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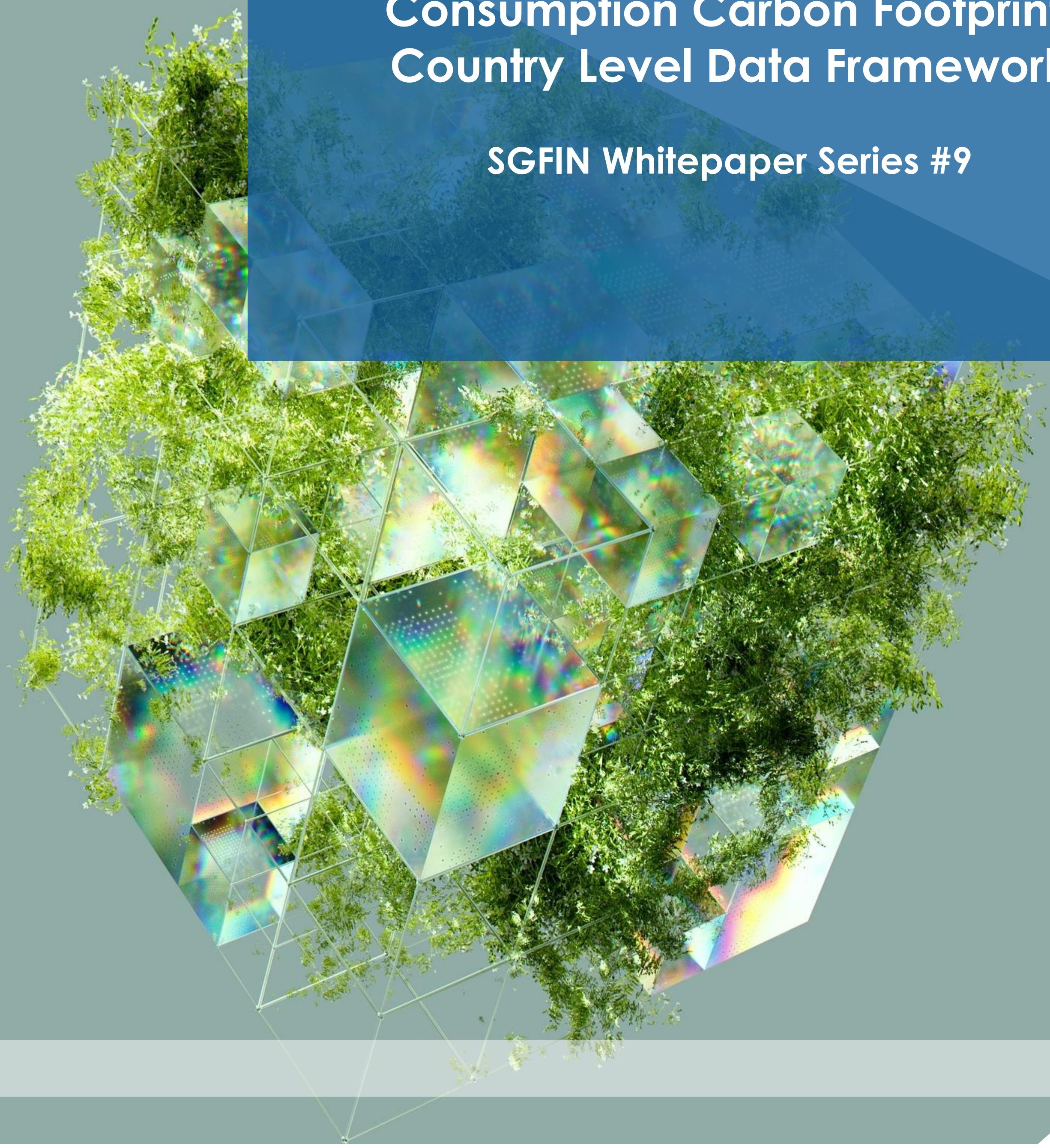
Consumption Carbon Footprint: Country Level Data Framework

SGFIN Whitepaper Series #9



Flavia Badarinza | Johannine Enerio | Devansh Joshi | Johan Sulaeman | Sumit Agarwal

Consumption Carbon Footprint: Country Level Data Framework

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National University of Singapore

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Abstract

This Whitepaper presents a country-agnostic algorithm for estimating household and individual carbon footprints based on personal consumption baskets. The algorithm approximates cradle-to-grave lifecycle environmental impact of the goods and services consumed. The framework differs from traditional carbon footprint estimation methodologies by offering a bottom-up, hybrid, scalable model, which can absorb various data formats and adapt its parameters and assumptions. The algorithm is designed to ingest both Physical and Monetary Emission Factors (EFs) and defines mechanisms for conversion, adjustment, extrapolation and aggregation of these EFs. It thus addresses practical challenges affecting today's sustainability data landscape, such as data scarcity, heterogeneity and unreliability. Intended for country-level use, it aims to spark discussion on more transparent, parsimonious, and robust carbon footprinting infrastructure.

Keywords: GHG emissions estimation algorithm, Consumption carbon footprinting, Products & Services carbon footprinting, Emissions embodied in international shipments, Individual carbon footprint, Household carbon footprint, Physical emission factors, Monetary Emission Factors, Emission Factors conversion, Emission Factors extrapolation, Sensitivity analysis.

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About SGFIN

The Sustainable and Green Finance Institute (SGFIN) is a research institute established by the National University of Singapore (NUS). SGFIN aims to develop deep research capabilities in sustainable and green finance with a focal point on Asia, and to provide thought leadership and shape sustainability outcomes in policymaking across the financial sector and the economy at large. Supported by exceptional domain experts across NUS, SGFIN equips businesses with critical cross-disciplinary knowledge, training, and toolkits to integrate sustainability dynamics into their business strategies and investment decisions to better quantify the environmental and social impacts of their business developments, operations, products, and services. In essence, SGFIN aims to help companies embed sustainability as a key pillar in their business decisions.

Disclaimer

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Foreword

As the imperative for urgent, broad and deep climate mitigation action across all segments of our society becomes ever clearer, so is the need for individual households to play their part. While countries, governments, companies, and civil society work towards the Paris Agreement climate goals, albeit with debatable results, the call for action extends to individuals and households, to consider the environmental impact of their lifestyles and intentionally reduce their carbon footprint.

Meaningful action stems from education, and education starts with information. We at SGFIN would like to contribute to the global effort of empowering individuals with actionable insights on sustainable lifestyles, by building a country agnostic model allowing for the estimation of household carbon footprints.

The sustainability insights ecosystem is plagued by data scarcity, data heterogeneity, data unreliability, opaque methodologies, misaligned taxonomies and effort intensive calculations which make household carbon footprinting models complex and unscalable exercises. Our framework addresses these challenges by offering a transparent data framework for computing the carbon footprint of key consumption categories, targeting a cradle-to-grave coverage of GHG emissions associated with typical goods and services consumed.

As public debates continue to dispute who bears the responsibility to act, when and how much, we believe that there is an effort we all need to make at a personal level – to understand the environmental impact of our consumption, and to strive to make changes towards more sustainable lifestyles. This framework aims at supporting such efforts not only as a transparent calculation methodology, but also as a conversation starter on how it can be improved, enriched, and adapted for practical applications.

Prof. Sumit Agarwal
Managing Director, SGFIN
Low Tuck Kwong Distinguished Professor of Finance at NUS Business School Professor of Economics and Real Estate
President of Asian Bureau of Finance and Economic Research
August 30th, 2025

Executive Summary – Key Takeaways

1. Households account for a significant share of global carbon emissions, driven primarily by the consumption of products and services. To take action, individual consumers need to be equipped with insights into the carbon footprint of their consumption.

2. Commercial, academic or public interest studies into the carbon footprint of individual consumption typically run into challenges related to data heterogeneity, scarcity, complexity and reliability issues, particularly related to Emission Factors.

3. We offer an end-to-end computational algorithm applicable to households in any given country of residence, that can facilitate the estimation of the carbon footprint related to consumed products and services, subject to the availability of specified focal country contextualized data sets.

4. Our model takes into account the cradle-to-grave lifecycle of products, and details a methodology of mapping, conversion, adjustment, extrapolation and aggregation of Emission Factors data, based on various hypotheses and assumptions.

5. We stress test the model and identify the confidence intervals and the data sets introducing the most significant uncertainty.

6. We launch a call to action to academic and commercial researchers to refine the model by conducting further research into the hypotheses considered, the uncertainty sources identified and the continuously evolving emission factors data landscape.

About the Authors

Flavia Badarinza was a Strategic Industry Initiatives Lead at the Sustainable and Green Finance Institute (SGFIN). She has more than 15 years of leadership experience in the technology sector with HP, Oracle and Microsoft, having built and overseen complex teams, programs, operations and institutional relationships. She holds an MBA in Corporate Strategy from the National University of Singapore, and an M.Sc. in International Financial Risk Management from the Academy of Economic Studies in Romania. Flavia coordinated research operations for this Whitepaper during her tenure at SGFIN.

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1. Introduction - Climate Change Imperative

As scientists find national emission pledges currently unlikely to limit global warming to 1.5C (IPCC, 2023), there is an increasing focus globally on **demand-side mitigation** of climate change (Cap et al, 2024), with a broadening recognition that low-carbon lifestyles, some of which involving significant changes in patterns of consumption, are essential for coming closer to the Paris Agreement targets (Richter et al, 2024). Far from a low-hanging fruit, demand-side climate action at scale requires strategies addressing household and individual behavior and consumption, with a focus on influencing cultural norms and decision-making processes (Creutzig et al, 2018).

Driven primarily by living standards and the level of consumption, **households' emissions** are found to be significantly accounted for by consumption of goods and services (Vita et al, 2019). Educating consumers and empowering them for action starts with easy to obtain and easy to understand actionable information, bringing closer to the point of decision-making insights on what the actual carbon footprint associated with purchases of goods and services is. We consider therefore sustainability information, and in particular products and services carbon footprint, to be the cornerstone of individual action.

Globally, household consumption has been found to account for as much as 72% of global emissions, with distinct differences between and within countries, and with a clear correlation with the overall level of expenditures (Hertwich and Peters, 2009).Climate education and climate action at an individual level remain elusive however, subject to **compounding challenges** generated by education gaps, data scarcity and unreliability, lack of standardization, as well as the sheer data architecture complexity required to bring products and services carbon footprint datapoints to the point of purchase decision making.

Current approaches to household emissions estimations typically rely on national level **macro-economic models** based on national emissions inventories computed either through production based or consumption-based carbon accounting methodologies. These models entail high degrees of technical difficulty and often produce results at high levels of aggregation offering national averages difficult to customize and adapt to specific consumers.

Through our study, we intend to address these challenges by proposing a country agnostic **carbon footprinting algorithm** that allows for the estimation of the carbon footprint associated with the consumption baskets of individuals and households. Our framework offers a hybrid model allowing for sourcing of both Physical and Monetary Emission Factors, mapped to a cradle-to-grave lifecycle model for goods and services, and used in junction with commodity imports patterns, price points and international shipping routes data, to create focal **country-contextualized, consumption-based, Monetary Emission Factors.** We also propose a methodology for Monetary Emission Factors lateral and vertical **aggregation** at different levels of resolution, for application to spend data which may be available at various levels of granularity.

In addition, we propose a methodology for Emission Factors **conversion**, to address data heterogeneity challenges, as well as a methodology for Emission Factors **extrapolation** to various countries of origin, based on country technological and energy mix carbon footprint similarities, to address data scarcity challenges.

Our framework thus offers a **scalable model**, that can ingest further (and better quality) data, as and when it becomes available, and that is mapped to the immediate decision information available to consumers – their consumption. Our spend-based model aims at alleviating some of the methodological and computational difficulties of traditional approaches, offering an **actionable understanding** of individuals' and households' carbon footprints.

By transparently sharing this model and opening it up for discussion and improvement in further bodies of work, we also aim to offer the broader international community an easy-to-use tool for **consumption carbon footprint studies**, recognizing the limitations of time, effort and resources such studies would have to accommodate. We also hope to invite constructive criticism and inputs into how this model can be further evolved for more robustness, accuracy and applicability.

2. Household carbon footprinting methodologies

2.1 Carbon accounting – from national inventories to household level

The established methodologies for the estimation of **country level** carbon emissions, are either production-based accounting (PBA), or consumption-based accounting (CBA)[1].

The spirit of the **PBA approach** is assigning emissions accountability to producers within a country's territory (Munksgaard and Pedersen, 2001), and the PBA emissions are correspondingly also known as production-based emissions. The PBA methodology is used by UNFCCC and follows the guidelines of the IPCC (Mangır and Şahin, 2022). There are however several known gaps within the PBA methodology, such as not taking into account international trade flows, and the related GHG **emissions embodied in trade** (Mangır and Şahin, 2022; Peters and Hertwich, 2008; Davis and Caldeira 2010; Aichele and Felbermayr, 2012; Naegele and Zaklan 2019), or emissions related to **international transportation** (Franzen and Mader, 2018).

On the other hand, within the **CBA approach**, the end consumers are the ultimate drivers of sourcing, production and distribution choices (Mangır and Şahin, 2022, Munksgaard and Pedersen, 2001; Wiedmann, 2009; Clarke, 2017; Afionis et al, 2017). Through the CBA methodology, national GHG inventories can be calculated as the PBA based national GHG inventory plus the net GHG emissions embodied in trade (imports minus exports) (Mangır and Şahin, 2022¿ Khan et al, 2020). Subsequently, environmentally extended input-output (**EEIO**) models are extensively used to assess the environmental impact of economic activities within and between countries (Mangır and Şahin, 2022). Leveraging input-output tables, the CBA method allows for reconstituting emissions generated along international value chains, attributing to the country of consumption all upstream emissions of products and services up until the point of consumption, including for raw materials and intermediate products, across all the countries where the value chain has touchpoints in (Pottier et al, 2020).

While CBA based estimations provide a more complete view of national emissions as they take into account emissions embodied in trade (Pottier et al, 2020, Hertwich and Peters, 2009), they also require **complex calculations** and incorporate **higher uncertainty** (Mangır and Şahin, 2022). Overall, the CBA methodology is recognized in the literature as involving more data-intensive calculations and having **higher transaction costs** than PBA (Liu, 2015).

Going from the country level to the **individual level** involves far higher complexity and uncertainty. The methods we oftentimes encountered in the literature are using either PBA or CBA national level emissions of a country, divided by the population, to derive the average level of emissions per capita.

[1] We present this summary of carbon accounting methodologies and the relevant literature behind them in our related Whitepaper "Consumption Carbon Footprint: Singapore Case Study". Acknowledging the content overlap, we preferred to keep this overview in both papers, to facilitate for our readers the understanding of both the general framework we offer in this Whitepaper, and its application for Singapore in its companion Whitepaper.

While top-down methodologies such as PBA and CBA are the most common approaches to estimating household or individual carbon footprints in academic studies, other methodologies are also emerging both in academia and carbon calculators, allowing for **bottom-up computations** of carbon footprints starting from insights related to consumption. These can provide more granular and adaptable results beyond national per capita averages.

For instance, **Physical data based estimations** use Physical Emission Factors (EFs) associated with quantifiable activities or actual consumed product quantities[2]. These EFs are typically the result of product/service lifecycle analysis (LCA) inventories, for which we are seeing increasing data availability for academic, commercial and public use, from multiple data providers. We discuss the data challenges involved with leveraging this type of datasets, as well as potential workarounds, in sections 4.4 and 5 of this Whitepaper.

On the other hand, **monetary data based estimations** use the monetary EFs derived through CBA Environmentally Extended (EEIO) based methodologies for different categories of products depending on the emissions of the industry that generated them (Pottier et al, 2020). These EFs have high geographical representativeness as they are by nature contextualized for the country of consumption. Their uncertainty however is higher relative to physical EFs.

On top of these, **hybrid** methodologies have emerged as well, opportunistically combining Physical and Monetary EFs and applying them to consumption parameters in order to derive an individual's or household's carbon footprint. In Table 1 we recap these different approaches, along the advantages and disadvantages of using each method.

***Table 1**: Accounting frameworks for household carbon footprints estimation*

Accounting framework	1.Production-based accounting (PBA)	2.Consumption-based accounting (CBA)	3.Physical consumption quantities	4.Monetary consumption expenses	5.Hybrid methods (combination of 3 & 4)
Output	**Average** national GHG emissions per capita or per household	**Average** national GHG emissions per capita or per household	**Personalized** GHG emissions per capita or per household	**Personalized** GHG emissions per capita or per household	**Personalized** GHG emissions per capita or per household
Scope	Emissions occurring within jurisdiction, resulting from **production** and other processes	Emissions occurring within jurisdiction, resulting from **consumption** of goods and services	Emissions coverage **depends** on the underlying EFs system boundaries	Emissions coverage **depends** on the underlying EFs system boundary (typically **consumption**-based)	Emissions coverage **depends** on the underlying EFs system boundaries
Approach	***Top down:*** Starting from National GHG inventories	***Top down:*** Starting from PBA inventory + Net emissions embodied in Trade	***Bottom-up:*** Physical EFs connected to consumption physical quantities	***Bottom-up:*** Monetary EFs connected to consumption expenses	***Bottom-up:*** Combining both Monetary and Physical EFs

[2] Such Emission Factors can act as multipliers associated with the respective activities or consumption items GHG emission kwh for electricity, or by liter for petrol, or by kg for bananas (Physical EFs).

Methodology	***National GHG inventory***: National stock take following UNFCCC standards	***MR / SR EEIO***[3]: (National GHG inventory reconciled with net international trade flow IO data)	Leveraging product/services ***LCA*** outputs	Leveraging **CBA** based products & services EFs	**Combining** Physical and Monetary EFs
Typical applications	**Academic** research, National GHG Inventories	**Academic** research	Commercial or public **calculators**	Commercial or public **calculators**	Commercial or public **calculators**
Advantages	Relative **ease of calculation** versus CBA. Higher **data availability** given UN reporting requirements	Takes into account global **supply chains** and emissions embodied in trade	Potentially lower **uncertainty** if high quality Physical EFs are considered	Higher **practicality** (easier to retrieve consumption data format)	Higher data **availability** due to combination of Physical and Monetary EFs
Disadvantages	Does not include emissions embodied in **international trade** and international **transport**	More **complex** and effort intensive calculations relative to PBA. Higher **uncertainty**	**Data availability** limitations. Emissions coverage dependent on EFs **LCA boundaries**	Higher **uncertainty.** Attribution of **industry averages** at product level[4]	Higher **uncertainty**. Methodological **inconsistency**
Source: *Table produced by our project team, based on insights and inferences from Afionis et al, 2017, Aichele and Felbermayr, 2012, Clarke, 2017, Davis and Caldeira 2010, Franzen and Mader, 2018, Hertwich and Peters, 2009, Khan et al, 2020, Liu, 2015, Mangır and Şahin, 2022, Munksgaard and Pedersen, 2001, Naegele and Zaklan 2019, Peters and Hertwich, 2008, Pottier et al, 2020, Wiedmann, 2009.*					

2.2 How our algorithm differs from current methodologies

The end objective of our model is to enable **easily computable** consumption carbon footprint estimations of individuals and households in any country in the world (which we henceforth refer to as "focal countries"). We consider the most convenient way to track household or individual consumption is through **expenditures**, which is especially feasible in countries where cashless transactions are predominant. Regardless of payment mode and the structure of actual transactions, and absent real financial transaction information, there are other ways to infer key consumption items, leveraging for instance household expenditure surveys and other reports that serve as the basis for CPI and inflation computation in most countries. Our model is centred around building a set of focal country **contextualized, monetary, consumption based EFs** (defined as emissions per $).

The algorithm we propose aims at solving several significant challenges that plague efforts to assess individual or household carbon footprinting, whether these efforts are within an academic, commercial or public interest projects:

1. **Computational complexity**: we develop a ready to use framework for focal country household carbon footprinting, fit for real life project limitations. We consider the need to recognize research projects have limited resources, be it in terms of time, budget, resources or team members skillsets. We factor in the need for minimum necessary data sets, publicly available ideally, and clear processing steps.

[3] Multi Region (MR) or Single Region (SR) Environmentally Extended Input Output (EEIO) models.
[4] Industry sectors average production and average emissions are uniformly attributed to all products and services resulting from that industry (Pottier et al, 2020)

2. **Country of origin integration:** our model considers different EFs for each country of origin for product imports[5].

3. **Data heterogeneity**: we propose a holistic methodology for converting at scale EFs from Physical to Monetary denomination, to allow for building agile, expandable and broadly interoperable EF libraries. Ex: international shipping.

4. **Data scarcity**: our methods can ingest both monetary and physical EFs, from any given country of origin. We noticed however there is limited data publicly available covering relevant combinations of (country of origin & end user products/services EFs). We therefore propose a method that could allow for the extrapolation of EFs where they are not available to project teams, based on the difference in the carbon intensity of electricity for any given country of origin (we refer to this method as the " б hypothesis ". Our call to action for further research on this topic is to prove, disprove or refine this assumption further.

5. **Data aggregation challenges**: algorithm for navigating across various levels of expenditure data resolution. We propose 2 methodologies for EF data aggregation – lateral and vertical, to allow for easy navigation of 2 key dimensions of data (and the related data scarcity challenges):

5.1 Horizontal aggregation – for EF data scarcity issues

5.2 Vertical aggregation – for Expenditure data scarcity or granularity issues

6. **Data interoperability**: our framework output in terms of sets of Monetary EFs is directly interoperable with different levels of granularity of expenditure data, ranging from low resolution expenditure data points from national surveys to potentially more granular financial transactions.

7. **Data reliability**: we offer methodology and results of multi-scenario sensitivity analysis, along with the prioritization of key assumptions introducing uncertainty, for further iterations.

[5] While the carbon intensities of different countries are known to be substantially different, most studies of consumption-based emissions at national level assume "identical carbon intensities of imported and domestic products" (Hertwich and Peters, 2009).

3. Algorithm structure

Our model can be applied to households and individuals in any country of study, which we will hereon refer to in this Whitepaper as "**focal country**", which we abbreviate to **CTY** in our formulas. We will refer to its currency as "**focal country currency**", which we will abbreviate to "**$**"[6]. All the various datapoints are indexed to **2023** as a common year of refence for comparability purposes, applying inflation rates for the focal country per the methodology we describe in the next sections.

In the subsequent sessions we will detail the methodology, the assumptions and the formulas that are part of our proposed algorithm, along with the sensitivity and uncertainty analysis of the estimation outcome.

3.1 Hybrid, bottom-up, spend-based methodology

The consumption carbon footprint estimation logic is focused on estimating Monetary Emission Factors (**Monetary EFs**) that can be attributed to products and services purchased by typical households, to estimate the carbon footprint of average consumption baskets (Figure 1). This approach is similar to that taken by multiple publicly available tools and calculators designed for individual consumers, which leverage spend-based factors to estimate emissions based on household spending actual data or partners. The approach is also in line with the spend-based method for estimating carbon emissions attributable to purchased goods and services, as detailed in The Greenhouse Gas Protocol Technical Guidance for Calculating Scope 3 Emissions (version 1.0) (WRI, WBCSD, 2011b)[7]

***Figure 1**: Consumption carbon footprint estimation logic*

We define Monetary Emission Factors as **spend-based Emission Factors**, which are particularly useful in the absence of actual physical data. Throughout this paper we will refer to them as **Monetary EFs**. They quantify the mass of greenhouse gases emissions per unit of spend and are thereby denominated as **kg CO2e / $**[8].

3.2 Expenditure data

[6] To differentiate between the focal country currency and US Dollar, we use USD to refer to the latter for all datasets and formulas that will be leveraging data in US Dollars.
[7] We apply this method to the specific context of Singapore in our companion Whitepaper "Consumption Carbon Footprint: Singapore Case Study". This section might therefore have overlaps with the content in the companion Whitepaper.
[8] CO2e stands for carbon dioxide (CO2) equivalent, which is the standard unit used to convert GHGs to CO2, based on the global warming potential (GWP) of each of the various greenhouse gases (GHGs) (WRI and WBCSD, 2011a)

3.2.1 Expenditure data - key sources

The starting point in our calculation methodology is the typical households **expenditure basket** within the focal country (ideally alongside household composition statistics, which allows for better inference of the carbon footprint at individual level). This can be obtained from national expenditure surveys supporting Consumer Price Index (CPI) and inflation computations, which are broadly public for multiple countries, albeit at different levels of granularity.

Our framework is structured for interoperability with surveys based on the United Nations Classification of Individual Consumption According to Purpose (**UN COICOP**) (UN DESA, 2018). This is a broadly adopted standard for CPI calculations, with many countries benefiting from the standardized approach facilitating international comparison and regional inflation trends monitoring. The expenditures structure offers ~15 divisions, ~63 groups, ~186 classes and ~338 sub-classes (UN DESA, 2018). This structure may be implemented with slight variations across countries – such as the European Classification of Individual Consumption According to Purpose (**ECOICOP**) in the European Union (Eurostat, 2024), or the Singapore COICOP (**S-COICOP**) in Singapore (SG DOS, 2016), both customized to reflect local consumption specifics.

Our framework is interoperable with all UN COICOP-based expenditure structures, despite country nuances. In our framework, we refer to the 4 levels of the UN COICOP hierarchy structure as follows: "Expenditure Categories" for the divisions, "Expenditure Sub-Categories" for the groups, "Expenditure Item Classes" for the classes, and "Expenditure Item Types" for the sub-classes.

We find however that the Expenditure Item Type level, as defined in the UN COICOP hierarchy, is too broad for reliable attribution of both emission factors and countries of origin. For example, the Expenditure Item Type "Fresh Tropical Fruits" can include a variety of specific items (such as bananas, papaya, pineapples, kiwis, avocadoes and others), which would be imported from different countries of origin, and would have different carbon intensities. We therefore introduce a **5th level of granularity**, which we refer to as the "**Expenditure Item**". This is the level to which we map Emission Factors, following the steps we describe in sub-section 3.3 "Emissions data". This is also the level to which we map **commodities** as defined through the Harmonized System (HS) commodity codes (World Customs Organization, 2022) and extracted from the BACI: International Trade Database at the Product-Level (CEPII, 2023).

3.2.2 Inclusions, exclusions, resolution and taxonomy

In the effort to map the expenditure data available, a key consideration is the types of expenditures that are included or excluded from the data, as this **coverage** would determine the degree to which the household carbon footprint covers holistically (or not) the carbon emissions associated with household consumption.

Certain consumption components may not be included in the typical definition of "consumption" in the first place, such as usage of residential space for **accommodation** (through rentals, mortgages or ownership). **Investments** may also not be considered in households expenditure surveys. Our framework can capture both emissions associated both with investment and accommodation, as long as there are cashflows (actual or imputed) captured in the expenditures list.

We also recognize that for any given household or individual, consumption data may or may not be easily retrievable at a deep enough **resolution level** (ex: quantity of cheddar cheese purchased in a month, along with details such as country of origin, international shipping mode, brand, etc.), and be available instead at variable, and oftentimes lower, degrees of resolution (ex: $ spent on dairy).

As we target to achieve a high degree of granularity (and therefore actionability) of estimated emissions, we factor in a few more dimensions of consumed goods and services : **country of origin** of imported goods (as we anticipate production processes in different countries and local sources of energy lead to significantly different embodied carbon for manufactured goods) and the **mode of transportation** to the focal country (as transportation related emissions differ depending on whether the shipping of goods is by road, ship or air).

Therefore, a key part of the model revolves around the **taxonomy** of expenses, and the methodology that can be applied when navigating vertically such levels of resolutions of consumption and expenses and emissions estimation reliability, as well as mitigating risks and minimizing uncertainty related to the conversion, adjustment, extrapolation and mapping of emission factors accordingly.

3.3 Emissions data

The second key component in the framework is represented by **emissions data**. We take a holistic approach whereby we attribute to end consumers the emissions generated throughout the entire lifecycle of goods and services – targeting to cover as much as possible the cradle-to-grave lifecycle for goods (broadly speaking, from raw materials sourcing and production to waste management). For goods in particular, we define the key steps in their **lifecycle journey** (which we refer to as LCA stage), and we target identifying and mapping Emission Factors specific to each, along with other datasets required for the Emission Factors conversion, adjustment or extrapolation.

We also consider the geographical location of the specific journey step, such as the country of origin or shipping route for international transportation. As many of the available original Emission Factors may be Physical, we also source product cost/price datapoints allowing us to thus obtain (**Monetary EF x LCA stage**) combinations which we eventually sum up to obtain cradle-to-grave, focal country contextualized, Monetary EFs, attributable to the specific Expenditure Items mapped to them.

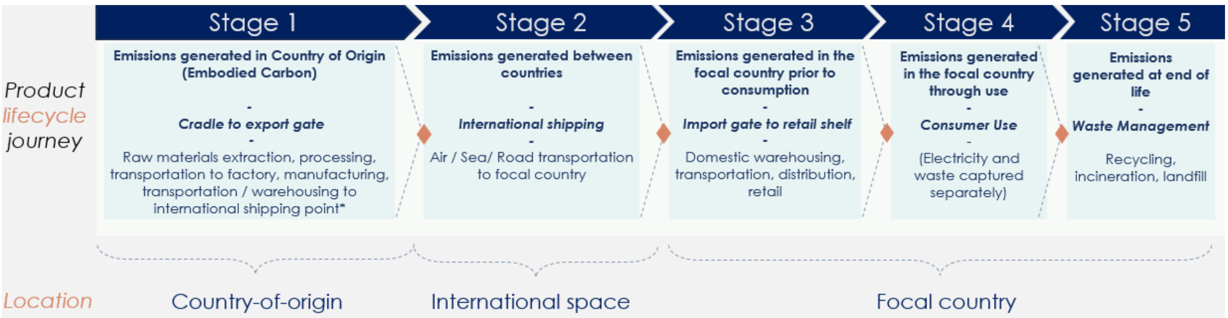
In the following sub-section we share the overarching emissions attribution logic, and the datasets used at each step.

3.3.1 Product Lifecycle Journey

Our framework attributes to the consumer[9] all emissions associated with the **entire lifecycle** of the goods and services they purchase. Due to practical limitations, the treatment of products and services is different. For **products**, we recommend ideally covering all LCA stages starting from extraction of raw materials, processing and transportation to manufacturing facilities, all the way through production, assembly, packaging, international shipping, warehousing, domestic distribution, retail operations, use and disposal. For **services**, as we discuss in section 11 "GHG Emissions associated with Services" we take a simplified approach whereby we source Emission Factors which present with boundaries which are either defined as, or we infer to be, consistent with the cradle-to-grave lifecycle.

For products we take a **simplified LCA** (lifecycle assessment) approach[10], whereby we map the key stages in the expenditure item lifecycle journey, and we look to source Physical or Monetary EFs that are attributable to the specific combination of (**Expenditure Item x LCA stage X location**), as detailed in Figure 2.

***Figure 2**: Emissions allocation logic – products*



Source: Figure produced by our project team incorporating guidelines from The Greenhouse Gas Protocol: Product Life Cycle Accounting and Reporting Standard (WRI and WBCSD, 2011a), and leveraged also in our companion Whitepaper "Consumption Carbon Footprint: Singapore Case Study"

- **Stage 1**: **Cradle to export gate**, which covers all net emissions generated up to the point of international shipping. At this stage in the framework, we map Expenditure Items to internationally traded commodities (using Harmonized System commodity codes)[11], to allow for further mapping of **countries of origin**, as well as imported quantities and values for each Expenditure Item, from each country of origin. Importantly, for certain countries reliant almost exclusively on imports for consumer goods (such as for Singapore[12]), this framework is applicable as such. For focal countries with significant local production, we recommend sourcing production data labelled with the same commodity codes from the Harmonized System Nomenclature, which would allow for data integration with our framework's formulas. The focal country itself thus becomes another country of origin in the model.

[9] We assimilate the consumer with the user of the goods and services purchased, as members of the household purchasing the respective goods and services.
[10] In alignment with the GHG Protocol Product Life Cycle Accounting and Reporting Standard (WRI, WBCSD, 2011a).
[11] As defined in the HS (Harmonised System) Nomenclature 2022 edition (World Customs Organization, 2022).
[12] We discuss this framework application to Singapore in detail in our Whitepaper "Consumption Carbon Footprint: Singapore Case Study"

- **Stage 2: International shipping**, which covers the lifecycle journey between the point of export and the point of import in the focal country. At this stage in the framework, we map Expenditure Items most likely **freight mode** for imports into the focal country – air, sea and road, from each country of origin, based on 1/distance between the 2 countries, and 2/goods perishability.

- **Stage 3: Import gate to retail shelf**, which covers emissions related to domestic logistics including warehousing and retail. For simplicity of calculation, we do not include in our framework any further mapping at this stage.

- **Stage 4: Consumer use**, which covers emissions related to the use of products or services. These emissions could come from **electricity** consumed (for example, from the usage of electrical appliances), **fuels** (for example, for cooking or usage of personal vehicles), **water** or **waste** (for example, for the usage of fresh fruits or clothing items). We expect most national household CPI/expenditure surveys include key items covering these sources (electricity, water, fuels and waste). In other words, we consider emissions from product usage to be generally captured elsewhere in the consumption basket. We therefore do not source any data related to this stage.

- **Stage 5: End of life,** which covers emissions associated with the collection and treatment of domestic waste. For this, expenditure related to waste collection and management are typically part of the expenditure survey already. Additional statistics may be required however, such as the focal country's domestic waste quantity, recycling rates and composition. Manual mapping of waste categories to expenditure items can allow for an attribution of emissions related to waste generated to different categories of items.

3.3.2 Product Emissions Journey

We then source and map emissions related data, to each of the stages discussed above, as follows.

- **Stage 1**: We recommend sourcing Physical or Monetary Emission Factors (EFs) whose boundaries match, to the largest extent possible, the **cradle to exporter gate** boundary, by country of origin. Absent such data (which more often than not would be the case), we recommend sourcing EFs with a **cradle to retail gate** system boundary. As the products we examine at this stage are imported, we consider these boundaries are applicable within a certain country of origin for products meant for export, just as well as for products meant for domestic consumption. This is due to the logistics related emissions that would be factored in cradle to retail gate emission factors, required to ship goods to the point of distribution/retail, which arguably are comparable with logistics required to ship goods to the point of distribution/export.

  We are looking therefore for as many (**Expenditure Item EF x country of origin**) combinations as it is feasible to source in a relatively short timeframe. Importantly, for missing (Expenditure Item EF x country of origin) combinations, of which there will be many due to the overall sustainability data scarcity issues which we discuss at length in section 12, we propose an extrapolation algorithm using the electricity GHG Emissions Differential between countries of origin. We dedicate section 7 of this Whitepaper to the equations, underlying assumptions, and opportunities to further refine this methodology.

- **Stage 2**: We recommend sourcing EFs differentiated by freight mode (**air**, **sea** and **road**), where possible with granularity aligned to logistics requirements for specific goods (such as cold chain for sea or road transportation for perishable goods, differentiated by frozen or chilled state requirements). For simplicity purposes, in our framework we consider the usage of 3 EFs across all logistics conditions for each specific freight mode[13]. We then consider international shipping routes between each country of origin and the focal country(with at least two shipping points by country – one airport and one seaport, and the distances to the focal country for each route[14]).

- **Stage 3**: We source focal country contextualized EFs for Warehousing and Retail services, which would typically be Monetary. In case such EFs are not easily retrievable for the focal country, proxies can be used, such as the EFs for Wholesale and Retail operations from the UK and England's carbon footprint can also be used as a proxy (UK DEFRA, 2023).

- **Stage 4**: If expenditure data covers usage related expenses such as electricity, fuels or water consumption bills, then it suffices to source EFs representative for the carbon footprint of these utilities in the respective focal country. The resulting estimation should then cover the emissions produced during the usage stage of products such as electronic appliances, vehicles, or foods prepared at home.

- **Stage 5**: We recommend sourcing, if available, focal country contextualized EFs for specific waste management practices (we expect most countries to have a mix of practices such as landfill and incineration). If such EFs are not easily retrievable, then proxies can be used, such as the domestic waste management EFs for UK, from the UK Government GHG Conversion Factors for Company Reporting (UK DESNZ and UK DEFRA, 2023).

- **Across all stages**: Overarching previous stages, we recommend sourcing **Electricity EFs** for all countries of origin, which can be retrieved for instance from the Yearly Electricity Data (Ember Climate, 2023). These will be useful not only in the computation of the Electricity carbon footprint within the focal country, but also for extrapolation purposes in order to contextualize sourced EF, as per the algorithm described in section 6.

3.3.3 Product Price Journey

- **Stage 1**: The conversion of EFs from Physical to Monetary will require usage of price datapoints. Datasets such as BACI: International Trade Database at the Product-Level (CEPII, 2023) can offer valuable insights into **average exporter price** by commodity. Using the quantities and Free-On-Board (FOB) value of the commodities average exporter prices can be inferred. These can be further on rolled up to Expenditure Item level using the average of the commodities mapped for each.

[13] Sources: Ritchie, 2020, Weber and Matthews, 2008a.
[14] For major global exporters with larger geographical areas and multiple international shipping hubs (such as US, China and India), we recommend capturing at least two shipping locations.

These estimated exporter prices can be further processed to add **markups** allowing for inferring average **retail prices** in the focal country, which can be later on be used for Physical EFs (expressed as kg CO2e / kg) conversion to Monetary EF (expressed as kg CO2e / $). In addition, to support the conversion of EFs expressed in denominators other than kg, we recommend manually sourcing retail prices relevant for the year of study in the focal country.

- **Stage 2**: The conversion from Physical to Monetary for EFs specific to international goods shipping can be done using the FOB (Free-On-Board) quantities and values of internationally shipped commodities. In our framework we use the FOB price with an average Retail Price Markup, alongside distances travelled for each product, to perform EF conversion from Physical (kg CO2e / ton.km) to Monetary (kg CO2e / $).

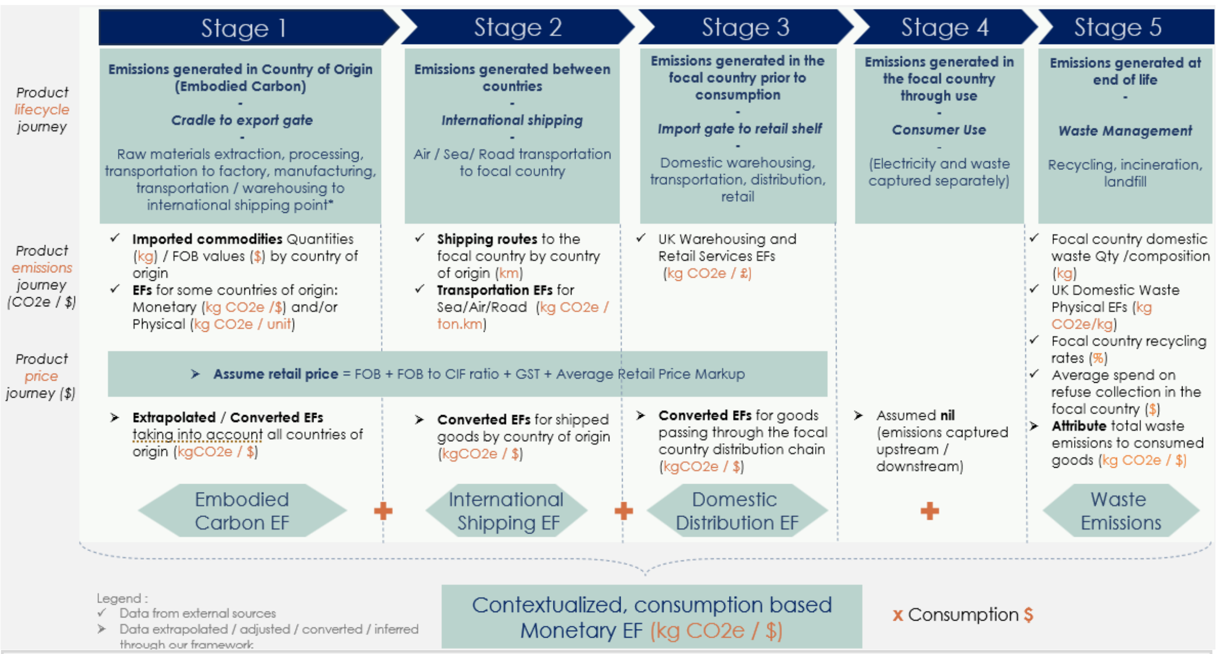
- **Stage 3**: If the EFs sourced in the previous phase Monetary, then there is no need for further data points for EF conversion.

- **Stage 4**: No further data is required at this point as expenditures related to usage of products are already captured in other categories.

- **Stage 5**: Waste-related expenditures are necessary for further computations and would typically be captured in household expenditure surveys in the utilities-related section.

3.3.4 Lateral Aggregation of EFs at Expenditure Item (L5) Level

***Figure 3**: Datasets mapping simplified life cycle stages*



Source: Figure produced by our project team incorporating guidelines from The Greenhouse Gas Protocol: Product Life Cycle Accounting and Reporting Standard (WRI and WBCSD, 2011a), and presented as such also in our companion Whitepaper "Consumption Carbon Footprint: Singapore Case Study".

In Figure 3 we share the summarized mapping of emissions and price datasets allowing for the eventual estimation of Monetary EFs by LCA stage. We then perform a **multi-layered lateral aggregation**[15] of the EFs thus obtaining Expenditure Items:

- The first layer of lateral aggregation is for Stage 1 in our LCA mapping, covering **Embodied Carbon**[16]. All (**Expenditure Item EF & country of origin**) combinations aggregated into a single, focal country contextualized, consumption-based Expenditure Item IF, through weighted average across all countries of origin, using as weight each country of origin's $ contribution to the total $ imports of commodities mapped to the respective Expenditure Item[17].
- The second layer of lateral aggregation is across all 5 Stages in our LCA mapping. We aggregated by summing up all EFs for each LCA stage, to obtain unique, focal country **contextualized, consumption-based, Monetary EFs**, at the granularity of Expenditure Item (L5) level, which are obtained by summing up Monetary EFs from each LCA stage.

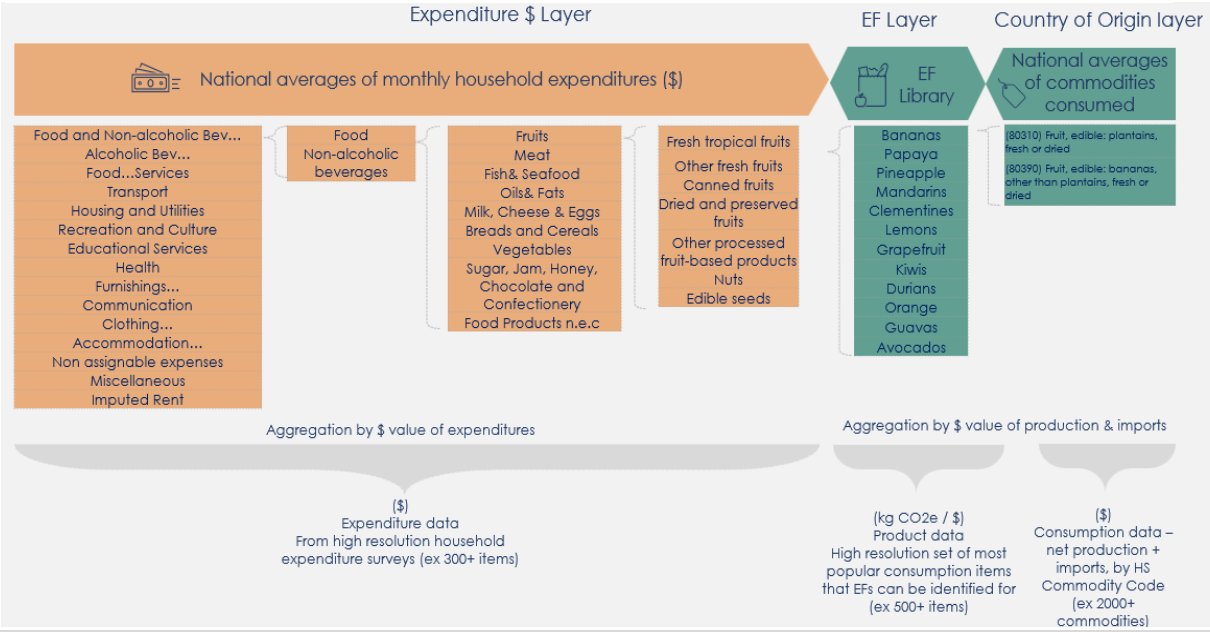
The list of laterally aggregated, focal country contextualized, consumption-based, Monetary EFs at Expenditure Item (L5) level will effectively act as the focal country **EF library,** that can be later on interoperable with expenditure data available at L5 level of granularity. For focal countries where expenditure data scarcity may be a challenge as well, we define in the next sub-section our approach to vertical aggregation.

3.3.5 EF vertical aggregation across expenditure hierarchy levels

After conducting the lateral aggregation of Emission Factors described above, the next step will be the vertical aggregation of EFs, to allow for easy navigation across different levels of expenditure data. In Figure 4 we describe how we use Imports Data and $ spend data to navigate the different levels of resolution for expenditures:

[15] We use the term "lateral aggregation" to refer to the aggregation of Emission Factors across the 5 sequential LCA stages we have defined, as well as across all countries of origin for the LCA Stage 1 (covering "embodied carbon").
[16] We use the term "embodied carbon" to refer to the GHG emissions associated with the cradle to export gate stage in a product's lifecycle.
[17] In our model for simplicity of calculation we assume local production to be null. The algorithm can be adapted if local production data is available at HS commodity code level, by factoring in the local country and treating it like a country of import, with an Electricity GHG Emissions Differential of 1 if focal country contextualized EFs are available (as no EF extrapolation would be required in that situation).

***Figure 4**: Data aggregation example across products resolution levels*



Source: Figure produced by our project team based on extracts from SG DOS, 2019 (sample of expenditures structure) and from BACI CEPII, 2023 (sample of commodity codes and names). A similar view is shared also in our companion Whitepaper "Consumption Carbon Footprint: Singapore Case Study".

- From **Expenditure Item (L5)** to **Expenditure Item Type (L4)** levels, the EFs are rolled up by using weighted averages, whereby the weight of each EF is determined by the **value of imports** for all HS commodity codes associated with the respective Expenditure Item (working under the assumption that domestic production is null). By applying this method, we effectively take into account the country of origin mix within any Expenditure Item Type consumption basket. The advantages of this approach are not only factoring in import patterns, but also bypassing the lack of spend $ data at such a granular level (L5). For countries where this assumption does not apply, we recommend adapting this framework by factoring in the focal country as another country of origin to be added to the model.

- From **Expenditure Item Type (L4)** level **above**, if $ data is offered in national household expenditure surveys, then the $ weighted average of Monetary EFs can be performed when moving to the next levels. The resulting EF Library will thus be enriched with Monetary EFs at Expenditure Category (L1), Expenditure Sub-Category (L2), Expenditure Item Class (L3), Expenditure Item Type (L4), in addition to the previously obtained Expenditure Item (L5) level. This increased the EF Library interoperability with Expenditure data provided either through surveys or through actual financial transactions data.

4. Emission Factors Processing Methodology

4.1 EF data library considerations

The goal at this stage is to build a Consumer Products and Services **Library**, with incremental levels of granularity and associated EFs, which can be connected to consumer financial transactions data - either actual transaction data, which we are developing our model to support and aim for at a later stage, or statistical average data from household expenditure surveys, which can be used as a proxy as described here below.

The key considerations in the sourcing of emission factors are the coverage of countries of origin and appropriate **LCA stage**. Another area of focus in our study concerns the **country of origin** for imported products. This focus stems from the body of literature substantiating how different production technologies, processes, and energy sources deployed in different countries or regions impact significantly the embodied carbon of goods produced within the respective geographies, as "the energy and emissions intensities of products produced in different countries can be quite different, reflecting a combination of differences in the structure and efficiency of economies and in the product mix being produced" (Ivanova et al., 2016). Other country level studies for Norway and the United States found the country of production can have a major impact on the embodied carbon of imported goods (Ivanova et al., 2016, Hertwich and Peters, 2009, Weber and Matthews 2008b).

4.2 EF data types

The datasets that can be sourced publicly offer both Physical EFs (expressed as kg CO2e / a variety of units of measurement, such as kg, l, unit of product) and Monetary EFs (expressed as kg CO2e / currency). We harmonize the data into a focal country relevant Monetary EF format (expressed as kg CO2e / $), by performing either currency conversion (for Monetary EFs referencing other currencies), or by using price proxies (for Physical to Monetary EF conversion).

4.3 EF data challenges

Relevant EF data representative for **consumer-ready goods and services** can be sourced from a variety of publishers, such as public sector agencies, academic bodies, non-profit organizations or commercial data providers.

4.3.1 Data scarcity – Conversion and extrapolation requirement

Ideally, we should target sourcing EFs for each commodity and for each country of origin. Factoring in brand variations as well, the datasets required for precise estimations could easily revolve around millions of consumer ready goods and services EF datapoints. In our research we were were not able to find such extensive data, and we anticipate project teams researching this space may face similar data scarcity issues. In our framework we therefore assume EFs representative of a few combinations of (country of origin x expenditure item) would be available, and they would have to be analyzed, mapped and processed in order to extrapolate them to the missing data points.

4.3.2 EF data heterogeneity – Manual mapping requirement

Importantly though, even the scarce data points that may be practically available would likely be affected by heterogeneity concerns, which are prevalent in the sustainability data ecosystem. The most common heterogeneity parameters we have seen are:

1. **Methodological alignment**: EF data points are obtained by applying specific methodologies which can be aligned to GHG Protocol, ISO 14040:2006 or others. Different underlying methodology may yield different EF results.
2. **Global Warming Potential (GWP) multipliers**: EF data points are obtained by applying GWP multipliers to the greenhouse gases (GHGs) associated with a specific item, in alignment with the IPCC guidance in the 4th, 5th or 6th Assessment Reports (ARs). However, the GWP multipliers guidance itself has changed as the underlying science evolved, from each AR to the next.
3. **Greenhouse Gases (GHGs) covered**: EF datapoints are obtained starting from a predefined scope of GHGs. Some datasets may cover the GHGs referenced in the Kyoto Protocol (CO2, CH4, N2O, HFCs, PFCs, SF6)[18], some may include also NF3, while some others may be limited to just the key three (CO2, N2O, CH4).
4. **System boundaries:** EF datapoints are obtained through studies employed specific boundaries which may differ from one dataset to another (some studies may cover a cradle-to-grave lifecycle for specific goods[19], while some others may cover a cradle-to-retail gate cycle[20])
5. **Uncertainty:** some EF datasets offer publicly accessible, explicit uncertainty percentages for each EF, while others may offer uncertainty indications implicitly (inferable from EF data quality ratings for instance), and others may not publish it at all.
6. **EF Data provider**: publicly accessible datasets can be available from Government agencies in different countries, NGOs, academic studies or commercial organizations.
7. **EF Data format**: publicly available EF datasets can be in Physical (kg CO2e / unit) or Monetary (kg CO2e / currency) format.
8. **Country representativeness**: EF datapoints are usually contextualized for a particular country, and the number of countries covered in each dataset is usually limited.
9. **Temporal representativeness**: EF data points are specific to a particular year of study, and the yearly coverage of EF data is usually very limited in the datasets we studied. Similar lifecycle analysis (LCA) studies may yield different results in different years, driven by changes for example in the energy mix within a specific country.

In section 11 we describe the **sensitivity analysis** methodology and results, covering both the uncertainty introduced by the original EFs sourced (introduced primarily by the data heterogeneity dimensions discussed in this sessions), as well as the

[18] WRI and WBCSD, 2011b.
[19] For example, in the study from Podong et al, 2020.
[20] For example, in the data set published by US EPA, 2023.

uncertainty introduced by the algorithm we are putting in place to process these original EFs (introduced primarily by assumptions and computational workarounds).

5. EF conversion and extrapolation algorithm

Historically, the calculation of emissions embodied in a variety of products is hindered by the lack of **consistent** and **comparable** emission factors, amplified by the opacity in the collection, reporting and validation of data (Hawkins et at, 2016[21]). Consistency of Emission Factors, especially for products embodied carbon, is however challenging to achieve. Data gaps in terms of Emission Factors availability for all products and all countries of origin are a roadblock to overcome. Therefore, after completing the first rounds of EFs data collection and assessment, the next stage is processing the data to identify and address issues around data incompatibility, heterogeneity, scarcity, unreliability and uncertainty, and apply, where feasible, workarounds.

This section and the next are dedicated to the algorithm we use to **convert**, **adjust**, **extrapolate** and **aggregate** Emission Factors. While all the calculations are done using Python coding, we are capturing here for transparency and discussion purposes the formulas used at each step.

5.1 Emission Factors format

The **unit of measurement (UoM)** spans both monetary and physical units, and thus we have in our collected dataset EFs expressed as kg CO2e / €, kg CO2e / £, kg CO2e / liter, kg CO2e / unit of product, and many more.

Besides the unit of measurement, there are other parameters as well that we need to map, such as the temporal and geographic representativeness.

$$EF_{UoM,YYYY,COO} = \frac{kg\ CO2e}{UoM}$$

$$(for\ products\ manufactured\ in\ country\ COO, in\ the\ year\ YYYY)$$

, where UoM is the denominator of the EF
, YYYY is the year of EF publication
, COO is the country of origin of the EF

- **YYYY** = Temporal representativeness (**year** of measurement)
- **COO** = Geographical representativeness (**country** where the goods were produced or services were performed), which we assimilate to country of origin (COO). In our model this is particularly relevant for goods, which we look at from a weighted imports perspective.
- **UoM** = **Unit of Measurement** or **Denominator** (measurement unit the GHG emissions were estimated in). We see various denominators depending on the EF original source and the type of LCA study informing it, such as kilogram of product (ex kg of rice), currency unit (ex USD, EUR, SGD), or other measurement

[21] While the authors studied agricultural food products in the work quote above, we consider the conclusions broadly applicable to various classes of consumer goods. Two key requirements highlighted in the same study as critical in the selection of EFs for emissions calculation are comprehensiveness and consistency. In our work we follow the same principles. We intend to address the need for **comprehensiveness** by pursuing whole-of-lifecycle coverage.

units (for example liter of milk, kwh of electricity, museum entry ticket, passenger.km, book, and more).

Our goal is to process all monetary and physical EFs we sourced and convert them from production-based EFs from a variety of countries measured at different historical times, to consumption-based EFs contextualized for the focal country as of 2023:

$$EF_{\$,2023,CTY} = \frac{kg\ CO2e}{\$}\ \ (for\ products\ consumed\ in\ CTY, in\ 2023)$$

, where $ is the Focal Country currency
, where CTY is the Focal Country (the object of study)

We then create a unique EF identifier to map each EF to an Expenditure Item (Level 5) in many-to-many relationships.

5.2 Algorithm overview

The next steps we take to harmonize the EFs are the following.

1. **EF parameters assessment**: For the unit of measurement (**UoM**), we manually catalogue the denominator type: currency, mass, distance, energy, other units. Depending on the denominator type the next steps in the conversion and extrapolation will follow.
2. **Denominator conversion:**

a. For **Monetary EFs** (where the UoM is a currency), we apply the **currency conversion**, either in a single step, as described in section 5.3, or concomitantly with the temporal adjustment, as described in section 5.5.

b. For **Physical EFs** (where the UoM is a physical unit), we apply the physical to monetary conversion, leveraging **price proxies**, as described in section 5.6
   - **Converting Physical EFs denominated in kg,** per the methodology described in section 5.7.
     - We infer **exporter prices** from BACI: International Trade Database at the Product-Level (CEPII, 2023). We do so by extracting the import quantity (in kg) and import value at Free-On-Board (FOB) exporter price (in USD) by commodity[22] by country of origin.
     - We extract the **FOB values[23] by commodity** by country of origin, which we obtain by dividing import value over import quantity for each commodity.
     - We obtain the **FOB value by Expenditure Item (L5)** by vertical aggregation, using averages of commodity level FOB values.
     - We apply an average estimated **mark-up[24]** to account for cost/price uplifts occurring post the point of export, such as international shipping and insurance, domestic warehousing, distribution and retail, and GST/VAT.
     - We convert the prices from **USD to $** by using currency conversion and inflation adjustment.

[22] In this dataset commodities are classified by commodity codes, following the HS (Harmonized System) Nomenclature 2022 edition (World Customs Organization, 2022).
[23] As specified in the BACI CEPII methodology (BACI CEPII, 2023).
[24] This mark-up will need to be estimated for each focal country, subject to specific research. In our companion Whitepaper "Consumption Carbon Footprint: Singapore Case Study" we share an example of how this concept can be applied to a specific country of study.

- We use this price point to convert the EF to kg CO2e / $, which we consider to be the EF for the respective product, when imported into CTY (the focal country) from the respective COO (country of origin).

  - **Converting Physical EFs denominated in other units**, according to the methodology described in section 5.8.
    - For Expenditure Items (Level 5) that have physical (non-currency) UOMs other than mass, as we don't have a consolidated, vetted source for prices, we need to rely on **case-by-case sourcing or sampling** of unit prices, as **average price proxies**.
    - For each Item that we needed prices for, we looked for available data or reports as described further on, and, where these were not available, we have applied a sampling of **price data points**, which we have averaged and used as a price proxy.
    - Due to practical difficulties, we do not consider the country of origin. The price proxies we derive are for the average product consumed into CTY (the focal country).

3. **Temporal adjustment**: For each EF, we apply an inflation adjustment to update them to the year (**YYYY**) of reference (which in our calculation example is 2023).
4. **(COO) Extrapolating EFs to other countries of origin**, per the methodology described in section 6.
   - The steps taken up until this point have been about **harmonizing existing EF data** - namely, the format of original EFs we were able to source.
   - The steps taken after this point are about **compensating for missing EF data** - by extrapolating the thus harmonized EFs, which still apply to their respective country of origin, to other countries of origin.
   - In order to extrapolate EFs to other countries of origin, we will assume the carbon footprint of a product manufactured in a specific country depends on how advanced **technological capabilities** are within the respective country (for which we take as a proxy GDP per capita), as well as how green **energy production** is within the respective country (for which we take as a proxy the carbon intensity of electricity, expressed as kg CO2e/kwh), as well as qualitative/cultural aspects which may impact manufacturing and distribution related activities (for which we don't use a proxy per se, but against which we conduct a "sanity check" on country grouping as described here below)
   - Based on these 2 proxies, **GDP per capita** and **kg CO2e/kwh** by country, we map countries into 3 baskets based on their technological and energy mix proximity to a **central anchor country**, represented by the country for which a critical mass of EFs has been reached in the data collection efforts. In our experience, such a critical mass of EFs can be collected for example from CN, US, and UK, and in our framework we will use them as examples.
   - We use each original EF to extrapolate to other countries of origin **within the same basket** as the original EF COO.
   - For extrapolation, we use the electricity emission factors for all countries.
   - We henceforth refer to these as **CIEG** (Carbon Intensity of Energy Generation).
   - For extrapolation to a new country, we multiply the original EF with the **electricity carbon intensity "differential"** between the 2 countries (namely the division of kg CO2e for electricity production in the country of the EF we need / kg CO2e for electricity production in the country of the EF we have).
5. **EF aggregation – moving from production based to consumption based EFs**

- The step above was about **filling in the gaps** in terms of EF data for each Item, for each country of origin.

- The next step is about **consolidating** this extrapolated data, to move from a production based to a consumption-based perspective. Basically, we want to define the **embodied carbon EF for an "average" item consumed in the focal country**, considering where it is imported from, and the emission factors for those countries of origin.
  - For this, for each Item we average all extrapolated EFs for all relevant COOs, weighing each COO by the value of imports from the respective COO.
  - The CTY specific EFs thus obtained will be applied to spend information, to derive the carbon footprint of the respective Item expenditure.

In the following subsections we detail each step in this methodology, adding the formulas that we used along with the applicable assumptions taken at each step.

5.3 Monetary Emission Factors – Currency Conversion

To convert monetary EFs with denominators other than $ we applied the currency exchange rate as of the year relevant for the EF calculation:

$$EF_{\$,2023} = \frac{EF_{K,2023}}{FX\,rate\,(K_{2023},\ \$_{2023})} = \frac{kg\ CO2e}{\$_{2023}} = \frac{kg\ CO2e}{Currency\ K_{2023}} \ \Big/ \frac{\$_{2023}}{Currency\ K_{2023}}$$

$$FX\ rate\ (K_{2023}\ ,\ \$_{2023}) = \frac{\$_{2023}}{Currency\ K_{2023}}$$

, where $ is the currency of the focal country
, K is the currency of the country the Original EF was computed for
, FX rate is the exchange rate between currency K and currency $

5.4 Monetary Emission Factors – Temporal Adjustment

For cases where the monetary Emission Factors were reported as of a historical year before 2023, we have used inflation rates for temporal adjustments:

$$EF_{\$,2023} = \frac{kg\ CO2e}{\$_{2023}} = \frac{kg\ CO2e}{\$_{YYYY}} \Big/ \frac{\$_{2023}}{\$_{YYYY}} = EF_{\$,YYYY}\ \ / \ Inflation\ Rate\ (2023, YYYY)$$[25]

$$Inflation\ Rate\ (2023, YYYY) = \frac{CPI\ \$_{2023}}{CPI\ \$_{YYYY}}$$

, where $ is the focal country currency
, K is the currency in the country the Original EF was computed for
, YYYY is the year the Original EF was computed for

[25] Similar recommendations are shared or can be inferred from the GHG Protocol guidelines (WRI, WBCSD, 2011a, and WRI, WBCSD, 2011b)

5.5 Monetary Emission Factors – Simultaneous conversion and adjustment

In most cases the currency and temporal EFs conversion was required simultaneously, in which case we have used the formula:

$$EF_{\$,2023} = EF_{K,YYYY} \,/ FX\,rate\,(K_{YYYY}, \$_{YYYY}) / Inflation\ Rate\,(2023, YYYY)^{26}$$

$$EF_{\$,2023} = \frac{kg\ CO2e}{Currency\ K_{YYYY}} / \frac{\$_{YYYY}}{Currency\ K_{YYYY}} / \frac{\$_{2023}}{\$_{YYYY}}$$

$$EF_{\$,2023} = \frac{kg\ CO2e}{Currency\ K_{YYYY}} * \frac{Currency\ K_{YYYY}}{\$_{YYYY}} * \frac{\$_{YYYY}}{\$_{2023}}$$

, where $ is the focal country currency
, K is the currency in the country the Original EF was computed for
, YYYY is the year the Original EF was computed for

5.6 Physical to Monetary EF Conversion – general approach

The riskiest conversions, however, are the ones requiring moving from physical to monetary EFs. To bridge this gap, we use price proxies where and as available. This is the second biggest driver of incremental uncertainty[27] into the model, as we will detail in section 11. Depending on data availability, we use two different methods for price estimation:
(1) **For products for which we have EFs expressed as kg CO2e / kg**, we use data from CEPII, 2023, from which we can derive a proxy for Exporter Prices as a basis for our calculation.
(2) **For products for which we have EFs expressed as kg CO2e / other denominators**, or where we did not have insights by county in the CEPII, 2023 dataset we manually source and average price datapoints for each product.

5.7 Physical (kg CO2e/kg) to Monetary Emission Factors Conversion

For products for which the EFs retrieved are expressed as kg CO2e / kg, we used the insights from the **CEPII BACI database**[28].

The database provides the focal country with import data in terms of the total kg quantity imported in 2018 (by commodity, by exporting country), and respectively

[26] Similar recommendations are shared or can be inferred from the GHG Protocol guidelines (WRI, WBCSD, 2011a, and WRI, WBCSD, 2011b)
[27] We define incremental uncertainty as the uncertainty introduced by adjustments, conversions and compilation of EFs. All these steps add a degree of risk on top of the uncertainty embedded in the EF calculation itself, as published by the data providers. At this stage in our study, we have not quantified this incremental uncertainty.
[28] The dataset offers values and quantities for each commodity imported into the focal country (identified by the respective HS code), and from each country of import (217 countries/territories of import are provided). For simplicity of calculation, we have considered the country of import to be the same as the country of origin for all commodities. In our model we also assume the entire production cycle for all commodities up until the point of export takes place with the country of origin. The model can be adapted for focal countries where the local production and exports are tracked, with data available at commodity HS code level.

total USD_{2022} value (by commodity, by exporting country, at FOB value), for a set of ~**5,200 commodities** classified by the Harmonized System nomenclature[29]. The data we have extracted is as of 2022, which was the most recent data available during 2023, at the time of our study. A newer version has been released as of Jan 2024, which can be used within this same algorithm subject to the respective inflation indexing differences.

5.7.1 Import patterns mapping: countries of origin, values and quantities

To leverage the CEPII BACI 2023 dataset, we manually examined the ~5,200 commodities (identified by HS codes) to determine which are likely to be attributable to, or closely represent the import patterns of, end user finished goods. We thus identified **1,416 commodities** which we mapped to the Expenditure Item Types in our list (L5) in many-to-many relationships (2,096 in total relationships mapped). We use this mapping to both identify import patterns and to derive FOB values for respective products. The mapping can be both **one-to-one** (one commodity mapped to a single Item, which is the predominant case) or **many-to-many** (several commodities mapped to several Items), due to differences in nomenclature between the 2 lists.

A key assumption in our model is that the production & distribution activities up until the point of export occur in the country of import. However, we do know that global supply chains are fragmented, with touchpoints in different countries at different stages in the production and distribution chain. Embodied emissions estimated for goods could vary, depending on specific products and services value chain (which can have variances down to manufacturer, brand, and SKU level). Another assumption we make for simplicity of calculation is that domestic production of consumer goods is null, and all end consumer items are imported. For countries with significant domestic production, this can be absorbed into the model as long as it is mapped to the same commodity structure. The focal country can be treated as a country of import itself to account for significant domestic production.

5.7.2 Import data: estimating FOB price proxies

At the next step, we pull all the **FOB Import Values** (available in k USD as of 2022), and **FOB Import Quantities** (available in tons) for all HS codes that are mapped to an Expenditure Item Type (Item ID), by country of import. We estimate the FOB Price Proxies in USD_{2022} dividing FOB Import Value by Import Quantity datasets.

$$FOB\ Import\ Value_{Item\ ID,COO}\ in\ USD_{2022} = \sum_{1}^{k} FOB\ ImportValue_{HS\ Code\ i,COO}$$

, where FOB refers the Free On Board Incoterm
, FOB Importer Value is the exporter price
, ItemID is the unique identifier for an Expenditure Item (L5)
, COO is the country of origin
, HS Code is the commodity code as per the Harmonized System Nomenclature (WCO, 2022)
, i is from 1st HS code linked to an Item ID to the k-th HS code linked to the same Item ID

$$FOB\ Price\ Proxy_{\ USD,Item\ ID,COO}\, in\ ^{USD_{2022}}/_{kg} = \frac{FOB\ Import\ Value_{Item\ ID,COO}}{FOB\ Import\ Quantity_{Item\ ID,COO}}$$

[29] World Customs Organization, 2022.

, where FOB refers the Free On Board Incoterm
, FOB Importer Value is the exporter price
, ItemID is the unique identifier for an Expenditure Item (L5)
, COO is the country of origin

$$FOB\ Import\ Quantity_{ItemID,COO}\ in\ USD_{2022} = \sum_{1}^{k} FOB\ Import\ Quantity_{HS\ Code\ i,COO}$$

, where i is from 1st HS code linked to an Item ID to the k-th HS code linked to the same Item ID
, where FOB refers the Free On Board Incoterm
, FOB Importer Value is the exporter price
, ItemID is the unique identifier for an Expenditure Item (L5)
, COO is the country of origin
, HS Code is the commodity code as per the Harmonized System Nomenclature (WCO, 2022),
i is from 1st HS code linked to an Item ID to the k-th HS code linked to the same Item ID

We then estimate **Retail Price Proxies** in CTY (the focal country) by applying an average mark-up. This mark-up needs to cover the FOB to CIF ratio, the local VAT/GST, the import markup and the wholesale to retail markup at a minimum.

$$Estimated\ Retail\ Price\ Proxy_{USD,ItemID,COO}\left(\frac{USD_{2022}}{kg}\right) = FOB\ Price\ Proxy\ \times (1 + Retail\ Markup)$$

, where the Estimated Retail Price Proxy is the average retail price for an Item ID
, Item ID is the unique identified for an Expenditure Item (Level 5)
, COO is the country of origin
, FOB is the Free On Board incoterm
, FOB Price Proxy is the average exporter price for an Expenditure Item (Level 5)
, Retail Markup is the uplift from exporter price in the country of origin, to retail price in the focal country

As a next step we convert the estimated Retail prices to $\$_{2022}$ using the 2022 USD-$ exchange rate, and we temporally adjust it by applying the focal country **inflation rate of 2023**.

$$Estimated\ Retail\ Price\ Proxy_{\$,ItemID,COO}\ in\ \frac{\$_{2023}}{kg} = Estimated\ Retail\ Price\ Proxy_{USD,2022,ItemID,COO} *\ FX\ rate\ (K_{YYYY}\ ,\$_{YYYY}) * Inflation\ Rate\ (\$_{2023}\ ,\$_{2022})$$

, where the Estimated Retail Price Proxy is the average retail price for an Item ID
, $ is the currency of the focal country
, Item ID is the unique identified for an Expenditure Item (Level 5)
, COO is the country of origin
, FX rate is the exchange rate between the currency of the focal country and USD
, Inflation Rate is the Inflation Rate in the focal country

$$Etimated\ Retail\ Price\ Proxy_{SGD,ItemID,COO}\ in\ {}^{\$_{2023}}\!/_{kg} = \frac{USD_{2022}}{kg} * \frac{\$_{2022}}{USD_{2022}} * \frac{\$_{2023}}{\$_{2022}}$$

, where the Estimated Retail Price Proxy is the average retail price for an Item ID
, $ is the currency of the focal country
, Item ID is the unique identified for an Expenditure Item (Level 5)
, COO is the country of origin
, FX rate is the exchange rate between the currency of the focal country and USD
, Inflation Rate is the Inflation Rate in the focal country

5.7.3 Converting Emission Factors

Each EF we sourced is specific to only one country of origin. We will refer to the country of origin of the respective EF as **COF**[30]. In this section we describe how we compute the **Monetary EFs** for Expenditure Items (L5), with $\$_{2023}$ as denominator. We are not performing any temporal adjustment using inflation as these are Physical EFs – we consider the temporal adjustment to have been performed by using 2023 updated estimate retail price proxies.

$$\mathrm{EF}_{\$,2023}\mathrm{in}\ {}^{kgCO2e}\!\big/_{\$_{2023}} = \mathrm{EF}_{\mathrm{Kg,YYYY}}\ \ /\ \mathrm{Estimate\ Retail\ Price\ Proxy}_{\$,\mathrm{ItemID,COF}}$$

, were \$ is the currency of the focal country
, where the Estimated Retail Price Proxy is the average retail price for an Item ID
, \$ is the currency of the focal country
, YYYY is the year the Original EF was computed for
, the Estimated Retail Price Proxy is the average retail price for an Item ID
, Item ID is the unique identified for an Expenditure Item (Level 5)
, COF is the country the original EF was computed for

5.8 Physical (kg CO2e / UoM) to Monetary Emission Factors Conversion

For Items with units other than mass (and for which we could not derive price proxies using import data), we recommend searching for insights available either in public, free to use, statistical reports, such as **CPI reports**. For other Items for which such data is not available, **manual sampling** of price points available on several online retail platforms popular in the focal country can be performed. Indexing with inflation can be performed to bring manually collected prices to the same reference year as targeted for the household carbon footprint study.

$$EF_{\$,2023}in\ {}^{kgCO2e}\!\big/_{\$_{2023}} = EF_{UoM,YYYY}\ \ /\ Manually\ Sourced\ Price_{\$,2023}$$

, where \$ is the currency of the focal country
, UoM is the denominator of the Original EF
, YYYY is the year of study of the Original EF
, Manually Sourced Price is the average estimated retail price of the item the Original EF was computed for

[30] We use the acronym COF to refer to the countries that Emission Factors published by different providers are representative of.

6. EF extrapolation to all relevant Countries of Origin

The steps taken up until this point have been about **harmonizing existing data** - namely, the format of the original EFs sourced. The steps taken after this point are about **compensating for EF data we don't have** - by extrapolating for each Expenditure Item (L5) the harmonized sourced EFs, which still apply to their respective country of origin, to other countries of origin, that we were not able to source any EF for. We thus create placeholder EFs to allow us complete coverage of (**EF x country of origin**) combinations for each Expenditure Item labelled as Product.

A guiding principle in building our model has been readiness to connect emission factors to actual consumer financial transactions, with high product information granularity (price, quantity/volume, country of origin of items bought). In the future we hope that more broadly available EFs data will allow studying the variability of **emissions intensity** of specific items by country of origin – conclusions which could inform more sustainable import and consumption choices for businesses or households. Until we reach such a data rich environment, we will have to work with assumptions, quantify uncertainty and build data frameworks as modular structures in which better pieces can replace placeholders, when and as they become available.

The technique we apply to estimate EF data points beyond the range we were able to collect, is based on **logical assumptions** on products and services GHG emissions' dependency on energy (as reflected in electricity EFs), for any given product in any given country. Unlike for more typical extrapolation exercises, we do not use observed patterns in the EF data for extrapolation due to data scarcity. Our technique is close to **imputation**, in the sense that our goal is to fill in missing EF by product by country, as a placeholder until a global database is in place.

6.1 Products and services electricity dependency

The workaround we have found for the data scarcity challenge has been to extrapolate the EFs that we do have (which are primarily from US, China and UK) to the rest of the countries that we don't have EFs for, based on country comparability criteria and an extrapolation algorithm which we describe below.
Our fundamental assumptions are that:

1/ the chief contributor to a product or a service carbon footprint is the **energy consumed** in the process of extracting, processing and transporting raw materials, manufacturing, distribution and delivery.
2/ depending on the **carbon footprint structure** of a good or service, that contribution of energy would vary by a degree of dependency we refer to as б
3/for any 2 countries that have similar technological advancement and energy resources, the **degree of dependency б** is the same.

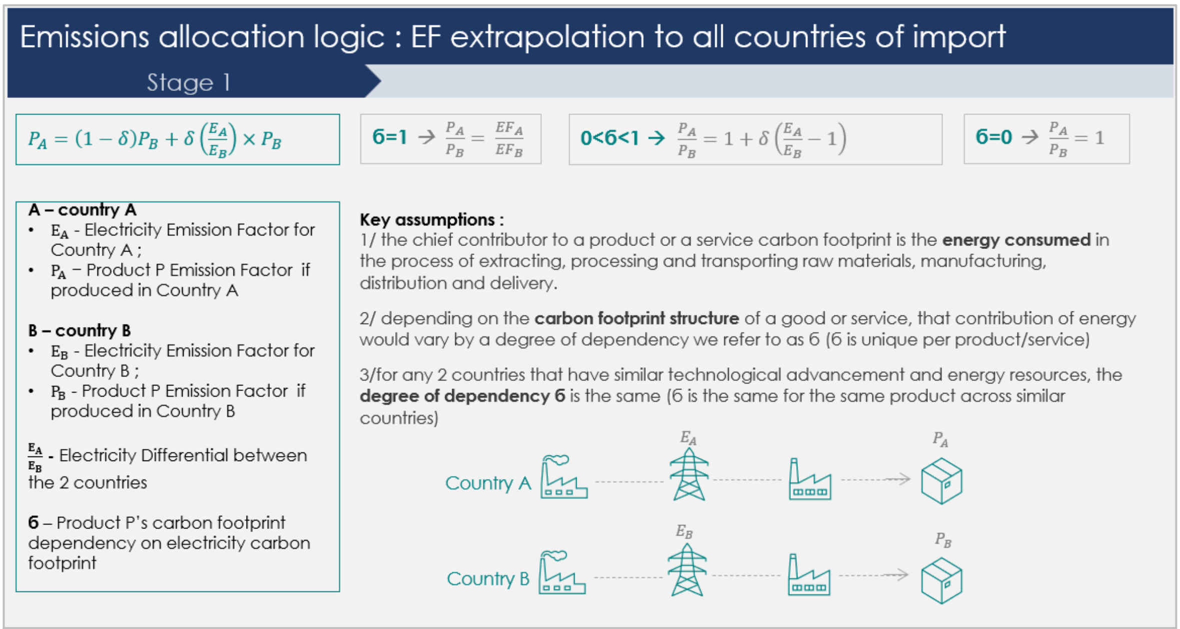
$$P_A = (1-\delta)P_B + \delta\left(\frac{E_A}{E_B}\right) \times P_B$$

, where P is any given consumer product or service
, P_A is the Emission Factor for product or service P, if P is produced in country A
, P_B is the Emission Factor for product or service P, if P is produced in country B
, E_A is the Emission Factor for electricity generated in country A

, E_B is the Emission Factor for electricity generated in country B
, б – product or service P's carbon footprint dependency on electricity carbon footprint

Essentially, б serves to answer the question: "to what extent would the GHG emissions associated with producing a good or service be different from one country to another? ". A б of **100%** would imply these emissions would be completely correlated with how electricity emissions are in the respective country. On the other hand, a б of **0%** would indicate there is no dependency on electricity (or energy for that matter) that we could easily identify at this stage. Absent any data to indicate otherwise, we assume the EF for the respective product or service to be the same in all countries as in the one we were able to source it for (or the average thereof, if multiple such EFs were available). We summarize this hypothesis in Figure 5.

Figure 5: EFs extrapolation to all countries of origin - б hypothesis



Sources: Figure produced by our project team based on our emissions extrapolation logic and overall GHG emissions estimation algorithm.

To conduct this extrapolation to other countries, we consider that there are both differences and similarities between the emission footprint of Items manufactured in different countries.

In terms of similarities, we assume that manufactured products have a **similar set of contributors to embodied carbon**, of which energy is the most important one. Defining, however, the set of contributing factors, and the likely contribution of each to the carbon footprint of a product, comes down to completing informed Life Cycle Assessment exercise by product, capturing country differences.

In terms of differences, we assume that **technological advancement** and deployment of green manufacturing capabilities would lead to a lower carbon footprint of finished goods. We also assume that the **cleaner the energy sources** available in a particular country, the less emissions intensive the finished goods would be in general. We thus infer a full set of comparable and consistently computed **Extrapolated EFs**, corresponding to consumer goods and services from all relevant countries of origin[31].

In our algorithm, to increase the relevance of EFs extrapolation to other countries, we preferred to use three different **country anchors** instead of one. We assigned countries to their anchor in a grouping model based on a set of logical assumptions pertaining to the comparability of production processes and practices in different countries, as well as the emissions intensity of the energy used along the goods lifecycle.

As EF datasets for consumer goods and services become more widely and easily available across countries, we recommend benchmarking and ideally replacing Extrapolated EFs with reliable and representative EFs sourced from reputable studies

6.2 Country baskets grouping logic

We grouped all 217 countries of import[32] in 3 baskets, based on 3 dimensions which we consider having a material influence on the emissions intensity of products manufactures and services delivered in the respective countries:

- **National average electricity emissions intensity**. As energy consumption is the main driver of embodied carbon emissions, we expect products manufactured or services rendered in countries with vastly different energy mixes to have proportionally different carbon footprints. The proxy indicator for this characteristic is the national average of kg CO2e / kwh[33].
- **Technological advancement**, especially in terms of green technology implementation and adoption. We expect this characteristic to depend on the general technological advancement in the country, and the degree of investment in clean manufacturing facilities and processes. The proxy we consider is the GDP / capita[34].
- **Cultural and/or geographical proximity**. While we do not associate a particular proxy or indicator to this characteristic, we do take it into account as a sanity check for grouping presented below. We used this dimension as a qualitative sanity check of the grouping resulting from leveraging the 2 proxies above.

6.2.1 Country baskets grouping methodology

To define the country baskets, we perform the following calculations:

- We build the datasets for GDP per capita (GDPC) and Carbon Intensity of Electricity Generation (CIEG) for all 217 countries and geographies relevant as Singapore trade partners per the BACI CEPII dataset.

$$\mathrm{GDPC_i} \quad \mathrm{CIEG_i}$$

, where GDPC is a country's GDP per capita
CIEG is a country's Carbon Intensity of Electricity Generation
i is the country of import

[31] A similar concept of using one country's EFs for different products, to calibrate the EFs from another country, has been discussed by Hawkins et al (2016).
[32] We use the term including special territories and regions, as per the nomenclature used in CEPII, 2023.
[33] At the time of this study we found extensive electricity EFs available from Ember Climate, 2023.
[34] At the time of this study we found extensive GDP per capita data available from World Bank, 2024.

- We normalize the GDPCi and the CIEGi using the following formulas yielding results between 0 and 1.

$$X_i = Normalised\ CIEG_i = \frac{CIEG_j - MinCIEG}{MaxCIEG\ - MinCIEG}$$

, where MinCIEG is minimum value of CIEG among all countries
MaxCIEG is maximum value of RGCF among all countries

$$Y_i = Normalised\ GDPC_i = \frac{GDPC_i - MinGDCP}{MaxGDPC\ - MinGDPC}$$

, where MinGDPC is minimum value of GDPC among all countries
MaxGDPC is maximum value of GDPC among all countries

- Using Xi and Yi we plot a scatter plot; bubble sizes are based on $value that Singapore imports from that specific country.
- We calculate country similarity indicators of each country of origin from the anchor countries (US, China and UK) through the following distance formulas. In this context, "distance" refers to technological and energy efficiency similarity:
  We use the minimum of the three country similarity indicators to select the Country Basket for each respective country.

$$Basket\ Country = Country\ of\ Min(D_{USA}, D_{GBR}, D_{CHN})$$

$$D_{i,CHN} = \sqrt{(X_i - X_{CHN})^2 + (Y_i - Y_{CHN})^2}$$

$$D_{i,GBR} = \sqrt{(X_i - X_{GBR})^2 + (Y_i - Y_{GBR})^2}$$

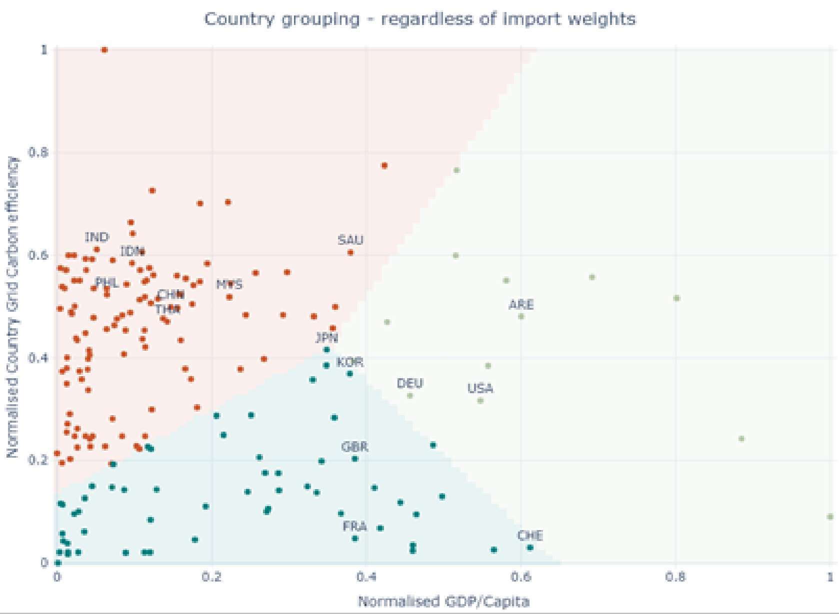
$$D_{i,USA} = \sqrt{(X_i - X_{USA})^2 + (Y_i - Y_{USA})^2}$$

6.2.2 Country baskets grouping results

The resulting map can help us separate countries of import in 3 baskets (Figure 6).

Red basket: carbon intensive energy, developing technology adoption
The country basket anchored by China EFs regroups Asian trading partners such as Malaysia, Indonesia, Thailand, India and Philippines. Volume and value wise, these are the most relevant trading partners for Singapore, accounting for more than half of all imports. These are also the geographies with the most emission intensive electricity production, and arguably the least access to efficient technology across the broad spectrum of manufacturers and producers involved global value chains.

***Figure 6**: Country grouping within extrapolation baskets*



Sources: Figure produced by our project team processing electricity EF data from Ember Climate, 2023, and GDP per capita from and World Bank, 2024.

Green basket: carbon intensive energy, advanced technology adoption
The country basket anchored by US EFs regroups Middle East, Japan and Korea and Germany fall into this grouping as well driven by their notably higher carbon emissions intensity of electricity production. They are countries for which we assume access to advanced and efficient technologies to be broadly available for manufacturers and producers, and where electricity related emissions are globally in the mid- range.

Blue basket: clean energy, advanced technology adoption
The country basket anchored by UK EFs regroups remaining European trading partners such as France and Switzerland. These countries have in common both high technological advancement, and some of the greenest electricity production in the world (driven primarily by the country's energy mix with heavier nuclear and hydropower components). This is unfortunately not only the smallest group of countries globally, but also some of the least relevant trading partners (in terms of annual import value)[35].

6.2.3 Extrapolation of all available EFs to all countries of import

As a starting point we have listed the original EFs, for which we have data points available from the data collection exercise, and which we previously converted and/or adjusted to be expressed as kg CO23/ $\$_{2023}$ (where COF = Country of original EF). For the majority of items, we were able to source multiple such EFs, typically each from different countries.

[35] Issues around carbon leakage and ecological impact of outsourced production are widely discussed in the academic literature, we are however not discussing these implications in our paper here as our focus is at micro, rather than macroeconomic.

The overarching format describing them is the following. Our intention is to map each EF we will subsequently have to extrapolate, to the Item ID it is for, the country of origin it is from, and how many other EFs are available for the same Item ID (for triangulation/averaging purposes as described later on):

$$\mathrm{EF}_{ItemID,COF,k}\, in\ {}^{kg\ CO2e}\!/_{\$_{2023}}$$

, where k ϵ K, and K is total number of emission factors available for a specific Item ID

We source electricity emission factors for all countries of import.

$$CIEG_{country}\, in\ {}^{kg\ CO2e}\!/_{kwh\ Energy\ Produced}$$

We extrapolate emissions factors to estimate what emission factor will be in other countries:

$$\text{EF-\$}_{ItemID,j,k}\quad in\ {}^{kg\ CO2e}\!/_{\$_{2023}} = \text{EF-\$}_{Item\ ID,COF,k}\left(\left(\frac{CIEG_j}{CIEG_{factor}}\times\delta\right)+(1-\delta)\right)$$

, where EF-$\$_{ItemID,j,k}$ is the Monetary Emission Factor that we need to define, for country of import j
, j is the index of the country of import (that we need to extrapolate to)
, k is the index of the EF that we are extrapolating (in case we have multiple available for the same Item ID)
, COF is the country of origin of the EF we have
, Б is the degree of dependency on electricity and
EF-$\$_{Item\ ID,COF,k}$ is the Emission Factor that we were able to source, for the country of origin that the EF was defined for

6.2.4 Selection of extrapolated EFs based on Country Baskets

At this stage, all available original EFs are extrapolated to all relevant countries of import for the respective Item IDs.
The next step consists in selecting the appropriate EFs (or average thereof) to be assigned to each country of import[36].
The first check point is on whether an original Emission Factor exists in the EF library, for that specific country of origin.

1. If at least one original EF is available for an Item ID for a particular country of origin.
   - The original EF will be selected for that country of origin.
   - If multiple original EFs are available (namely, multiple EFs for the same product from the same country), then a simple average thereof (unextrapolated EFs) is selected.
   - These 2 scenarios are represented by the "***EF AVAILABLE FOR COUNTRY***" branch in the decision flow below.
2. If no original EF is available for the respective country, we look for other original EFs, for other countries, within the same basket.

[36] Throughout this Whitepaper we use the terms country of import and country of origin interchangeably, as we assume the entire value chain of products in within the country of import of the respective goods.

  - If such EFs exist, then the simple average of extrapolated EFs is selected (if only a single such extrapolated EF exists, then it is taken as such).
  - This scenario is represented by the "***EF AVAILABLE IN THE BASKET***" branch in the decision flow below.
3. If no original EF is available for within the same country basket, original EFs for countries in other baskets are searched for and their simple average is selected.
  - This scenario is represented by the "***EF AVAILABLE IN OTHER BASKETS***" branch in the decision flow below.

$$wef_{Item\ ID,p,q} = \begin{cases} \frac{1}{N_q} & if\left(p \in \bigcup_{r=1}^{K} cof_r\right) \bigwedge (p = cof_q) & (EF\ AVAILABLE\ FOR\ COUNTRY) \\ \frac{1}{N_{CB}} & if\left(CB_p \in \bigcup_{r=1}^{K} CB_r\right) \bigwedge (CB_p = CB_q) \bigwedge \left(p \notin \bigcup_{r=1}^{K} cof_r\right) & (EF\ AVAILABLE\ IN\ THE\ BASKET) \\ \frac{1}{K} & if\left(CB_p \notin \bigcup_{r=1}^{K} CB_r\right) \bigwedge \left(p \notin \bigcup_{r=1}^{K} cof_r\right) & (EF\ AVAILABLE\ IN\ OTHER\ BASKETS) \\ 0 & OTHERWISE & \end{cases}$$

, where wef_Item ID, p,q is weight for q-th Emission Factor for p-th country of origin (COO)
, P is the country under evaluation
, K is the total number of emission factors available for ItemID
, cof_r is country of factor for r-th emission factor
, N_{CB} is total number of emission factors that are available for CB_q
, N_q is the total number of emission factors for country p
, CB_p is Country Basket for p-th COO
, CB_r is Country Basket for Country of Emission factor for r-th emission factor

6.2.5 Averaging selected extrapolated EFs for each country of import

The Emission Factor for each Expenditure Item (identified by Item ID) and country of import (COO) is obtained through by averaging the selected EFs. Essentially this is a simple average, as the weights applied to each extrapolated EF are determined by the total number of selected EFs for the particular country of import.

$$EF\text{-}\$_{ItemID,p} \, {}^{kg\ CO2e}\!\big/_{\$_{2023}} = \sum_{q=1}^{K} wef_{ItemID,p,q} \times EF\text{-}\$_{ItemID,p,q}$$

6.2.6 Aggregating extrapolated EFs for the focal country

Up until this point, we were able to estimate the carbon footprint of a particular Expenditure Item, for each country of origin it could be imported from. We basically put in place an **extended library of EFs** for all Expenditure Items labeled as Products, for all countries of import. This can act as a **placeholder** set of EFs, that can be enhanced at future stages either through sourcing more original EFs (for example derived from reputable LCA country level studies) or enhancing the extrapolation algorithm.

The next step consists of determining the carbon footprint of the **"typical" product** consumed in the focal country, which we do by incorporating the import pattern for the specific item – namely, the weights of import values for each country of import. We consider this equivalent to creating **consumption-based Emission Factors** for each Expenditure Item.

The **weights we assign to each country** are represented by the value of imports for a specific Expenditure Item from that country, relative to the total value of imports into the focal country for the respective Expenditure Item.
The aggregated extrapolated EF at the focal country level for a specific Expenditure Item is then obtained through weighted averaging of the respective extrapolated EFs for each country of origin. This aggregated extrapolated EF is already expressed as kg CO2e / $\$_{2023}$

$$wimport_{ItemID,j} = \frac{ImportValue_{ItemID,j}}{\sum_{p=1}^{J}(ImportValue_{ItemID}, p)}$$

, where Item ID is the unique identifier assigned to each Expenditure Item (L5)
, j is the index of the country of import
, J is the total number of countries of import
, Import Value is the sum of FOB import value (USD, annual) for all commodities associated with an Item ID

$$\text{EF-\$}_{ItemID} in \; {kg\ CO2e}/{\$_{2023}} = \sum_{p=1}^{J}\left(wimport_{ImteID,p} \times \text{EF-\$}_{ItemID,p}\right)$$

, where $\text{EF-\$}_{ItemID}$ is the aggregated extrapolated EF for any given Item ID
, Item ID is the unique identifier assigned to each Expenditure Item (L5)
, J is the total number of countries of import
, p is the index of the country of import
, $wimport_{ImteID,p}$ is the weight of import from country p
, $\text{EF-\$}_{ItemID,p}$ is the extrapolated EF for Item ID imported from country p

6.3 EF Vertical Aggregation

At the next step, the weights for Expenditure Items (Item IDs) within the "Expenditure Item Type" they are mapped to are computed using total annual value of imports for the respective Expenditure Item (from all countries of origin), relative to the total annual value of imports for all Expenditure Items mapped to the respective Expenditure Item Type (essentially, the total sum of imports at L4).

$$witem_{ItemID} = \frac{ImportValue_{ItemID}}{\sum_{i=1}^{n} ImportValue_{i}}$$

, where $witem_{ItemID}$ is the weight (contribution) of the Item ID into the Expenditure Item Type (L4)
, Item ID is the unique identified assigned to the Expenditure Item (L5)
, $ImportValue_{ItemID}$ is the total annual value of imports for an Expenditure Item into the focal country

Subsequently, we roll up the data points from Item ID to Expenditure Item Type by taking average of EFs weighted by import values at L5 level:

$$\text{EF-\$}_{ItemType}\, in\ {}^{kg\ CO2e}\!/_{\$_{2023}} = \sum_{i=1}^{n} witemt_i \times \text{EF-\$}_i$$

, where $\text{EF-\$}_{ItemType}$ *is the EF associated with the Expenditure Item Type (L4)*
, witemt$_i$ *is the weight of the Expenditure Item (L5) into the Expenditure Item Type (L4)*
, i is index of the Item ID (Expenditure Item)

As a last step, we compute the monthly footprint of households related to carbon embodied in goods consumed by using the following formula:

$$footprint_{ItemType,\, month, households}\, in\ kg\ CO2e = \text{EF}_{ItemType} \times expenditure_{ItemType, month, households}$$

7.Emissions from International Shipping

7.1 Methodology overview

To compute emissions related to international transportation of imported goods, we are taking into account several factors:

- Selection of freight mode by product (sea, air or road transportation),
- International shipping ports by country of export[37], for sea, air or road transportation,
- Shipping distance for sea and air routes between all relevant countries of origin and Singapore, and
- Emission Factors for air / sea / road.

7.2 Selection of freight mode by product

For simplicity of calculation, we assign a single freight mode by product and use the following nomenclature:

$$FreightMode_{ItemID}$$

- For all non-perishable items we have selected **sea** as transportation mode.
- For all perishable items we have selected **air** as transportation mode
- For all imports from close neighbors[38] (perishable or non-perishable) we select **road** as transportation mode

7.3 Selection of international shipping ports

For simplicity of calculation, we limit the mapping to a single seaport and airport by country for all countries, except for US, India, Australia and China for which we have mapped several seaports per country (and only 1 airport). The reason for this exception is that the shipping routes and shipping distance to a focal country may vary materially depending on shipping port, and also the value and volume of imports to the focal country may be significant within the range of all countries of import.

$$Ports_{COO}$$

- For Sea we select one or several ports based on size of the countries, as geographically larger countries may have ports that geographically separated by a material distance
- For landlocked countries we use the nearest seaport in their neighboring countries
- For Air, we have used largest airport within the country.

[37] Throughout this paper we use the terms country of export and country of import interchangeably. In all contexts, we refer to the same: the countries from which Singapore is importing specific end user finished goods.
[38] We recommend considering "close neighbors" all country from which perishable items are transported by road in a larger proportion then by sea or air. This would be determined by actual distance, road infrastructure and feasibility for cold chain road transportation.

7.4 Distance mapping by shipping route

For sea freight we recommend mapping the sea distance to the focal country from the respective shipping ports by country of origin (COO), and similarly for air freight we have recommend mapping the air distance to the focal country from the respective airports by country of origin (COO). If multiple ports have been selected for the same freight model for a particular country, then we average the distance for calculation simplicity :

$$AVG\ Distance_{FreightMode,\ COO\ ,\ ItemID}$$

7.5 Emission Factors selection

We select a single emission factor for each freight mode[39]. We acknowledge however there would be variations in emissions related to international transportation of goods depending on the temperature control required during freight (which would be different for fresh perishable items, frozen perishable items, and non-perishable items). We recommend sourcing and using more granular emission factors in future iterations of this study or other projects building on this body of work.

7.6 Emission Factors conversion

We collate the data, such that for each Item ID we map the transportation mode, the applicable emission factor to be used, and the distance, for all countries of import:

$$FOB\ Import\ Quantity_{ItemID,COO}\ in\ kg = \sum_{i=1}^{k} FOB\ Import\ Quantity_{i,COO}$$

, $FOB\ Import\ Quantity_{ItemID,COO}$ *is the estimated FOB import quantity computed for each Item ID, coming from each country of origin*
, Item ID is the unique identifier assigned to each Expenditure Item (L5)
, COO is the country of origin (term used interchangeably with country of import)
, where i is from 1st HS Code linked to an Item ID to the k-th HS Code linked to the same Item ID

7.6.1 Emission Factors conversion – from kg CO2e/tonne.km to kg CO2e/ton

$$\text{EF-TKM}_{\text{FreightMode,ItemID}}\ in\ kg\ CO2e/ton.km$$

, EF-TKM$_{FreightMode,\ ItemID}$ is the EF for the Freight Mode assigned to the Item ID
, TKM is the unit of measurement of the EF (tonne-kilometre)
, tonne is assumed to be the same as metric ton (equivalent to 1,000 kg)

We multiply the emission factor and distance to get to a reduced emission factor – converting **EFs from kg CO2e/tonne.km to kgCO2e/ton**[40]:

[39] We have leveraged the emission factors published by Hannah Ritchie, 2020 and Weber and Matthews, 2008a.
[40] Throughout the paper we interpret tons and tonnes to refer to metric tons (1000 kg).

$$EF\text{-}T_{ItemID,COO} \ in \ {}^{kg\ CO2e}/_{ton} = EF\text{-}TKM_{Freightmode,ItemID} \times AVG\ Distance_{FreightMode,COO}$$

, where $EF\text{-}T_{ItemID,COO}$ is the EF for the Item ID, from a particular COO, expressed as kg CO2e/tonne of imported Expenditure Item
, T refers to tons
, Item ID is the unique identifier assigned to the Expenditure Item (L5)
, COO is the country of origin for the Expenditure Item (L5) (the term is used interchangeably with country of import)
, TKM refers to ton.kilometer
, Freight Mode is the unique freight mode assigned to the Item ID (sea, air or road, based on perishability and COO)
, $AVG\ Distance_{FreightMode,COO}$ is the average distance between the country of origin and Singapore, based on the freight mode selected

7.6.2 Emission Factors conversion – from kg CO2e/ton to kg CO2e/$

For the next step we will look to use **price proxies** (USD/kg) to **convert the EFs from kg CO2e/tonne to kg CO2e/USD**. The first step consists of sourcing estimated import and retail price points in USD, based on import data.

We pull USD_{2022}[41] Import Value per Item ID per COO by summing up the import values of all commodities (as identified through HS codes) mapped to the Item ID:

$$FOB\ Import\ Value_{ItemID,COO} \ in\ USD2022 = \sum_{i=1}^{k} FOB\ Import\ Value_{i,COO}$$

, $FOB\ Import\ Value_{ItemID,COO}$ is the estimated FOB import value (exporter price) computed for each Item ID, coming
, from each country of origin
, Item ID is the unique identifier assigned to each Expenditure Item (L5)
, COO is the country of origin (term used interchangeably with country of import)
, where i is from 1st HS Code linked to an Item ID to the k-th HS Code linked to the same Item ID

For each product, we pull the FOB Import Quantity per COO by summing up the quantity of all HS Codes that have been mapped to an Item ID:

$$Estimated\ Retail\ Price\ Proxy_{USD,ItemID,COO} in\ {}^{USD_{2022}}/_{kg} = \frac{FOB\ Import\ Value_{ItemID,COO}}{FOB\ Import\ Quantity_{ItemID,COO}} \times Retail\ Markup$$

[41] At the time of our study (in 2023), the most recent data we found available in the import data set we sourced from BACI CEPII, 2023, was expressed in USD values as of 2022.

$$Estimated\ Retail\ Price\ Proxy\ _{SGD,2023,ItemID,COO} in\ {}^{\$_{2023}}\!/_{kg}$$
$$= Estimated\ Retail\ Price\ Proxy_{USD,2022,ItemID,COO} in\ {}^{USD_{2022}}\!/_{kg}$$
$$\times\ FX\ rate\ (USD_{2022}\ ,\ \$_{2022}) \times Inflation\ Rate\ (2023,2022)$$

, where Estimated Retail Price Proxy $_{\$,2023,ItemID,COO}$ is the Estimated Retail Price Proxy expressed in \$ as of 2023
, Item ID is the unique identifier assigned to each Expenditure Item (L5)
, COO is the country of origin (term used interchangeably with country of import)
, FX rate (USD_{2022} , $\$_{2022}$) is the currency exchange rate USD-\$ as of 2022
, kg is the quantity in kg of the imported goods (aggreggated at Expenditure Item level)
, $Inflation\ Rate\ (2023,2022)$ is the inflation rate in Singapore between 2022 and 2023

We then **convert the EFs from kgCO2e/tonne to kgCO2e/\$2023** (accounting for the tons to kg conversion):

$$EF\text{-}\$_{ItemID,COO} in\ {}^{kg\ CO2e}\!/_{\$_{2023}} = \frac{EF\text{-}T_{ItemID,COO}}{Price_{ItemID,COO}} \times \frac{1}{1000}$$

, where EF-$\$_{ItemID,COO}$ is the EF for an Item ID from country of origin COO, expressed as kg CO2e/\$
, EF-$T_{ItemID,COO}$ is the EF for the Item ID, from a particular COO, expressed as kg CO2e/tonne of imported Expenditure Item
, T refers to metric tons (1,000 kg)
, Item ID is the unique identifier assigned to the Expenditure Item (L5)
, COO is the country of origin for the Expenditure Item (L5) (the term is used interchangeably with country of import
, $Price_{ItemID,COO}$ is the domestic retail price of the respective Item ID

7.6.3 Emission Factors conversion – aggregation to the focal country

This becomes then a unique set of EFs by country of origin, by Expenditure Item, which need to be aggregated at focal country level, taking into account import patterns from all countries of origin.

Essentilly, we are creating a **unique International Shipping EFs for each product**, representative of the "typical" Expenditure Item consumed in the focal country.
The formula we use to factor in imports from each COO is based on import weights, considering the sum of import value from each country of origin, relative to the total import vale for each Expenditure Item (product).

$$wimport_{ItemID,k} = \frac{ImportValue_{ItemID,k}}{\sum_{i=1}^{n}(ImportValue_{ItemID}, i)}$$

, where Wimport_ItemID,j is weight of imports from country k for Item ID
, n is total number of countries we have import values from in BACI dataset

We computed the weighted average using *wimports* as weights of EF factors, This is the equivalent of consumption based transport carbon emission factor by Item ID consumed in the focal country:

7.2.4 Emission Factors roll up from L5 to L4

The weights for ItemID within an "Expenditure Item Type" are computed using Total USD value imported:

$$witem_{ItemID} = \frac{FOB\ Import\ Value_{ItemID}}{\sum_{i=1}^{n} FOB\ Import\ Value_{i}}$$

, where n is list of all item ID under an expenditure ItemType

$$EF_{ItemID} in\ {}^{kg\ CO2e}\!/_{\$_{2023}} = \sum_{i=1}^{n} wimport_{ItemID,i} \times EF_{ItemID,i}$$

, where n is total number of countries, we have from BACI dataset.

We roll up from Expenditure Item (Item ID, L5) to Expenditure Item Type (L4) by taking weighted average of EF with "witem" as weights:

$$\mathrm{EF}_{ItemType} in\ {}^{kg\ CO2e}\!/_{\$_{2023}} = \sum_{i=1}^{n} (witemt_{i} \times \mathrm{EF}_{i})$$

, where n is total number of Item ID (L 5) under each Expenditure Item Type (L 4)

As a final step, we calculate the monthly carbon footprint associated with international transportation for typical household through the following formula:

$$footprint_{ItemType,\ month,households} in\ kg\ CO2e = \mathrm{EF}_{ItemType} \times expenditure_{ItemType,month,households}$$

8. GHG Emissions from Warehousing and Retail

The next category emissions in the products lifecycle occurs domestically, in between the point of import into the focal country, and the points of consumption. These emissions cover domestic distribution, warehousing and retail operations and are added to all Items (L4) that are flagged as "Products".

To estimate these emissions, we use as a model EFs from UK DEFRA, 2023, which we found differentiated for wholesale and retail trade services. We sum them up in a combined EF to cover the entire lifecycle through warehousing and retail stages.

We use this EF uniformly for all applicable products, and we process this EF by applying similar methodological steps as for the rest of Emission Factors:

We then apply the currency exchange rate and the inflation adjustment to upgrade the temporal representativeness and convert the unit of measurement:
We also perform as described in previous sections the extrapolation to the focal country, using the carbon intensity of electricity generation CIEG (average national

$$EF\text{-}GBP_{retail-warehousing}\ in\ {}^{kgCO2e}/_{GBP}$$

, where $EF\text{-}GBP_{retail-warehousing}$ is the Combined EF for "Wholesale and Retail Services" expressed as kg CO2e / GBP (British Pound)

$$EF\text{-}\$2023_{retail-warehousing}\,in\ {}^{kgCO2e}/_{\$} = EF\text{-}GBP_{retial-warehousing} \times \frac{1}{FX\ rate\ (GBP_{2020}, \$_{2020})} \times \frac{1}{Inflation\ rate\ (2023{,}2020)}$$

, where $EF\text{-}\$2023_{retail-warehousing}$ is the EF for "Wholesale and Retail Services" converted to kg CO2e/$\$_{2023}$
, $EF\text{-}GBP_{retial-warehousing}$ is the EF for "Wholesale and Retail Services" expressed as kg CO2e/GBP_{2020}
, $FX\ rate\ (GBP_{2020}, \$_{2020})$ is the currency conversion rate from GBP to $ as of 2020
, $Inflation\ rate\ (2023{,}2020)$ is the composite inflation rate from 2020 to 2023 in the focal country

electricity emission factors) for both UK and the focal country:

$$\text{EF-}\$_{2023\,retail-warehousing}\,in\ {}^{kgCO2e}/_{\$} = \text{EF-}\$_{2023\,retail-warehousing} \times \frac{CIEG_{\$}}{CIEG_{UK}}$$

, where $EF\text{-}\$_{2023\,retail-warehousing}$ is the EF for "Wholesale and Retail Services" converted to kg CO2e/$\$_{2023}$
, $CIEG_{\$}$ is the carbon intensity of electricity generation in the focal (electricity Emission Factor)
, $CIEG_{UK}$ is the carbon intensity of electricity generation in UK (electricity Emisison Factor)

We then attribute this emission factor to all Items classified as "Products" in our list, to account for emissions related to warehousing at the point of import, local distribution, and retail operations.

$$footprint_{ItemType,\ month,\mathrm{households}}\, in\ kgCO2e = \mathrm{EF\text{-}\$}_{retail-ware\mathrm{housing}} \times expenditure_{ItemType,month,\mathrm{households}}$$

9. GHG Emissions from Waste

9.1 Overarching methodology

To estimate the GHG Emissions associated with waste generated by consumption of products, we apply a different overarching methodology, based on processing physical EFs[42] to convert them to the focal country CTY Monetary EFs, differentiated by Expenditure Category.

We start by leveraging country-level **waste composition statistics**, under the assumption of a similar waste composition pattern for domestic and non-domestic waste, as well as the total **quantity of domestic waste** per household. We then factor in **national recycling rates**, to infer the total unrecycled disposed waste attributable to households. We can thus further refine the disposed (unrecycled) waste composition at a household level, and associate the total unrecycled waste generated to the consumption categories most likely to have produced it. We therefore map unrecycled waste components to applicable **Expenditure Categories** (L1). Through our framework we calculate the estimated kg waste per $ spent on the respective Expenditure Categories, which act as estimated "**Waste Intensity**" of expenditures, measured **in kg Waste / $.**

We can then associate this waste intensity with the country specific Physical Emission factors for Waste, measured as **kg CO2e / kg Waste**, creating as such Expenditure Category specific **Monetary Emission Factors** for Waste. This estimate is then used across all product items to quantify the waste related GHG emissions for each expenditure category.

Opportunities for further refinement include sourcing more detailed domestic waste composition statistics and improving the granularity of data attribution. Such enhancements could allow for more accurate mapping of household waste generation across various expenditure levels, offering deeper insights into the relationship between consumer behaviour and waste emissions in different national contexts.

9.2 Waste management EF sources and aggregation

The computational steps start with sourcing **waste management EFs,** if possible focal country-specific for processing household residual waste. Absent granular and contextualized EFs, more general ones, such as Physical EFs for landfill and incineration can be used. If 2 such EFs are retrieved, an aggregate EF based on the waste management practices statistics can be estimated, based on the formulas below.
We **do not extrapolate** the resulting composite EF via our current methodology (which leverages electricity Emission Factors), as we assume waste related emissions to be triggered by physical and chemical processes rather than energy consumption.

[42] We are considering as an example EFs for waste management and treatment from UK DESNZ & UK DEFRA, 2023.

$$EF\text{-}KG_{waste} in \, {}^{kgCO2e}/_{kg} = \sum_{i=1}^{n} w_i * EF_{kg,i}$$

, where $EF\text{-}KG_{waste}$ is the average Emission Factor attributable to domestic waste (expressed as kg CO2e / kg Waste)
, w_i is the weight (%) of domestic waste handled through the waste management process i
, $EF_{kg,i}$ is the Physical Emission Factor for waste management process i (expressed as kg CO2e / kg Waste)
, n is the number of Emission Factors sourced
, i is the type of waste management process (such as landfill or incineration)

9.3 Unrecycled domestic waste and waste composition estimation

The next step is sourcing the **average daily domestic waste** per capita or per household in the focal country, taking into account the domestic recycling rate, to derive the inferred average monthly disposed (unrecycled) waste per household (in kg).

To understand potential association of waste with expenditure categories, we look at generic waste composition in the focal country, after applying all up focal country recycling rate, under the assumption recycling processes can and are applied post waste collection (such as for ferrous metals recovery).

We then **map the respective waste components to Expenditure Categories (L1)**. Where the association was relatively clear, we performed a 1 to 1 mapping, such as for “Food” waste component, which is mapped to “Food and Non-Alcoholic Beverages” L1 Expenditure Category. Where the association was ambiguous absent more granular data, we performed a 1 to many mappings, attributing “ambiguous” waste components to Expenditure Categories based on the Expenditure Categories relative average $ spend weight.

$$W_{annual,CTY,ECi} = W_{direct,EPi} + W_{dollar-weighted,ECi}$$

, where CTY is the focal country of the study
, ECi is Expenditure Category (L1) i
, $W_{annual,CTY,ECi}$ is the contribution of Expenditure Category(L1) ECi to annual household waste
, $W_{direct,ECi}$ is the contribution of a waste component which is entirely attributable to a single Expenditure Category ECi
, $W_{dollar-weighted,EPi}$ is the $ weighted contribution of a waste component attributable to several Expenditure Categories

We then derive the relative % contribution of each Expenditure Category (L1) to the total Household monthly disposed waste, to estimate the domestic waste that can be associated with each (in kg).

9.4 Waste EFs by Expenditure Category estimation

We can then use this average quantity of waste by Expenditure Category (kg) in relation to the average expenditure by Expenditure Category (in $), to derive a proxy for **“Waste Intensity” (kg Waste / $)** for each Expenditure Category. We multiply this proxy with the focal country CTY Waste Composite EF (kg CO2e / kg Waste), to infer a new set of Expenditure Category specific Waste EFs, which we further on refer to as **"CTY Waste Expenditure Category EFs" (kg Waste / $).**

$$Intensity_{waste,L1}\ in\ {}^{kg}/_{\$} = {}^{W_{monthly,household,L1}}/_{Expenditure_{L1}}$$

$$\text{EF-\$}_{waste,L1}\ in\ {}^{kgCO2e}/_{\$} = Intensity_{waste,\text{ECi}} \times \text{EF-}KG_{waste}$$

$$W_{monthly,household,L1} = \frac{W_{annual,CTY,p}}{\sum_{i=1}^{P} W_{annual,CTY,i}} \times W_{monthly,household}$$

We then add these newly inferred EFs to the EF Library we have set up. We attribute these EFs to all Expenditure Item Types (L4) that fall under these specific Expenditure Categories (L1) and are labelled as Products. We consequently associate the resulting emission factors strictly with **products**.

For **services** we consider in our framework that the EFs sourced cover end to end the services lifecycle, due to the fact these are monetary EFs resulting from EEIO methodologies following the complete cycle of both financial and emission flaws. At further stages we recommend validating this assumption, and, if needed, investigating the value chain and related carbon footprint of services, in order to insure complete coverage of lifecycle emissions for services transactions as well.

We then compute the total emissions from waste as follows, attributing the new Expenditure Category specific EFs, to all Expenditure Items (L4) labelled as "Products" that fall within that respective Expenditure Category.

$$footprint_{household,monthly} = EF\text{-\$}_{waste,ECi} \times Expenditure_{L4}$$

10.GHG Emissions associated with Services

The methodology we apply to compute emissions associated with Services is a simplified version of the approach we are taking for Products.

We are assuming all services to have **value chains exclusively in the focal country** and consequently we are not associating any imported commodities or overseas activities with Expenditure Items (L5) labelled as such. Consequently, we are not attributing any emissions related to internal shipments or other financial or physical flows.

We are also not attributing any emissions related to warehousing and retail operations, or waste, as our working assumption is that the EFs we have sourced cover the **entirety of the service delivery lifecycle**. The majority of the EFs we have used are monetary (kg CO2e / currency), and are the result of EEIO studies, which we assume cover holistically the attribution of emissions to financial flows for industry sectors and sub sectors. For specific cases (BUS and MRT Services, Electricity and Food Serving Services), we recommend sourcing Physical EFs as well, expressed as kg CO2e / passenger.km, kg CO2e / kwh and respectively kg CO2e / meal. We assume these emission factors to be holistic, covering the service's lifecycle until the point of consumption with adequate coverage of post-sales related emissions.

For Physical EFs in particular, in order to convert these EFs to a **monetary format** we are sourcing **price points**, or estimating average prices based on manually sourced data. We are then contextualizing EFs for the focal country by using electricity **EF differentials**, similar to the approach we are taking for Products. As we consider services to have value chains exclusively in the focal country, we are not factoring in any import data. The extrapolation is thus single step, applied to each emission factor for contextualization to the focal country (without any need to extrapolate to multiple "countries of import", or to re-aggregate the extrapolated emission factors based on import weights).

10.1 Services EFs -conversion using service prices

If **Monetary EFs** for services are sourced from publishers such as UK DEFRA, 2021 and US EPA ORD, 2023, then the following formulas apply:

$$EF_{Services}\ in\ ^{kg\ CO2e}/_{\$} \qquad\qquad EF_{Service}\ in\ ^{kg\ CO2e}/_{£}$$

We then perform temporal adjustment using **inflation indexing** and **currency conversion**:

$$Inflation\ rate\ (2023, YYYY) = \frac{\$_{2023}}{\$_{YYYY}}$$

$$FX\ rate\ (K_{2023}\ ,\ \$_{2023}) = \frac{\$_{2023}}{Currency\ K_{2023}}$$

$$EF_{\$,2023} in \ {kg\ CO2e}/_{\$2023} = EF_{Currency\ K,YYYY} \times {1}/_{FX\ rate} \times {1}/_{Inflation\ rate}$$

, where $EF_{\$,2023}$ is the Monetary EF converted to $, updated to 2023
, $EF_{Currency\ K,YYYY}$ is the Original Monetary EF, expressed as kg CO2e/foreign currency, valid for the year of computation YYYY

Physical EFs can also be sourced from sources such as UK DESNZ and UK DEFRA, 2023, and can be used for Bus, MRT, Electricity and Food Serving Services. We detail all of these in the subsequent case studies section. In order to **convert** them to Monetary EFs estimated prices can be used, as follows:

$$EF_{\$,2023} in \ {kgCO2e}/_{\$2023} = EF_{UoM,YYYY} \ / \ Manual\ Price_{\$,2023}$$

, where $EF_{\$,2023}$ is the where $EF_{\$,2023}$ is the Monetary EF converted to $, updated to 2023
, $EF_{UoM,YYYY}$ is the Physical EF, expressed as kg CO2e/UoM, valid for the year of computation YYYY
, UoM is the unit of measurement of the EF (kwh, meal, passenger.km)
, $Manual\ Price_{\$,2023}$ is the estimated price point for the UoM as of 2023

10.2 Services EFs - extrapolation

We then perform the **extrapolation** to the focal country for both Physical and Monetary EFs by using the **electricity GHG emissions** differential between the respective countries of origin and the focal country.

For all services, we assume the carbon footprint of the service, and the carbon footprint of electricity to move in the same direction in a specific country. The underlying assumption is the more carbon intensive it is to produce electricity, the more carbon intensive it will be to produce any product or service. We assume the degree of dependency to be different by type of service, as follows:

- For the majority of services, we assume energy accounts for 100% of the carbon footprint (with the below exceptions). **σ is 100%** for these cases.
- For **Bus and train/subway services**, we assume the carbon footprint is mostly accounted for by the fuel consumed in transit (we neglect thus contributions such as infrastructure embodied carbon). We therefore assume **σ is 0%** for these cases.
- For **Food Serving Services**, we assume the majority of the carbon footprint is accounted for by the energy consumed in the raw ingredients' extractions, processing, and preparation. We acknowledge however there are other sources of emissions, such as emissions resulting from land use change, fertilizer use, agricultural processes or enteric fermentation, which would not be accounted for by energy. We are not able to quantify at this point these contributions at a granular level, and we recommend this upgrade for future bodies of work leveraging this study. For the time being we use a **σ of 75%** as a placeholder.

The formula that we apply for all services for extrapolation to the focal country is:

$$\text{EF-\$}_{Item\ ID,j,k}\quad in\ {}^{kg\ CO2e}/_{\$2023} = \text{EF-\$}_{ItemID,cof}\left(\frac{GEF_{SG}}{GEF_{factor}} \times \delta + (1-\delta)\right)$$

, where $\text{EF-\$}_{ItemID,j,k}$ *is the Monetary EF for a specific Expenditure Item*
, Item ID is the unique identifier for the Expenditure Item (L5)
, GEF_{CTY} *is the Grid Emission Factor for the focal country CTY (measured as kg CO2e / kwh)*
, GEF_{factor} *is the Grid Emission Factor for the country the original EF was computed for (measure as kg CO2e / kwh)*
, б is the degree of dependency of GHG emissions associated with producing a service, and producing electricity in the same country

For cases where we have several EFs sourced for the same Expenditure Item (L5), we perform a simple average of the resulting EFs to obtain a unique EF that will then be applied in all calculations involving the respective Expenditure Item.

To **roll up EFs to Expenditure Item Type (L4)**, from Expenditure Item (L5), for which we have higher granularity, we have used either manually defined weights (specifically for Food Serving Services, for which we describe the logic in the next sub-section), or equal weights for all Expenditure Items (for all other services). The formula applied is the same:

$$\text{EF-\$}_{Item\ Type} in\ {}^{kg\ CO2e}/_{\$2023} = \sum_{i=1}^{n} w\ Itemt_{\ i} \times \text{EF-\$}_i$$

, where $\text{EF-\$}_{Item\ Type}$ *is the Emission Factor for a particular Expenditure Item Type (L4)*
, $w\ \text{Itemt}_{\ i}$ *is the weight attributed to an Expenditure Item (L5)*
, EF-SGD_{i} *is the Emission Factor for the Expenditure Item (L5)*

$$carbon\ footprint_{Item\ Type,\ month,households} in\ kg\ CO2e = EF\text{-}\$_{Item\ Type} \times expenditure_{Item\ Type,month,households}$$

As a final step, to compute the GHG emissions associated with the consumption of a specific service, we multiply the EF derived per the method above with the spend associated with that Expenditure Item Type.

11. Data reliability challenges, uncertainty and sensitivity analysis

11.1 Average household versus segment of one

An important nuance in this model's uncertainty estimation is with respect to **who** the carbon footprint is estimated for. When the end goal is estimating the carbon footprint of an **actual household** with precisely computed insights and personalized sustainable consumption strategies, then the uncertainty incurred when applying the model would likely be higher, given that our framework is based on focal country's consumption baskets for "typical" households, with import patterns defining "typical products". Higher confidence could be achieved by factoring in more narrowly defined data (such as consumption baskets for demographic sub-segments representative for the specific household).

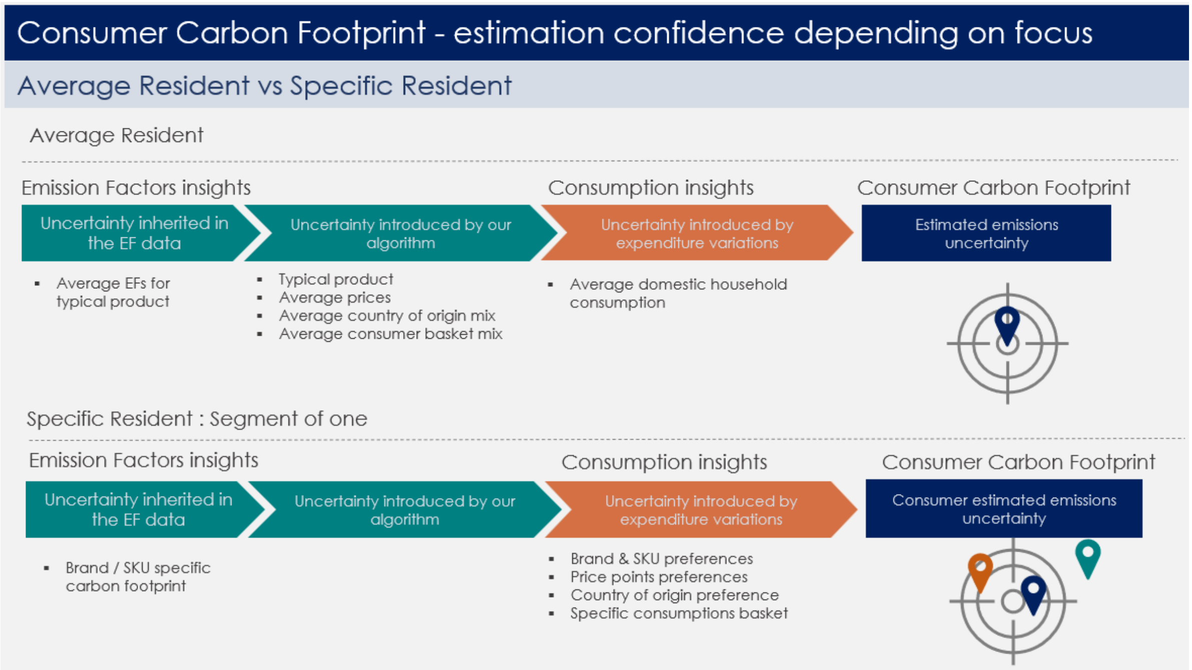
When the end goal is estimating uncertainty for an **"average" household** in a particular country, for whom the "average" consumption is defined in domestic household expenditure studies, then the current model should provide a result where potential variations in parameters and input data are likely to have offsetting effects, and thus result in a higher confidence estimation.

The reason for this important distinction is that the model is built for broad usage of **average EFs** (irrespective of brand / SKU), for 5 levels of resolution of products and services, the highest of which being Level 5 (Expenditure Items).

Products are assumed to have the same import pattern in terms of **country of origin mix** as the commodities manually mapped and associated with them. They are also assumed to roll up from Level 5 (Expenditure Items) to Level 4 (Expenditure Item Types), according to total import values of commodities associated with them, thus effectively defining a **consumption mix** at Level 4.

For this "typical" domestic resident, the result of the estimation will be subject to far less uncertainty than for any specific "real" domestic resident. A specific household and individual would likely have a different products and services mix of "Expenditure Item" (L5), within each "Expenditure Item Type" (L4), depending on their specific needs. They would also favor certain countries of origin for products bought, as well as specific brands for each product. Figure 7 showcases the sources of uncertainty for both the average and specific scenarios.

***Figure 7**: Consumer Carbon Footprint estimation confidence*



Our uncertainty analysis focuses on the sensitivity analysis for the average resident household.

11.2 Climate data's prevalent uncertainty sources

The uncertainty of **emissions estimations** is well known in the literature, at all levels of aggregation – be it in national inventory accounting, company reports, or at the level of individual consumption. The methodologies for measuring emissions and determining emission factors are the subject of debate, due to opacity in the collection, reporting, and validation of data for different national and international agencies and organizations around the world (Hawkins et al, 2016).

To begin with, **National GHG inventories** themselves, while expected to follow the IPCC Guidelines for National Greenhouse Gas Inventories, still bear embedded uncertainty attributable to statistical and institutional factors, with large and medium size enterprises being the primary source of energy consumption and other emissions related statistics, and smaller enterprises having neither the capabilities nor the qualified personnel to contribute to accurate emissions reporting (Guan et al, 2012).

Along the same lines, corporate **environmental sustainability performance** and reporting have been subject to scrutiny and credibility doubts ranging from difficulties of interpretation to allegations of greenwashing. As discussed in one of our previous SGFIN Whitepapers, **ESG ratings** publishers themselves can offer conflicting assessments of ESG performance for the same company (Hendratama et al, 2023).

Further down to the level of **product** and **services**, algorithmic assumptions and parameter boundaries become critically important in interpreting the quantification of carbon footprints. Different numerical assumptions result in vastly different results (Hawkins et al, 2016, MacLeod et al, 2013). For example, studies estimating EFs for pork meat produced specifically in Denmark range from 3.8 to 16.42 kg COE2/kg as showcased in the literature (Hawkins et al, 2016, MacLeod et at, 2013, Kramer et al, 1999). As described in previous sections, we work around the scarcity and heterogeneity of EFs for all the relevant countries of origin, by converting and extrapolating existing harmonized EFs we sourced from several countries. A challenge that remains however is that benchmarking these extrapolated EFs against EFs found in the literature may still be an assumptions-based exercise. Hawkins et al, 2016, show that while EFs with comparable boundaries and format may not fully match results from alternative studies, "the EFs from other studies similarly fail to match each other".

While uncertainty affects sustainability data across multiple dimensions, a step forward towards a more robust environment can be done by building a **data framework** that discloses transparently not only the computational algorithm, but also the **sensitivity analysis** of the resulting estimation. This allows for informed decisions on use cases for this framework in specific contexts, a better understanding of its limitations as well as its value add, and, most importantly, it can provide an avenue to further improvement opportunities of the quantitative model output.

In the previous sections we delved into the sourcing, assessment, mapping, conversion, extrapolation and aggregation steps in the algorithm. In this section we summarize:

- the key **assumptions** embedded into our model
- the **data parameters** that take into account the respective assumptions
- the **mitigation strategies** applied to reduce the uncertainty introduced
- the **variables affected** by the **residual uncertainty** (which remain unaddressed by the mitigation strategies)
- the **range of variation** we consider for the respective variable (with details as to why the specific range was considered)
- further **reduction strategies** that can be applied in future bodies of work building on this framework

In the following section we describe the results of our sensitivity analysis in terms of **model composite uncertainty**, as well as the uncertainty introduced by **each parameter individually**. We can thus identify the source of uncertainty which has the greatest impact and is therefore worth prioritizing in data collection and production.

11.3 Sensitivity and decomposition analysis methodology

In order to **stress test** the carbon footprinting quantification algorithm, we apply it first to an anchor country – Singapore. We describe in detail the specific application of our country agnostic framework to Singapore to our Whitepaper "Consumption Carbon Footprint: Singapore Case Study". While the numerical results on confidence intervals will be specific for Singapore (and are therefore described here for illustration only), the overall methodology and uncertainty quantification is generally applicable across countries.

We run **two Monte Carlo simulation scenarios**, as described below. Our objective in running two separate simulations rounds is to understand the prevalence of compounding and scale effects, as well any interaction effects between individual parameters.

- A **baseline** scenario based on what we consider to be the maximum likely range for each affected parameter's uncertainty. We use upper reasonable bounds for the uncertainty of all tested parameters under this scenario. We do so out of an abundance of caution, given the widespread measurement errors broadly affecting sustainability data.
- A **conservative** scenario, where we double the uncertainty range for each parameter.

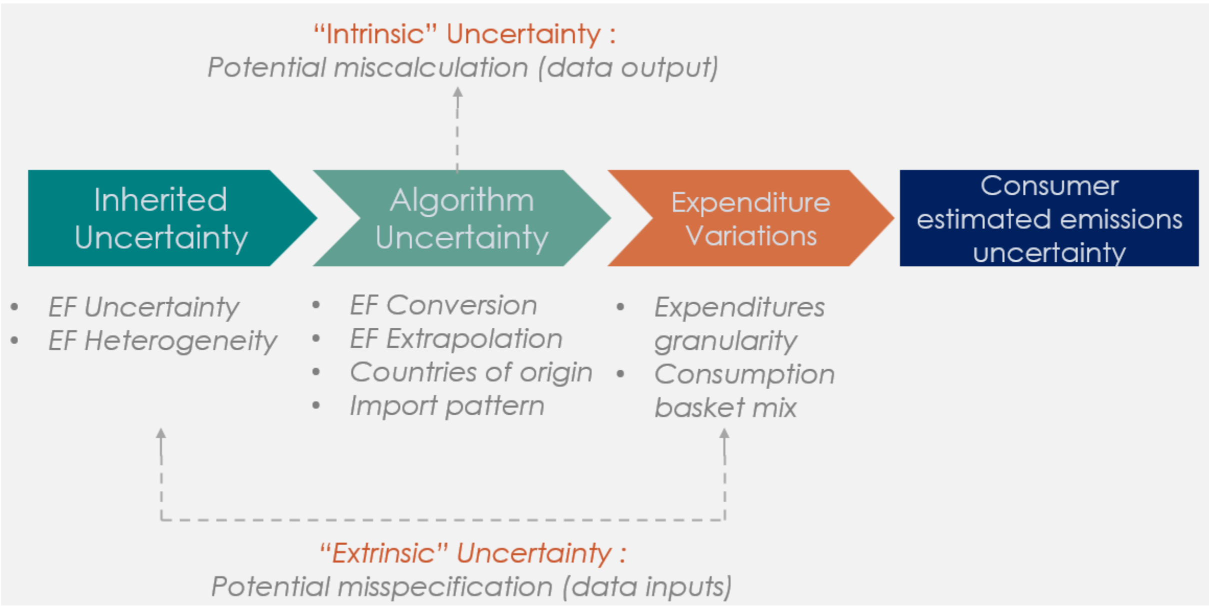
We then run a **decomposition analysis** to identify which set of parameters and assumptions are the biggest drivers of uncertainty, and to examine the potentially non-linear scaling of uncertainty between scenarios.

To differentiate between **intrinsic uncertainty** (introduced by the quantification model), and **extrinsic uncertainty** (introduced by the datasets sourced), we group parameters based on their type:

1. Uncertainty we **inherited** from the EF data we sourced, stemming either from the Original EF's inbuilt uncertainty, or from EF heterogeneity elements such as GWP alignment, recency, methodological alignment, or system boundaries alignment.
2. Uncertainty **introduced** by our algorithm, stemming from the EF conversion, EF extrapolation and б hypothesis.
3. Uncertainty introduced by product and expenditure **preferences variations** that can influence the estimation (pertaining primarily to expenditure granularity mapping to EFs).

The flow in Figure 8 showcases the summary of these uncertainty sources.

Figure 8: *Consumer Carbon Footprint Uncertainty Sources*



11.4 Uncertainty sources: Inherited Uncertainty

The first set of uncertainty sources are those associated with the input data. These refer to EF uncertainty (i.e., embedded in the calculation data itself, for which the % range may be indicated by the data provider), and EF heterogeneity (i.e., referring to variations in the underlying calculation methodology).

11.4.1 Original EFs in-built uncertainty

The original **EF data calculation uncertainty** pertains to assumptions and limitations injected into the calculation of the original EFs themselves – and which may or may not be published as such, depending on dataset or publisher. Also, if provided, the uncertainty score may follow different calculation methodologies.

- For **Monetary EFs**, this is driven by fundamental assumptions underlying their methodology. As they are based on EEIO or EE MRIO models, which combine economic input-output tables with compatible industry level environmental data on GHG emissions , they carry over the commodity level or industry level averaging, based on the underlying assumption that "all commodities produced by a given industry have the same input requirements and same environmental profile, a common assumption in IO models" (Ingwersen, W. and M. Li, 2020).
- Similarly, while often deemed more reliable and recommended for better product resolution, **Physical EFs** are affected by other uncertainty drivers. As they are typically based on bottom up LCA assessments, the "use of process-based LCA can underestimate actual supply chain emissions, because supply chain cutoffs – missing inputs in supply chains – are intentionally or unintentionally applied, which results in omitted supply chain emissions" (Ingwersen, W. AND M. Li, 2020, Blanco et al, 2016, Lenzen, 2000).

In the first simulation round (**baseline scenario**), we assume that the measurement uncertainty of the variable "Original EFs" follows a **log normal** distribution for which the standard deviation is determined by the original EF uncertainty provided by the data publisher. For EFs with no uncertainty % range is published, we use the average uncertainty recorded in our database for each respective EF dataset: **+/- 38%** for physical EFs, and **+/- 78%** respectively for monetary EFs.

In the second simulation round (conservative scenario), we assume that the uncertainty ranges are double: **+/- 76%** for Physical EFs and **+/- 156%** for Monetary EFs.

11.4.2 Original EFs heterogeneity

The second assumption embedded into our model is that the Original EFs data sourced is sufficiently comparable. There are however different heterogeneity dimensions affecting this data, such as:

- **Methodological alignment**. Original EF datasets may have been produced following for example the GHG Protocol or ISO standards. We consider the affected variable to be the Original EFs, and we test it using a normal distribution for which the Standard Deviation is **+/- 10%** of the Original EF for each EF in the baseline scenario, and **+/- 20%** in the conservative one.
- **Global Warming Potential (GWP)** multipliers. Original EF datasets may have used in computation different GWPs. We consider the affected variable to be the Original EFs, and we use a normal distribution with a Standard Deviation of **+/- 10%** in the baseline scenario, and **+/- 20%** in the conservative one.

- **EF System Boundaries**. Original EF datasets may offer EFs computed for different LCA[43] boundaries. While we recommend sourcing and mapping EFs matching exactly the LCA stage for which they are used, an exact match may not always be available. We consider the affected variable to be the Original EFs, and we use a uniform distribution of **-10% / + 5%** for the range in the baseline scenario, and **-20%/+10%** in the conservative one.
- **EF publication year**. The carbon footprint of a product or service may be different depending on the year the LCA exercise was run. We consider the variable affected to be the Original EFs, and we test it using a normal distribution with a Standard Deviation of **+/- 20%** for the range in the conservative scenario, and **+/- 40%** in the conservative one.

For all of these assumptions we have assigned an indication of the risk introduced, and we summarized stress testing range for the affected parameters, as described in Table 2.

Table 2: *Sources of estimation uncertainty – "Inherited Uncertainty"*

Data parameter	Assumption	Uncertainty Introduced		Residual uncertainty - impact quantification			Further reduction strategies
		Impact	Uncertainty mitigation strategies applied	Tested variable	Variable distribution (baseline scenario)	Details	
EF Uncertainty	EF datapoints embedded uncertainty is acceptable and within industry standards	High	**Embedded EF uncertainty** can significantly impact the uncertainty of the model estimation. EFs sourced from datasets other than HCC and CPCD do not list an Uncertainty % or Quality %.	Original EFs	**Log normal distribution**: Where available, we assume the Uncertainty % for each EF to represent the Std Dev as % of the Original EF.	We use the uncertainty %s we know from EFs with published uncertainty: **Average Uncertainty for Physical EFs: 38%** - use it as Std Dev for Physical EFs **Average Uncertainty for Monetary EFs: 78%** - use it as Std Dev for Monetary EFs For all EFs with published uncertainty we take it as such.	* **EF uncertainty benchmarks** identification in literature (further research effort)
EF Heterogeneity	**GWP multipliers** differences do not materially impact the CO2e EFs of goods and services	Low	GWP multipliers are used for conversion of GHG to CO2. While the GWP multipliers for CH4 and N2O change in opposite directions from AR4 to AR5 to AR6, the changes may not fully offset each other and could affect original EFs if they were "normalized".	Original EFs	**Normal distribution**: Std Dev is 10% of Original EF for each EF		* **EF data collection** enhancement (targeting AR6 aligned EFs, , efforts to enhance the EF library with EFs aligned to AR6 methodology

[43] Life Cycle Analysis

	Methodological alignment underpins EF calculation	Low	EF datasets are aligned to different standards and frameworks. While we assume complete methodological compatibility between ISO 14040/14044/14067 standards and GHG Protocol, there may be discrepancies that would affect the original EFs if they were "normalized".	**Original EFs**	**Normal distribution**: Std Dev is 10% of Original EF for each EF		
	EF system boundary is compatible by product by database	Low	While we prioritize sourcing and mapping EFs that are aligned to the LCA stage they are sourced for, this was not always feasible (typically due to data scarcity).	**Original EFs**	**Uniform distribution: -10% / + 5%** range Original EF for each EF	We assume **overestimation** is more likely than underestimation due to potential inclusion of warehousing and retail emissions in original embodied carbon EFs, to which later on we add warehousing and retail emissions specific EFs.	* Further research on product **LCA mapping** * Further **data assessment** of existing Original EFs datapoints / re-mapping * Further data collection for EFs with clearer system boundaries.
	EF publication year differences can be mitigated for through inflation indexing (Monetary EFs), or usage of current prices (Physical EFs)	Medium	The carbon footprint of a product or service may be different depending on the year of production, therefore the EFs themselves may be different. Price adjustment mitigates only partially this uncertainty.	**Original EFs**	**Normal distribution:** Std Dev is 20% of Original EF for each EF		* **Data collection** efforts to enhance the EF library.

11.5 Uncertainty introduced by our algorithm

In addition to the uncertainty associated with the input data, there are sources of uncertainty pertaining to our algorithm itself (which we refer to as "intrinsic" Uncertainty). The overarching assumption is that our calculation framework is robust and that conversions and extrapolations steps using exchange rates, inflation rates, estimated retail prices and the degree of dependency of electricity 6 are accurate. All of these steps are however workarounds, necessary to address data heterogeneity and data scarcity issues:

- **Currency exchange rates** are used to convert Monetary EFs from kg CO2e / currency to kg CO2e / \$. Monetary EFs are however typically the result of EEIO[44] studies and could vary from one economy to another. We consider the affected variable to be the FX rate (which in this case acts as a conversion

[44] Environmentally Extended Input Output Studies.

factor[45]). We test it using normal distribution with a Standard Deviation of **+/- 5%** in the baseline scenario, and **+/- 10%** in the conservative one.

- **Free on Board (FOB) prices** are used, with an estimated average Retail Price Markup, to convert Physical EFs to Monetary EFs. The actual retail prices might vary, however, relative to FOB prices, and we therefore consider the affected variable to be the FOB rate. We test it using a log-normal distribution, with a standard deviation of **+/- 50%** in the baseline scenario, and **+/- 100%** in the conservative one.
- **Manually sourced retail prices** are derived using a sample of approximately 5 price points per product. This average may prove to be different however if a larger dataset is sourced. We consider the affected variable to be the Estimated Retail Price in this case as well, with the same testing range described above.
- **Inflation rates** are used for Monetary EFs temporal adjustment, to bring for instance all Monetary EFs data points to the common currency denominator of $\$_{2023}$. If the emissions per unit of product remain the same, then indeed the inflation rate would be sufficient for accurate indexing. However, changes in the emissions themselves might have occurred, or the national yearly inflation rate might be different for specific products, both of which triggering a different converted EF result. We consider the affected variable to be the inflation rate (similar to the FX rate discussed above, it acts as a de-facto conversion factor). We implement this using a normal distribution with a standard deviation of **+/- 5%** in the baseline scenario, and **+/- 10%** in the conservative one.
- The degree of **dependency on electricity б** is assumed to capture the relationship between the emissions intensity of a certain good or service and the emissions intensity of electricity. While we know energy consumption is a key driver of embodied carbon for any product or service, it is not the only one. We consider the affected variable to be б, and we implement the uncertainty estimation using a normal distribution with a standard deviation of **+/- 50%** in the baseline scenario and **+/- 100%** in the conservative one.
- For the same dependency on electricity б discussed above, we assume б is the same for the same product or service across all possible countries of origin within the assigned country basket. However, the carbon footprint structure of a given product as revealed through detailed LCAs may differ from one country to another even if they have comparable technological advancement and energy mix. We consider the affected variable to be the **Extrapolated EFs.** We implement this using a normal distribution with a standard deviation of **+/- 20%** in the baseline scenario, and **+/- 40%** in the conservative one.
- The **country of origin assignment** is based on a simplified logic for ease of calculation. All goods consumed in the focal country are assumed to be imported[46], and all services consumed in the focal country with the exception of foreign travel are assumed to have value chains exclusively in the focal country. We consider the affected variable to be the country of import weight. We implement it using a normal distribution with a Standard Deviation of **+/- 10%** in the baseline scenario, and **+/- 20%** in the conservative one.

[45] Notably here, the uncertainty does not pertain to the FX rate itself, but rather to its usage as a conversion factor to leverage Monetary EFs specific to one country, for usage in another.
[46] We captured this assumption as such as we applied the model for Singapore in order to have a numerical baseline for the Monte Carlo simulations, however this can be modified to reflect the specific mix of imports and local production in the focal country studied.

- **Value chains** are assumed not to be segmented, i.e., all the value chain for the respective products is assumed to happen in the country of origin. We consider the affected variable to be the import country's weight. We implement the estimation using a normal distribution with a standard deviation of **+/- 20%** in the baseline scenario, and **+/- 40%** in the conservative one.

For all of these assumptions we have assigned an indication of the risk introduced, and we summarized stress testing range for the affected parameters, as described in Table 3.

Table 3: *Sources of estimation uncertainty – "Algorithm" Uncertainty*

Data parameter	Assumption	Uncertainty introduced		Residual uncertainty impact quantification		Options to further reduce uncertainty
		Impact	Description & Mitigation strategy	Variable tested	Variable distribution (baseline scenario)	
EF Conversion – Monetary to Monetary using **FX rate**	**Currency exchange rates** for specific years are used to convert Monetary EFs from kg CO2e/ other currencies to kg CO2e/SGD.	Low	Monetary EFs are typically the result of EEIO models based on the financial flows and emissions intensity of economic sectors within the country they were computed for. Applying currency exchange rate conversion may not fully capture structural carbon intensity differences relative to local prices.	**FX Rate**	Normal distribution: * Std Dev is **5%** of the used FX Rate	* **Data collection** efforts to enhance the EF library.
EF conversion – Physical to Monetary using **FOB Rates**	The estimated **FOB Exporter Price to Retail markup** is 141% across all product categories* Retail Price = FOB Value *(1+Retail price markup) Retail price markup=141%	Medium	We expect extensive variability across products and product types. The manual prices we estimated and used in the calculation are taken to be average price points for the respective products/services.	**FOB Rate**	Ln distribution: * Std Dev is **50%** of the FOB Rate	* Invest in more extensive literature review / price proxy manual research * Invest effort in **web scraping** more price data points by product. * Invest in focal country **retail market studies**.
EF conversion – Physical to Monetary using **Manual Prices**	The **price points manually sourced** are sufficient for their average to be representative of the entire SG market**	Medium		**Estimated Retail Prices**	Ln distribution: * Std Dev is **50%** of the estimated retail price	
EF conversion – Monetary EF temporal adjustment using **compounded inflation rates**	**Inflation rates** are used for temporal updates.	Low	The inflation rates used based on Singapore CPI evolution are representative of the price dynamic of the Singapore consumer basket. We acknowledge however that particular products or services may different and specific increases or decreases for any 2 years of comparison.	**Inflation Rate**	Normal distribution: * Std Dev is **5%** of the used Inflation Rate	* **Data collection efforts** to enhance the EF library.

EF extrapolation –assuming products& services **dependency on electricity (6)**	There is a **dependency 6** between the emissions intensity of goods and services and the electricity produced in any given country (which can vary by product/service category)	Medium	Energy consumption is a key driver of embodied carbon of a product, but not the only one.	**Extrapolated EF 6**	Normal distribution: * Std Dev is **50%** of assumed 6	* Manually **assess** additional original EFs, to gradually replace extrapolated EF. * Concomitantly with the above, run **regression analysis** to optimize the 6 dependency assumption.
EF extrapolation – assuming a product/ service **dependency on electricity (6)**	The **dependency 6** is the same for the same product/service across all countries.	Low	In addition, the carbon footprint structure of a product may differ from one country of origin to another.		Normal distribution: * Std Dev is **20%** of assumed 6	
EF extrapolation: Product & services **country of origin** assignment	All goods consumed in Singapore are **imported**.	Low	There is relevant local production for some products destined for consumer use, however we expect the impact to not to be material given SG high reliance on imports.	**Country of import weight %**	Normal distribution: * Std Dev is **10%** of actual weight * Sum equals 100%	* Research efforts on **value chain mapping** for goods and services.
	All services consumed in Singapore have entirely **domestic** value chains.					
	All production & distribution activities up until point of export occur in the **country of import**.		Global supply chains are fragmented, with touchpoints in different countries at different stages in the value chain		Normal distribution: * Std Dev is **20%** of actual weight * Sum equals 100%	* Invest in effort to source statistics on average number of country touchpoints per product for more robust uncertainty range.

11.6 Uncertainty Introduced by consumer preferences

Last but not least, consumer groups preferences matter and they can tilt the balance of the consumption basket towards preferred brands. This adds variation versus the typical consumption basket as defined in the model, which in turn adds uncertainty into the end calculation. We consider this category to be an inherited ("extrinsic") rather than algorithm-specific ("intrinsic") uncertainty. The underlying assumption is that the average EF mapped to each product and service is sufficiently representative for all goods or services brands or SKUs falling under the same product group. There can be significant differences however between more or less sustainable brands, which this framework cannot capture at this stage. We assume the affected variable to be the Original EFs, as this pertains to EF granularity (i.e., if EFs were available at brand level, this source of uncertainty would be reduced to zero). We implement this using a normal distribution with a standard deviation of **+/- 20%** in the baseline scenario, and **+/- 40%** in the conservative scenario.

For this assumption we have assigned an indication of the risk introduced, and we summarized stress testing range for the affected parameter, as described in Table 4.

***Table 4**: Sources of estimation uncertainty – Uncertainty Introduced by Consumer Preferences*

Data parameter	Assumption	Uncertainty introduced		Residual uncertainty - impact quantification			Options to further reduce uncertainty
		Impact	Description & Mitigation strategy	Tested variable	Simulation methodology	Variable distribution (baseline scenario)	
EF data **granularity**	**Average product/service level EF data is sufficient,** brand/SKU level EF granularity can be added later when/as available.	Moderate	Brand/SKU level carbon intensity can be vastly different for the same product type, especially if we are using monetary EFs (more expensive does not necessarily mean less sustainable).	**Original EFs**	**Normal distribution:** Std Dev is **20%** of Original EF for each EF	We expect the impact to be moderate, as the emission estimation is for the average Singaporean resident (with an "average consumption mix", purchasing "typical" products or services).	* Invest effort to source brand level emissions variation for the same product type, for a more robust stress testing range (dependence on adoption of emissions reporting and manufacturer level / brand level / SKU level carbon labels are in place).

11.7 Sensitivity analysis – stress testing model assumptions

To verify the impact of the assumptions we needed to take to facilitate the framework build, we run the algorithm for Singapore as an anchor country, and we obtain the average result of 12.034 t CO2e / year / capita[47].

We then conduct a sensitivity analysis exercise assessing the uncertainty brought by each parameter, and by groups of parameters, into the overall estimation. We have taken a simulation-based approach, using implied distributions for our parameters, to generate a set of GHG emissions per capita results (Monte Carlo simulation). The simulation yields confidence intervals which are specific to the anchor country, however we consider the uncertainty results to be applicable to any country and therefore to the model in general.

Figure 12 summarizes the 14 **uncertainty sources** we tested and their grouping in the 3 main uncertainty **categories** discussed above (Inherited Uncertainty, Uncertainty introduced by our algorithm, Uncertainty introduced by product variations). The first category, Inherited Uncertainty, is separated in 2 **sub-groups** (EF Uncertainty and EF Heterogeneity), for better visibility on how each contributes to the overall model uncertainty.
We run 1000 Monte Carlo simulations of the model for each of the 2 scenarios – the baseline and the conservative one. Within each scenario, we run the simulations for the 14 individual parameters, for the 3 groups and 4 sub-groups they belong to, and at a **composite level** all up for the model. We compute the uncertainty as simulated standard deviation / simulated mean, and the relative confidence intervals as the percent ratio between the standard deviation and the mean.

[47] A full overview of the Singapore application of this country agnostic framework is shared in our Whitepaper "Consumption Carbon Footprint: Singapore Case Study".

The following conclusions emerge, for each category of assumption (Figure 9):

- **Inherited Uncertainty** has by far the biggest contribution to model uncertainty. The uncertainty introduced by the EFs Inbuilt Uncertainty is **8.3%** (which we consider high) when tested individually, whereas the uncertainty introduced by the EF Heterogeneity is **3.4%** (which we consider moderate). From the EF Heterogeneity sources, EF recency is the highest contributing factor, with introducing an uncertainty of **2.8%** when individually tested. Cumulatively, these have the highest impact in the overall model uncertainty. As a result, the single most important action for increasing the reliability of the individual carbon footprint estimation is sourcing **high quality, recent, Emission Factors**, with the lowest available inbuilt uncertainty.

***Figure 9**: Consumer Carbon Footprint uncertainty estimation*

Inherited Uncertainty

1. EF Inbuilt Uncertainty

Source	Parameter affected / tested	Range	Introduced unc.
Original EFs inbuilt unc.	Original EF	+/-38% St Dev Log normal +/-78% St Dev Log normal =x% (x – published unc. for any given EF)	8.3%
Uncertainty :			**8.3%**

2. EF Heterogeneity

Source	Parameter affected / tested	Range	Introduced unc.
EF GWPs alignment	Original EF	+/- 10% St Dev Normal	1.4%
EF recency	Original EF	+/- 20% St Dev Normal	2.8%
EF Methodology alignment	Original EF	+/- 10% St Dev Normal	1.4%
EF System boundaries	Original EF	-10% / +5% St Dev Uniform	0.62%
Uncertainty :			**3.4%**

Uncertainty introduced by our algorithm

3. Data Scarcity

Source	Parameter affected / tested	Range	Introduced unc.
EF conversion – Monetary to Monetary using FX rate	FX rate	+/- 5% St Dev Normal	0.31%
EF conversion – Physical to Monetary using FOB rate	FOB rate	+/- 50% St Dev Log Normal	5.0%
EF conversion – Physical to Monetary using manual prices	Estimated Retail Price	+/- 50% St Dev Log Normal	3.8%
EF conversion – Monetary EF temporal adjustment using compounded inflation rate	Inflation rate	+/- 5% St Dev Normal	0.38%
EF Extrapolation – assuming products/services dependency on electricity б	б	+/- 50% St Dev Normal	2.1%
EF Extrapolation – assuming product/service LCA structure constant across countries	Extrapolated EF	+/- 20% St Dev Normal	1.8%
Country of origin mix – assuming o local product	Country of import mix	+/- 10% St Dev Normal	0.04%
Country of origin mix – assuming country of origin is the same as country of import	Country of import mix	+/- 20% St Dev Normal	0.08%
Uncertainty :			**6.6%**

Uncertainty introduced by product, household, and preferences variation

4. Product Variation

Source	Parameter affected / tested	Range	Introduced unc.
EF granularity	Original EF	+/- 20% St Dev Normal	2.7%
Uncertainty :			**2.7%**

Model uncertainty: 12.6% (Simulated Std Dev/Simulated Mean)

Mean: 11.89 t CO2e/individual/year
Median: 11.73 t CO2e
Std Deviation: 1.50 t CO2e
Our Result: 12.034

Model confidence interval: t CO2e / household / month
[2.42 , 3.61] at 90% confidence
[2.34 , 3.78] at 95% confidence

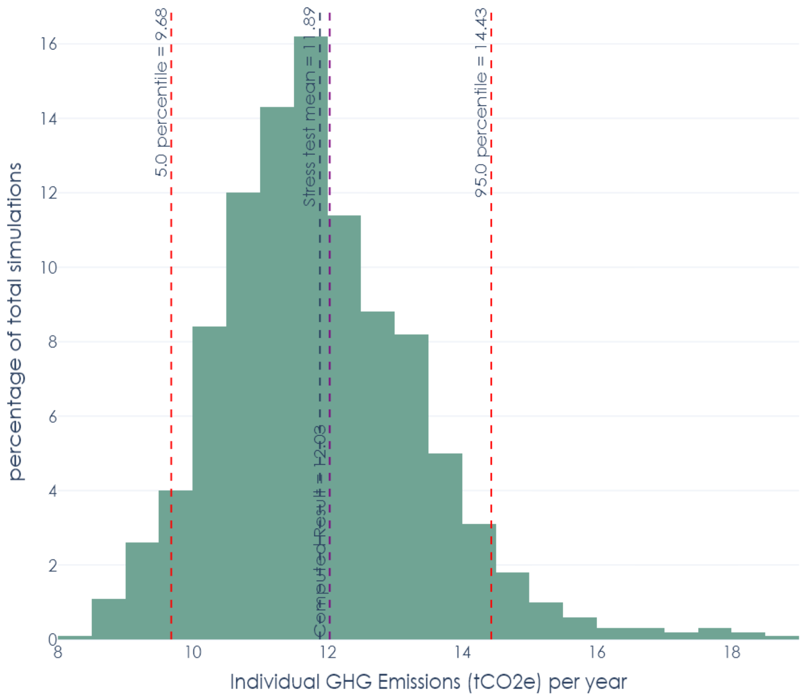
Model confidence interval: t CO2e /individual / year
[9.68 , 14.43] at 90% confidence
[9.35 , 15.13] at 95% confidence

- Our **Algorithm Uncertainty** introduces an uncertainty of **6.6%** when ran separately (across all its 8 parameters concomitantly). The key drivers are the estimation of **Average Retail Prices** by product (either through manually collected retail prices or through Exporter FOB prices). The range we assumed in this scenario for both parameters is extremely high, with a 50% Standard Deviation, as we felt for most countries average retail prices may require extensive market studies which may not be realistically available at a level of granularity warranting higher confidence. Therefore, the next most important action we recommend in order to increase model reliability is sourcing high quality retail prices datasets.

  Notably, our **б hypothesis** introduces relatively low uncertainty, of **2.1%** when measured individually (even if we assume a highly conservative Standard Deviation Range for б of 50%). Therefore, on the bright side, our yet to be proved hypothesis does not introduce significant uncertainty in the end result. We maintain however our call to action for enhanced emissions reporting and carbon labelling (which would gradually decrease the need for the "placeholder" EFs created through the use of б).

- Last but not least, the impact of EF granularity is relatively low as well, introducing an uncertainty of 2.7% when testing individually.

Figure 10: *Distribution of simulation outcomes*



In Figure 10 we further showcase the **uncertainty of the model** that we thus obtain for the **baseline scenario** is **12.6%** (computed as Simulated Standard Deviation / Simulated Mean). We find this to be a strong indication of the model's robustness, given the extensive number of parameters tested (14), and the broad ranges that we assumed for the parameters that we factored in (for example, we considered as discussed in the previous section, the Original Monetary EFs can have a range of +/- 78%). This algorithm thus acts as an **uncertainty mitigation tool**, similar to how a well-diversified portfolio has a far lower risk that the individual assets within, due to offsetting effects in stress scenarios.

Figure 11: *Distribution of simulation outcomes – baseline scenario*

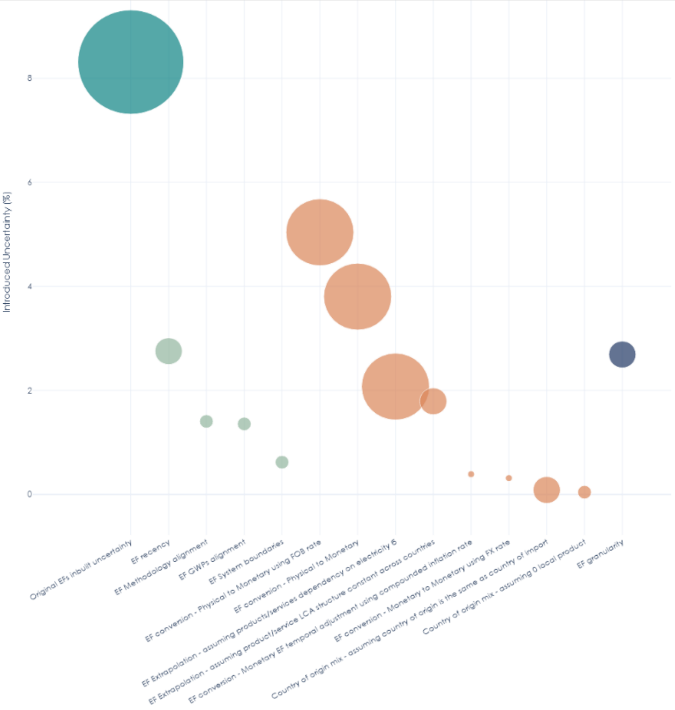
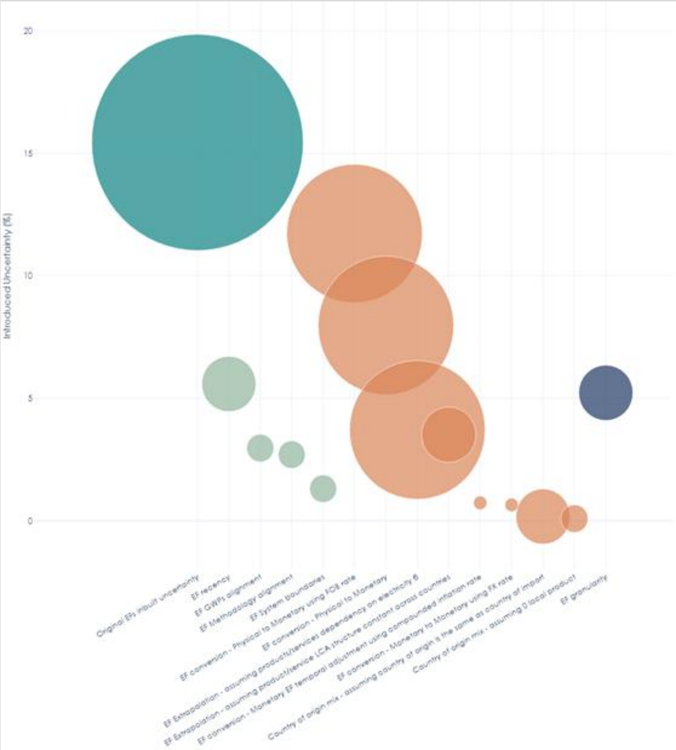


Figure 12: *Distribution of simulation outcomes – conservative scenario*



In Figure 11 we rank uncertainty drivers by their impact when they are individually stress tested (measured as Introduced Uncertainty %) according to the parameters listed above. The bubble radius is represented by the Standard Deviation range we apply to each parameter.

As mentioned in the previous section, the most impactful parameters impacting the robustness of the end estimation are EF Inbuilt Uncertainty (impact of 8.3%), FOB Rates (impact of 5.0%), Estimated Retail Prices (impact of 3.8%), and EF Recency (impact of 2.8%).

As mentioned earlier in this section, our baseline scenario already incorporates highly conservative ranges for each parameter affected by assumptions. We chose to do so out of an abundance of caution, and to encourage investment in the key uncertainty reduction actions, which are sourcing high resolution, high quality, recent EFs, and high quality retail prices datasets.

We wanted however to understand non-linear, compounding effects that our assumptions may have, which is why we explored an even more **conservative scenario** as well, whereby we double all the ranges in the baseline scenario. Figure 12 showcases the uncertainty introduced by each parameter individually, and the radius for each parameter is represented by its respective allocated range.

The resulting overall model uncertainty is **29.9%,** which is more than double. The ranking of top parameters remains the same: EF Inbuilt Uncertainty (impact of 15.5%), FOB Rate (impact of 11.7%), Estimated Retail Prices (impact of 8%), and EF Recency (impact of 5.6%). Inherited Uncertainty remains significantly higher than the Algorithm

Uncertainty though. This nonlinear effect strengthens the conclusion that further investments in sourcing high quality EFs and retail prices datasets is warranted. Incrementally worse input data has a disproportionate effect in increasing the model uncertainty, whereas incrementally better input data has a disproportionate effect in reducing it.

12. Conclusion

Our whitepaper offers a holistic computational framework for estimating the individual or household carbon footprints associated with the consumption of common products and services. This framework is theoretically applicable to any country of study, subject to the availability of key datasets such as typical expenditure baskets (at different levels of granularity), retail prices, and high quality emission factors data as representative as possible of the contextualized consumption basket.

Our framework also takes into account the country of origin of imported goods within a holistic cradle to grave lifecycle of consumed products, and is based on the hypothesis that the carbon footprint of both goods and services depends to a certain extent on the carbon footprint of electricity produced within the same country. While this hypothesis is not yet proven at the time of our study, it can offer a placeholder for contextualized Emission Factors until they become available through more extensive academic or commercial life cycle assessment studies.

Through the sharing of our assumptions and hypotheses based methodology, we address some of the concerns prevalent in the sustainability data landscape, such as data scarcity, heterogeneity, complexity, misalignment and unreliability. While we are certainly not solving for all these issues, we hope to facilitate the kick start of further and deeper research projects on these field.

Our model stress testing showcases both the strengths of the approach and the areas introducing the most significant uncertainty, highlighting the importance of continuous improvement of underlying data, hypotheses and assumptions. As households consumption remains an important driver of global emissions, advancing the conversation on how to simplify and scale carbon footprinting insights is critical towards accelerating climate action.

We therefore launch a call to action towards the research and practitioner community to further contribute to this conversation: expanding emission factor datasets, examining sources of uncertainty, and nuancing key assumptions. This could enable household and their providers to make better informed decisions and ultimately scale their climate positive impact.

References

1. Afionis, S., Sakai, M., Scott, K., Barrett, J. & Gouldson, A. (2017). Consumption-based carbon accounting: does it have a future? WIREs Clim Change, Volume 8(1). https://doi.org/10.1002/wcc.438

2. Aichele, R., & Felbermayr, G. (2012). Kyoto and the carbon footprint of nations. Journal of Environmental Economics and Management, Volume 63, Issue 3, p. 336-354, ISSN 0095-0696. https://doi.org/10.1016/j.jeem.2011.10.005

3. Blanco, C., Caro, F., & Corbett, C.J. (2016). The state of supply chain carbon footprinting: Analysis of CDP disclosures by US firms. Journal of Cleaner Production, Volume 135, p. 1189–1197, ISSN 0959-6526. https://doi.org/10.1016/j.jclepro.2016.06.132

4. Cap, S., de Koning, A., Tukker, A., & Scherer, L. (2024). (In)sufficiency of industrial decarbonization to reduce household carbon footprints to 1.5°C-compatible levels. Sustainable Production and Consumption, 45, 216–227. https://doi.org/10.1016/j.spc.2023.12.031

5. CEPII (Centre d'Études Prospectives et d'Informations Internationales). (2023). BACI: International Trade Database at the Product-Level. Version 202301. Retrieved on October 31, 2023 from http://www.cepii.fr/cepii/en/bdd_modele/bdd_modele_item.asp?id=37

6. Weber, C.L, & Matthews, H.S. (2008a). Food-Miles and the Relative Climate Impacts of Food Choices in the United States. Environmental Science & Technology, Volume 42(10), ISSN p. 3508-3513. https://doi.org/10.1021/es702969f

7. Clarke, J.C. (2017). The carbon footprint of an Icelander: a consumption-based assessment using the Eora MRIO database. https://skemman.is/bitstream/1946/27675/2/JCC%2001091988-4549%20FINAL%20THESIS%20.pdf

8. Creutzig, F., Roy, J., Lamb, W.F. et al. (2018). Towards demand-side solutions for mitigating climate change. Nature Clim Change 8, 260–263. https://doi.org/10.1038/s41558-018-0121-1

9. Davis, S.J., & Caldeira, K. (2010). Consumption-based accounting of CO2 emissions. Proceedings of the National Academy of Sciences, Volume 107(12), p. 5687-5692. https://doi.org/10.1073/pnas.0906974107

10. Ember Climate. (2023). Yearly Electricity Data. Data retrieved on July 17, 2024 from https://ember-climate.org/app/uploads/2022/07/yearly_full_release_long_format.csv

11. Eurostat. (2024). European Classification of Individual Consumption according to Purpose (ECOICOP) (Version 2015) [Data set]. Publications Office of the

European Union. http://data.europa.eu/88u/dataset/ecoicop (Original work published 2024)

12. Franzen, A., & Mader, S. (2018). Consumption-based versus production-based accounting of CO2 emissions: Is there evidence for carbon leakage? Environmental Science & Policy, Volume 84, p. 34-40, ISSN 1462-9011. https://doi.org/10.1016/j.envsci.2018.02.009

13. Guan, D., Liu, Z., Geng, Y., Lindner, S., Hubacek, K. (2012). The gigatonne gap in China's carbon dioxide inventories. Nature Climate Change, Volume 2, p. 672–675 https://www-nature-com.libproxy1.nus.edu.sg/articles/nclimate1560#citeas

14. Hertwich, E.G. & Peters, G.P. (2009, June 14). Carbon Footprint of Nations: A Global, Trade-Linked Analysis. Environmental Science & Technology, Volume 43(16), ISSN 6414-6420. https://pubs-acs-org.libproxy1.nus.edu.sg/doi/10.1021/es803496a

15. Hendratama T., Broadstock D.C. & Sulaeman J. (2023). ESG Data Primer: Current Usage and Future Applications, SGFIN Whitepaper #2023-02. https://sgfin.nus.edu.sg/wp-content/uploads/2023/12/SGFIN_WHITE_PAPERS_2023-02.pdf

16. Ingwersen, W. & Li, M. (2020). Supply Chain Greenhouse Gas Emission Factors for US Industries and Commodities. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-20/001. Retrieved in December, 2023 from US EPA Science Inventory: https://cfpub.epa.gov/si/si_public_file_download.cfm?p_download_id=540798&Lab=CESER

17. International Organization for Standardization (ISO). (2006). ISO 14040:2006 Environmental management – Life cycle assessment – Principles and framework. Geneva: ISO. Retrieved in October 2024 at https://www.iso.org/obp/ui#iso:std:iso:14040:ed-2:v1:en

18. IPCC. (2023). Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, p. 35-115. https://www.ipcc.ch/report/sixth-assessment-report-cycle/

19. Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A. & Hertwich, E.G. (2016). Environmental Impact Assessment of Household Consumption. Journal of Industrial Ecology, Volume 20(3), p. 526-536. https://doi.org/10.1111/jiec.12371

20. Khan Z, Ali S, Umar M., Kirikkaleli, D., Jiao, Z. (2020). Consumption-based carbon emissions and International trade in G7 countries: the role of environmental innovation and renewable energy. Science of The Total Environment, Volume 730, ISSN 0048-9697. https://doi.org/10.1016/j.scitotenv.2020.138945

21. Kramer K.J., Moll H.C., Nonhebel S., Wilting H.C. (1999). Greenhouse gas emissions related to Dutch food consumption. Energy Policy, Volume 27 (4), p. 203-216, ISSN 0301-4215. https://doi.org/10.1016/S0301-4215(99)00014-2

22. Lenzen, M. (2000). Errors in conventional and Input-Output—based Life—Cycle inventories. Journal of Industrial Ecology, Volume 4 (4), p. 127–14. DOI: 10.1162/10881980052541981

23. Liu, L. (2015). A critical examination of the consumption-based accounting approach: has the blaming of consumers gone too far? WIREs Climate Change, Volume 6(1), p. 1–8. https://doi.org/10.1002/wcc.325

24. MacLeod, M., Gerber, P., Mottet, A., Tempio, G., Falcucci, A., Opio, C., Vellinga, T., Henderson, B., & Steinfeld, H. (2013). Greenhouse gas emissions from pig and chicken supply chains – a global life cycle assessment. Food and Agriculture Organization of the United Nations. https://www.fao.org/3/i3460e/i3460e.pdf

25. Mangır, N., & Şahin, Ü.A. (2022). An environmentally extended global multi-regional input–output analysis of consumption-based and embodied import-based carbon emissions of Turkey. Environmental Science and Pollution Research, Volume 29, p. 54813-54826. https://doi-org.libproxy1.nus.edu.sg/10.1007/s11356-022-19290-z

26. Munksgaard, J., & Pedersen, K.A. (2001). CO2 accounts for open economies: producer or consumer responsibility? Energy Policy, Volume 29 (4), p. 327-334. https://doi.org/10.1016/S0301-4215(00)00120-8.

27. Naegele, H., & Zaklan, A. (2019). Does the EU ETS cause carbon leakage in European manufacturing? Journal of Environmental Economics and Management, Volume 93, p. 125–147. https://doi.org/10.1016/j.jeem.2018.11.004

28. Peters, G.P., & Hertwich, E.G. (2008). CO2 embodied in international trade with implications for global climate policy. Environmental Science and Technology, Volume 42(5), p. 1401-1407. https://doi.org/10.1021/es072023k

29. Podong, C., Ulbonsook, P., & Noinamsaib, S. (2020). Evaluation of the Carbon Footprint of Fresh Durian Grown in an Agroforestry System in Uttaradit Province, Thailand. Thai Journal of Science and Technology, Volume 9(3), p. 298–309. https://doi.org/10.14456/tjst.2020.20

30. Pottier, A., Combet, E., Cayla, J.M, De Lauretis, S., Nadaud, F. (2020, May). Qui émet du CO2? Panorama critique des inégalités écologiques en France, Revue de l'OFCE, Volume 169, p. 73-132. https://doi.org/10.3917/reof.169.0073

31. Richter J. L., Lehner M., Elfström A., Henman J., Vadovics E., Brizga J., Plepys A., Mont O. (2024). 1.5° lifestyle changes: Exploring consequences for individuals and households, Sustainable Production and Consumption,

Volume 50, 2024, Pages 511-525, ISSN 2352-5509.
https://doi.org/10.1016/j.spc.2024.07.018

32. Ritchie, H. (2020). "You want to reduce the carbon footprint of your food? Focus on what you eat, not whether your food is local" Published online at OurWorldInData.org. Retrieved in December 2023 from https://ourworldindata.org/food-choice-vs-eating-local'

33. Singapore Department of Statistics (SG DOS). (2016). Singapore Standard Classification of Individual Consumption According to Purpose (S-COICOP). Retrieved in Dec 2024 from https://www.singstat.gov.sg/-/media/files/standards_and_classifications/s-coicop/s-coicop-2016.ashx

34. Singapore Department of Statistics (SG DOS). (2019). Report on the Household Expenditure Survey 2017 / 18. ISSN:2661-4103. Full Report retrieved in October 2023 from https://www.singstat.gov.sg/ /media/files/publications/households/hes201718.ashx

35. Tukker, A., Wood, R., & Schmidt, S. (2020). Towards accepted procedures for calculating international consumption-based carbon accounts. Climate Policy, Volume 20(sup1), p. S90-S106. https://doi.org/10.1080/14693062.2020.1722605

36. UK Department for Energy Security and Net Zero (UK DESNZ) & UK Department for Environment, Food and Rural Affairs (UK DEFRA). (2023). UK Government GHG Conversion Factors for Company Reporting, "Conversion factors 2023: full set (for advanced users) - updated 28 June 2023". Data retrieved in November 2023 from https://assets.publishing.service.gov.uk/media/649c5358bb13dc0012b2e2b7/ghg-conversion-factors-2023-full-file-update.xlsx

37. UK Department for Environment, Food and Rural Affairs (UK DEFRA). (2023). UK and England's carbon footprint to 2020. UK full dataset 1990 - 2020, including conversion factors by SIC code. UK Footprint Results (1990 - 2020). Retrieved in November 2023 from https://www.gov.uk/government/statistics/uks-carbon-footprint

38. United Nations, Department of Economic and Social Affairs. (2018). Classification of Individual Consumption According to Purpose (COICOP) 2018. Retrieved in October 2023 from https://unstats.un.org/unsd/classifications/unsdclassifications/COICOP_2018_-_pre-edited_white_cover_version_-_2018-12-26.pdf

39. U.S. Environmental Protection Agency (EPA), Office of Research and Development (ORD). (2023). Database: US EPA Supply Chain Greenhouse Gas Emission Factors v1.2 by NAICS-6. Data retrieved in October 2023 from https://catalog.data.gov/dataset/supply-chain-greenhouse-gas-emission-factors-v1-2-by-naics-6

40. Vita G., Lundström J.R., Hertwich E.G., Quist J., Ivanova D., Stadler K., Wood R. (2019). The Environmental Impact of Green Consumption and Sufficiency

Lifestyles Scenarios in Europe: Connecting Local Sustainability Visions to Global Consequences. Ecological Economics, Volume 164, 106322, ISSN 0921-8009. https://doi.org/10.1016/j.ecolecon.2019.05.002

41. Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecological Economics, Volume 69(2), p.211-222, ISSN 0921-8009. https://doi.org/10.1016/j.ecolecon.2009.08.026

42. World Bank Group: International Comparison Program, World Bank | World Development Indicators database, World Bank | Eurostat-OECD PPP Programme. (2024). GDP per capita, PPP (constant 2021 international $). Data retrieved in July 2024 from https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD

43. World Customs Organization. (2022). HS (Harmonised System) Nomenclature 2022 edition. Data retrieved in October 2023 from https://www.wcoomd.org/en/topics/nomenclature/instrument-and-tools/hs-nomenclature-2022-edition/hs-nomenclature-2022-edition.aspx

44. World Resources Institute (WRI) and World Business Council for Sustainable Development (WBCSD). (2011a). GHG Protocol Product Life Cycle Accounting and Reporting Standard, Product-Life-Cycle-Accounting-Reporting-Standard_Pro041613.pdf (ghgprotocol.org)

45. World Resources Institute (WRI) and World Business Council for Sustainable Development (WBCSD). (2011b). GHG Protocol Corporate Value Chain (Scope 3) Accounting and Reporting Standard, provided at https://ghgprotocol.org/sites/default/files/standards/Corporate-Value-Chain-Accounting-Reporing-Standard_041613_2.pdf