issues of ownership (e.g. state-owned housing vs privately-owned buildings means that substantial final demand is either part of households, or government expenditures). Available MRIOs try to reconcile national definitions, data gaps, as well as often mismatching and conflicting data using various techniques requiring further harmonization (Tukker et al. 2018). [↑](#footnote-ref-9)
10. In support of their categorization of intermediate and end-use products, Aryapratama und Pauliuk 2019 take the ratio of intermediate versus final demand, thus somewhat reducing this bias. The exclusion of final demand in Partial Ghosh-IO also impedes the method-immanent inclusion of imports and exports of final end-use products (which are reported in the final demand matrix). [↑](#footnote-ref-10)
11. However, despite few data sources like EU KLEMS O’Mahony und Timmer 2009, data on investment matrices is scarce, low in resolution, and lacking details on investments for buildup & maintenance vs. demolishment Pauliuk et al. 2015; Södersten et al. 2020. [↑](#footnote-ref-11)
12. Also the use of all compartments of MIOT final demand might cause problems: Nakamura et al. 2014 describe that through the vector of exports and inventory changes, also intermediate products are reported in final demand. The authors use a type of output coefficient matrix of the Ghosh model (similar to equation 10) to allocate deliveries of intermediate to final products in a secondary calculation. To avoid the same problem for ‘materials’, the Ghosh-IO AMC method prohibits flows of materials to final demand by partitioning the latter (VI, Equation 7). [↑](#footnote-ref-12)
13. Nakamura et al. 2009 compared the material mass of iron, aluminum and polyvinyl chloride in a Japanese passenger car for the year 2000 via CBA and WIO-MFA with data from JAMA 2003 for 1997/2001. They found that CBA overestimated material content by 18-47% while WIO-MFA was fairly close to JAMA data (2-6% deviation). [↑](#footnote-ref-13)