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Scope 3 Emissions: Measurement and Management

Working Paper

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1 Introduction

Given that climate change is one of the biggest risks facing the real economy as well as the financial industry, there is an urgent need to measure and manage this risk (TCFD, 2017). For example, this risk may come from new regulation of a company's high emission products and shifts in end-product market demand driven by climate concerns. One way to measure this risk is the carbon (or carbon dioxide/CO_2) exposure of products and their corresponding supply chains (Economist, 2020).[1]

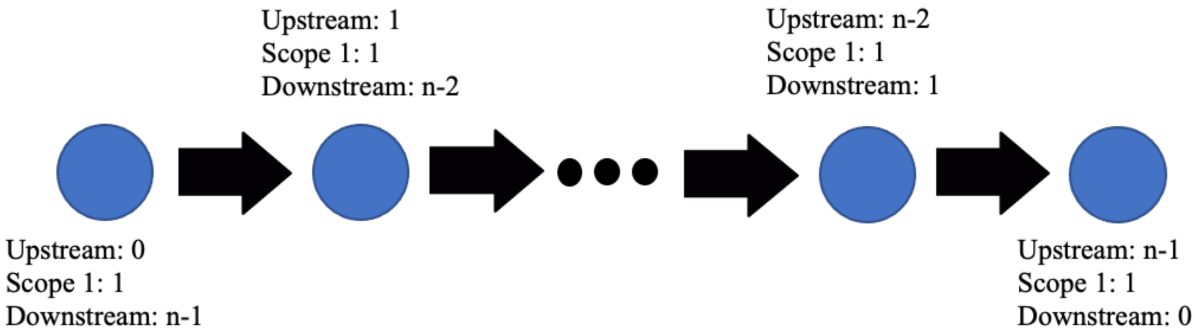
This risk can be internalized by these supply chains in presence of a universal carbon tax (Metcalf and Weisbach, 2009). However, such a universal tax, or even an equivalent cap-and-trade program, appears unlikely due to political economy related barriers (Cullenward and Victor, 2020). Nevertheless, even in the absence of such a tax, it is of tremendous value to measure and manage this carbon exposure, given that it provides a measure of the transition risk facing companies in these supply chains (Baker, 2020).[2]

Furthermore, many companies are under increasing pressure from their shareholders and stakeholders to commit to reducing their carbon footprints in a significant manner over time. Failing to do so may raise reputational concerns, with adverse implications for financial performance (GS, 2019). Recognizing these drivers, since the Paris agreement, more than 1200 companies have committed to climate action through the We Mean Business Platform and over 800 companies have committed to setting science-based targets (BSR, 2020). Recent examples of financial institutions setting net-zero target are Barclays,[3] HSBC,[4] and J P Morgan Chase.[5]

The carbon exposure of a business entity – e.g., a corporate or a financial institution – is typically measured in three different ways (WRI, 2017). Scope 1 emissions are the entity's emissions due to its own activities, e.g., coal power plant emissions for the corresponding power producer. Scope 2 emissions are the emissions from the electricity procured by the business entity, e.g., the coal power plant emissions for the corresponding buyer of electricity. Scope 3 emissions are the emissions of the remainder of the supply chain (minus electricity, i.e., Scope 2), of both upstream and downstream activities (Figure 1). Thus, in a way, Scope 2 emissions are a special kind of Scope 3 emissions, but they are counted separately due to historical reasons.

1 For financial institutions, other ways include the following (Economist, 2020): one, gauging greenness to see whether portfolios are aligned with the Paris agreement (e.g., by the 2 Degrees Investing Initiative); and two, assigning temperature scores to portfolios (Raynaud, 2020).
2 It is important to note that the carbon risk is not the only measure of climate risk (Busch, 2018; PCAF, 2015), given that such risks may include technology, markets, and policy risks as well. However, it is a useful proxy.
3 See https://home.barclays/society/our-position-on-climate-change/highlights/
4 See https://www.hsbc.com/our-approach/our-climate-strategy/becoming-a-net-zero-bank
5 See https://www.jpmorganchase.com/impact/sustainability

Figure 1: Scope 1 and Scope 3 (both upstream and downstream) emissions in a simplified setting



To get an accurate sense of a business entity's carbon risk, it is then pertinent that all three emissions are accurately calculated. Accurate measurement of these emissions would allow business entities to track progress towards their stated climate targets and transition pathways (SBTi, 2020; TPI, 2020). Companies have so far focused on measuring and reducing their Scope 1 and Scope 2 emissions, and they have been quite successful in doing do (BSR, 2020).

However, the greatest emission reduction opportunities lie in the Scope 3 emissions going forward, given that on average the Scope 3 emissions are 5.5 times the amount of combined Scope 1 and Scope 2 emissions (BSR, 2020). For example, for Lego and Walmart, Scope 3 emissions constitute 75% and 90%, respectively, of total emissions (Huang et al, 2020).[6] In fact, it has now been established that more than 50% of the world's carbon emissions are in eight supply chains (WEF, 2021).[7]

Therefore, while the historical focus has been on Scope 1 and Scope 2 emissions, now the focus is starting to shift to Scope 3 emissions, not only for assessing the carbon risk of the supply chain but also to hold business entities responsible for the whole supply chain. This also ensures that the carbon emissions of a business entity are not simply pushed to other parts of the supply chain (Chen et al, 2019; Granot et al, 2014).[8]

While the process of calculating Scope 1 and Scope 2 emissions is well established (Busch, 2018); the same cannot be said of Scope 3 emissions, despite multiple ongoing efforts by coalitions (GHP, 2020; PCAF, 2020; UNFCCC, 2015; SE, 2018) and industry actors (API, 2016; BHP, 2019),[9] as well as commercial data providers (Busch et al, 2018). Among these, GHP (2020) and PCAF (2020) are particularly instructive, given that the former is the overall industry standard, and the latter is the frontrunner standard for financial institutions, and we examine them more closely in our discussion paper.

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6 As other examples, Larsen et al (2012) shows that upstream Scope 3 emissions are up to 95% of Norwegian municipalities' total emission footprints; and CDP (2016) finds that most of the supply chain emissions are in bought or sold product categories, as defined by GHP (2020).
7 WEF (2021) further argues that most of these emissions can be eliminated using cheap carbon abatement measures (e.g., energy efficiency and renewable energy) costing about $10/ton, with eventual impact to customers being less than 5%.
8 For instance, according to Porter (2013), about a fifth of China's emissions are for products consumed outside its borders, and although Europe emitted only 3.6 billion metric tons of CO2 in 2011, 4.8 billion tons of CO2 were created to make the products Europeans consumed in that year. This is also evident from the global carbon import flows in WEF (2021). As another example (Chen et al, 2019), self-reported data from Wesfarmers in Australia shows a negative correlation between Scope 1 (or 2) emissions and Scope 3 emissions, indicating that Scope 3 emissions typically go up due to leakage as companies reduce their Scope 1 (or 2) emissions.
9 GHP (2020) is by the Greenhouse Gas Protocol, a partnership between the World Resource institute (WRI) and World Business Council for Sustainable Development (WBSCD). GHP (2020) is the de-facto standard, referenced by other frameworks: PCAF (2020) is by the Partnership for Climate Aligned Finance, a coalition of financial institutions; IFI (2015) is for international financial institutions; SE (2018) is for academic institutions; API (2016) is for the petroleum industry; and BHP (2019) is for the Broken Hill Proprietary Company (BHP). A brief history of these efforts pertinent to the financial industry is provided in the Appendix (Section 6.1).

For example, as of March 2020, only 18% of the constituents of MSCI ACWI IMI reported Scope 3 emissions (Baker, 2020), with considerable variability across sectors. As another example, there is increasing evidence that many of the worst polluters – both private (e.g., Exxon) and public (e.g., NIOC/Iran) – either under-report or do not report at all (Fick ling and He, 2020). Furthermore, the Scope 3 emissions data from commercial data providers tends to be high inconsistent, with correlations as low as 1%, which calls for not only increased transparency but also standardization (Busch et al, 2018).[10]

This may be due to various barriers, such as lack of transparency of supply chain, lack of direct connections with various tiers of suppliers, reduced leverage to influence action, and complex accounting principles (BSR, 2020). Furthermore, the industry standard (i.e., GHP, 2020) provides so much scope for discretion and ambiguity that the ultimate reporting, if it is there at all, can be inconsistent and misleading (Fickling and He, 2020). In this discussion paper, therefore, we focus on Scope 3 emissions, in both upstream and downstream parts of a business entity's supply chain.

As mentioned above, while there are many ongoing efforts by coalitions, and there are many organizations providing Scope 3 emissions data;[11] the focus of this discussion paper is on (a) identifying key issues – i.e., double counting as well as unreliable data – that still need to be resolved in order for Scope 3 emissions to become reliable sources of supply chain carbon risk, and (b) providing some initial thoughts on how these issues can be addressed, including existing approaches (Sections 2.1 and 3.2). In this process, we also recognize that the eventual goal may be to reduce carbon footprints of supply chains and, therefore, examine practical ways of doing so as well (Sections 2.2 and 3.3).

In this paper, we focus on the key issues of measurement and management of Scope 3 emission. In this discussion paper on Scope 3 emissions, the focus is not on developing a comprehensive framework. A lot of well-funded organizations and consortia are already working on such frameworks (see Section 6.1for a brief history of such frameworks for the financial sector). The idea here is to highlight some of the key issues facing such frameworks and suggest potential solutions.

The rest of the paper is organized as follows. In presence of reliable data, Section 2 examines how double counting can be appropriately addressed, whether for Scope 3 or for supply chain emissions. Section 3 then discusses methods and issues around measurement and management of uncertain and unreliable Scope 3 emissions. Section 4 concludes with ideas for future work.

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10 The low consistency of Scope 3 emissions can be attributed to (a) different data sources as well as (b) estimation methods. This is no different from other methods to track climate alignment – for example, analyzing 12 methods that assign temperature scores to portfolios, Raynaud (2020) finds scores ranging from 1.5C to 4C.

11 For example, the greenhouse gas protocol identifies more than 50 databases (see https://ghgprotocol.org/life-cycle-databases) for collecting data for product life cycle and corporate value chain – i.e., Scope 3 – emission inventories. Furthermore, Busch (2018) identifies nine commercial data providers, with eight providing Scope 3 emissions, including the following: Bloomberg, Carbon Data Market, CDP, Inrate, ISS ESG, MSCI, Sustainalytics, Thomson Reuters, and Trucost.

2 1st-Best Methods for Calculating Scope 3 Emissions

In this section, we provide a glimpse into an ideal method based on reliable data for measuring Scope 3 emissions, by examining the following questions: How to define boundaries and allocate emissions, using appropriate control method? What is the role & feasibility of compulsory measurement? How to take care of double counting? Etc.

One of the major issues with measuring Scope 3 emissions is the reliability (or accuracy) of data, including the mismatch in data quality in different parts of the supply chain (Busch et al, 2018). While we discuss how to address the issue of reliability, assuming that the data quality is not an issue, we first set some basic principles for calculating Scope 3 emissions. The data quality – on emissions as well as emission factors – can be made 100% reliable in an ideal world, whether it is either mandated by regulation (i.e., is compulsory), or is market driven via either demand pull or supply push. This would essentially mean that the bottom-up process-based methods can be applied universally, enabling reliable calculation of emissions and emission factors (GHP, 2020).

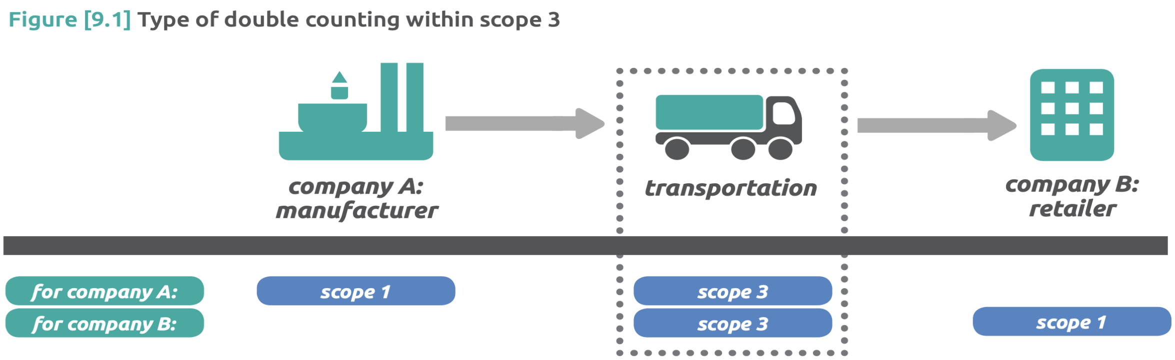
2.1 Addressing double counting in presence of reliable data

In this context, assuming 100% reliable data, the next biggest issue is the so-called double counting (BHP, 2019; PCAF, 2020). Supply chains are interconnected networks, and care needs to be taken to ensure that emissions are not counted multiple times in the Scope 3 emissions of a business entity (Lenzen, 2008).[12] While double counting may not ultimately be an issue if the ultimate goal is to drive the overall supply chain emissions to zero,[13] it is likely to be an issue in the interim, given that there is typically a need to compare different business entities and their progress towards stated climate targets.

Double counting can be of two kind: one that is inherent in calculating the Scope 3 emissions of different actors within a product's supply chain; and another that occurs due to entanglement of supply chains of different products. An example of the former (i.e., *within supply chain* double counting) is that the Scope 1 emission of an upstream entity is part of the Scope 3 emissions of multiple downstream entities at different levels (Figure 2), whereas an example of the latter (i.e., *across supply chains* double counting) is if the Scope 1 emission of an upstream entity is being assigned 100% to multiple immediate downstream entities that split up the use of the product from the upstream entity.

12 For example, PCAF (2020) identifies the following types of double counting with respect to financial institutions: between financial institutions, in co-financing the same entity or activity, between transactions within the same financial institution, across different asset classes, and within the same asset class.
13 Imagine that the Scope 3 emissions for a business entity are a sum of multiple emission numbers (all positive) from the supply chain. Now, if the sum goes to zero, all the constituent numbers also need to go to zero; and, double counting is unlikely to matter.

Figure 2: Within supply chain double counting [Source: GHP (2020)]



In this discussion paper, our assumption is that the former (i.e., within supply chain double counting) is organic in calculating Scope 3 emissions and should be allowed to accurately represent supply chain carbon exposure (i.e., risk) for all entities in the supply chain. We, therefore, focus on eliminating double counting for the latter (i.e., across supply chains double counting), and our coverage of double counting in the remainder of this paper is focused on eliminating across supply chains double counting, especially given that it has not received much attention in literature (GHP, 2020; Baker, 2020; PCAF, 2020).[14] However, we also cover the much covered issue of *fair attribution* – of attributing aggregate supply chain emissions to different actors, and avoiding the former as well – in Section 2.2.

Across supply chain double counting – our focus for the remainder of this paper – can be avoided by appropriate allocation of the upstream and downstream emissions to various downstream and upstream entities, respectively. These – i.e., upstream, and downstream emissions – can also be defined as *embedded* and *latent* emissions, respectively; given that upstream carbon emissions are already embedded in a product that is sold from a seller to a buyer; whereas downstream emissions are latent in a product, to be emitted later (or downstream) in the supply chain.

In the Appendix (see Section 6.2), starting with Scope 1 emissions (and corresponding emission intensities), we provide a simple recursive method of how Scope 3 emissions of the members in a supply chain can be calculated on a per product basis, with straightforward extensions to multiple products. We note that, while elements of this method exist in GHP (2020), our paper is the first to provide this recursive method explicitly.

In this context, we note that PCAF (2020) uses a similar method, while using the ratios of financed capital to enterprise values as the proportional fractions,[15] to calculate the Scope 3 emissions of a financial institution. While the use of enterprise value itself has come under criticism, given that it can change due to market dynamics (Economist, 2020), this is a welcome start, and one potential fix could be to use the more stable book values of debt as well as equity as opposed to dynamically changing market values.

14 It is pertinent to mention the approach used in Baker (2020), where they use a portfolio wide adjustment by a factor of 5. However, this multiplier is likely to change as more firms report accurate data. Another pertinent mention is the recommendation for real estate (GRESB, 2017; ICF, 2017), which allows across supply chain double counting in some cases, in-line with our original thinking about the long-term focus on elimination of supply chain emissions.
15 Enterprise value is defined as the sum of market value of equity and book value of debt. The reasons for using enterprise values include the following: first, to align with the EU TEG; and second, to avoid negative values.

2.2 Fair attribution and efficient management of supply chain emissions

A set of related issues are of fair attribution of total supply chain emissions to various actors in the supply chain, while avoiding double counting of any kind (i.e., both within and across supply chain), and ensuring 1st-best reduction of emissions (Lenzen, 2008). Here 1st best reduction of emissions is typically from a societal point of view and optimizes a social welfare function based on a given carbon price.

The key question in fair attribution is as follows: Given total supply chain emissions, what is the fair responsibility of each actor? The basic idea behind this fair attribution is to start with the total supply chain emissions – i.e., the sum of all Scope 1 emissions in the supply chain – and to attribute them across the actors in the supply chain in a fair manner. This would then enable comparisons across actors; allow tracking of how each actor reduces emissions that it is responsible for, including using carbon offsets; and enable further development of mechanisms for optimal reductions in emissions.

The approaches to address this question of fair attribution, and mechanisms for reducing supply chain emissions, include game theoretic approaches, both cooperative and non-cooperative ones (Caro et al, 2013; Gallego and Lenzen, 2005; Gopalakrishnan et al, 2020; Granot et al, 2014; Lenzen, 2008; US, 2020),[16] from economics. In what follows, we provide a summary of both approaches in an integrated manner, with focus on management of supply chain emissions.

We start with non-cooperative approaches (Caro et al, 2013; Li et al, 2019). Caro et al (2013) describes a framework with a carbon leader,[17] who first takes responsibility for all the supply chain emissions, commits to emission reduction targets, and assigns these emissions[18] as well as emissions reductions to different members of the supply chain. The carbon leader then enters legally binding contracts with these members (e.g., see Li et al, 2019), by paying them to achieve allocated emission reduction targets at an internal carbon price, which is typically less than the socially optimum carbon price, and subsequently penalizing them at the same price if they deviate from allocated targets.

That is, the presence of an exogenous carbon price is not required in this framework by Caro et al (2013), and an internal carbon price suffices in reducing carbon emissions. However, Caro et al (2013) then shows that some double counting may be necessary to for the carbon leader to incentivize firms to engage in their 1st-best behaviors in terms of eventual emissions reductions; and, more recently, Gopalakrishnan et al (2020) provides an upper bound on the so-called efficiency loss.[19] That is, these papers show that achieving the 1st-best emission reductions is inconsistent with footprint balancing, i.e., absence of double counting. This then raises the question: *What is the best (emissions reductions) possible in presence of footprint balancing?*

16 In a non-cooperative approach, all agents unilaterally optimize their respective utilities, even if the outcome may not be the best for each agent. On the other hand, in a cooperative approach, agents agree to cooperate on outcomes that are beneficial for all.
17 This carbon leader, for example, could be a dominant corporate buyer (e.g., Apple Computers) or a major financial institution (e.g., Bank of America). Caro et al (2013) provides further examples, such as Walmart (esp. see Project Gigaton - https://www.walmartsustainabilityhub.com/project-gigaton – which still appears to be voluntary and recognition based), Unilever, Dole, etc. Some other examples may be found at https://unfccc.int/news/leading-companies-cut-supply-chain-emissions-save-money as well as at https://www.wemeanbusinesscoalition.org. This carbon leader essentially takes place of a social planner (Chen and Chen, 2017), and may be easier to implement in practice, especially in decentralized settings.
18 Caro et al (2013) provides a potential allocation rule based on Holstrom (1982).
19 This efficiency loss is essentially the difference between the emission levels achieved by Caro et al (2013)'s scheme and the 1st-best emission reduction outcome.

The answer lies in the so-called Shapley Value allocation,[20] which requires examination of cooperative approaches (Gallego and Lenzen, 2005; Granot et al, 2014; Gopalakrishnan et al, 2020; Huang et al, 2020;[21] Lenzen, 2008). Granot et al (2014) is particularly instructive. Starting with the Scope 1 emissions of all actors, defining intermediate variables that track the direct and indirect emissions (of immediate neighbors in the supply chain) of actors, it shows that the Shapley Value of a cooperative game satisfies the following desirable properties of a solution: the responsibility of all emissions by the supply chain members is allocated without double counting, no actor is allocated emissions that are larger than emissions that they are directly or indirectly responsible for, each actor is incentivized to reduce its emissions as well as supply chain emissions, and it is easy to implement. That is, the Shapley Value allocation takes care of double counting as well as of fair attribution.

A more comprehensive version of Granot et al (2014) appears in Gopalakrishnan et al (2020). It postulates that a supply chain needs to be broken down into processes and shows that the responsibility of the total emissions of each process can be allocated equally – as a Shapley value allocation – to all the members in supply chain that influence the total emissions of the process, to achieve the best emission reduction outcome of all footprint balanced schemes. It further shows that this apparently naïve (i.e., equal) allocation works even in presence of uncertainty around members' influence on emissions as well as around abatement costs. It also shows that this Shapley Value allocation is in the so-called core of a cooperative game, where all participants not only agree to participate in the scheme but also have no incentive to unilaterally deviate either individually or in coalitions.[22]

Gopalakrishnan et al (2020) uses various assumptions, however, that require a deeper scrutiny from a practical perspective, such as the following: (1) an exogenous carbon price exists; (2) emissions of all processes are known with certainty; (3) a carbon leader exists who can jointly allocate responsibility for emissions; etc. On #1, it turns out that the assumption of an external carbon price is not necessary, and it can be relaxed to an internal carbon price, such as the one suggested in Caro et al (2013), and already in use by Microsoft.[23] However, #2 and #3 may require more work. Even here, while the former is addressable given increasing display of carbon leadership by many firms; the latter remains an open question for future research and needs to be investigated, potentially using the idea of risk charge (Marland et al, 2014).[24]

Furthermore, on the issue of carbon leadership, while Caro et al (2013) provides an illustrative example using a supply chain for Eastman Chemical, and Gopalakrishan (2020) does the same using a supply chain for Walmart, to the best of our knowledge, these approaches have not been tried in practice, indicating a potential avenue for future work. In this context, the aspect of the carbon leader holding the immediate neighbors jointly (and equally) responsible for Scope 3 emissions, while using an internal carbon price, is particularly instructive (Gopalakrishan, 2020; Pflug et al, 2012[25]), and needs to be further investigated in practice. Given a Scope 3 emission reduction

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20 A simple Shapley Value allocation is described in the next paragraph, as suggested by Gopalakrishnan et al (2020).

21 Huang (2020) is different from other approaches using an (exogenous or endogenous) carbon tax. It empirically examines the effectiveness of two specific approaches to managing Scope 3 emissions – monitoring and knowledge sharing – by a carbon leader. It shows that these approaches reduce the carbon emissions of a firm by 2.6% and 3%, respectively; and, of the supplier by 3.8% and 1.3%, respectively.

22 The Shapley value solution satisfies participation by all firms – i.e., they are better off by participating – and is incentive compatible – i.e., firms would choose the socially desired outcome. This socially desired outcome, given the constraint of footprint balancing, is not the 1st-best emission reduction outcome, however.

23 See Smith (2019) for a discussion of internal carbon price. Another option is to use a reward/penalize system such as by Volkswagen (Hetzner, 2019), or to provide financial incentives as by BNP Paribas and PUMA (BNP, 2016). The former relies on using an environment metric in procurement decisions, whereas the latter relies on provision of subsidized financing.

24 The idea of risk charge is borrowed from the insurance industry, where the goal is to price insurance based on expected cost as well as the uncertainty, with the latter resulting in a risk charge.

25 In presence of model uncertainty, in addition to the typically present process uncertainty, Pflug (2012) shows that an equal allocation of

target, a carbon leader may need to start with an internal carbon price and ratchet it up over time to ensure that the actual supply chain emission reductions by the members get to the target.

3 Practical Methods of Calculating and Managing Scope 3 Emissions

3.1 Reliability of Scope 3 emissions

So far, we have assumed that there are no issues with data reliability, which is a significant issue to begin with. In this section, we examine reliability of Scope 3 emissions, by examining the following questions: What are the known issues with reliability? Which sectors have more reliable information, which do not? Why is there variation of Scope 3 reliability across different sectors/actors? Etc.

Scope 3 data can be obtained/allocated in many ways (GHP, 2020). Physical allocation refers to allocating emissions of an activity based on an underlying physical relationship (e.g., number of units produced) between multiple inputs/outputs and total emissions. Economic allocation refers to allocating emissions of an activity based on the market value of each input/output. Finally, allocation can be based on industry-specific or company-specific methods.

As we have mentioned earlier, given different methods of measurement/allocation, one of the main issues with accurately calculating Scope 3 emissions is the reliability of constituent data, which requires assignment of data quality indicators at a minimum (Weidema and Wesnaes, 1996). For example, PCAF (2020) assigns different reliability scores to different types of data, as follows:

- Score 1 (highest): Audited emissions data or actual primary energy data.
- Score 2: Non-audited emissions data, or other primary data.
- Score 3: Averaged data that is peer/(sub)-sector specific.
- Score 4: Proxy data based on region of country.
- Score 5 (lowest): Estimated data with limited support.[26]

In this context, it is pertinent to highlight that these methods essentially fall into the spectrum defined by the top-down EEIO-based and the bottom-up process-based methods (GHP, 2020; Suh and Huppes, 2005). The former method is quick and comprehensive but can be imprecise[27] due to averaging at various levels (Agez et al, 2019; Perkins and Suh, 2019), which results in aggregation errors. The latter method, which originates from the well-developed field of lifecycle analysis (LCA) can be very accurate and precise in the ideal world; however, in practice, it can not only be slow but also be inaccurate given the truncation issue around system boundaries (Lenzen, 2000;

capital across available investment options – i.e., the 1-N strategy – is optimal. This strategy has been observed in practice in many situations, as outlined in Pflug (2012).

26 E.g., using the Environmental Extended Input Output (EEIO) analysis (Hendrickson et al, 1998; Hertwich and Wood, 2018), provided by the US-EPA (see US Environmentally-Extended Input-Output (USEEIO) Technical Content | Land and Waste Management Research | US EPA) as well as EU-EXIOBASE (see Exiobase - About EXIOBASE). These top-down approaches have the advantage of being more comprehensive at the cost of potentially losing specificity. More sophisticated approaches exist as well, using decentralized methods (Tuni and Athanasios, 2019) as well as scenario-based analysis (Li et al, 2020).

27 Being imprecise means having high level of uncertainties (e.g., as measured by variance of probability distributions) around central values of estimates; on the other hand, being inaccurate means under (or over) estimating the central values themselves (Perkins and Suh, 2019).

Perkins and Suh, 2019; Takahashi, 2003), which results in truncation errors.[28] This has resulted in the development of hybrid approaches that combine the benefits of the two approaches (Suh and Huppes, 2005; Suh and Nakamura, 2007), including iterative methods that allow for increasing both accuracy and precision (Perkins and Suh, 2019),[29] while avoiding double counting (Agez et al, 2019).

This raises the issue of how to combine and manage data of different quality when calculating the Scope 3 emissions of a business entity, which we discuss in the next sub-sections. That is, we focus on developing practical methods, by examining the following questions: What is the likely impact of the known issues on the first-best approach? How to improve on the reliability and relevance of measurement? What to do with noisy and unreliable data? Etc.

3.2 Managing uncertainty in calculating Scope 3 emissions

Uncertainty in Scope 3 emissions data may arise from multiple avenues, including parameters (e.g., from data on direct emissions, activities, emission factors, and global warming potentials), scenarios (e.g., from methodological choices on allocation methods, product use assumptions, and end-of-life assumptions), and models themselves (GHP, 2020).[30] All this results in the eventual data being unreliable.

The main issue with unreliable data is that it can change over time, making it difficult to track actual progress towards stated climate targets and pathways. For example, as data quality improves over time, even though the actual emissions are going up, it is possible that the reported emissions go down, or vice-versa; which may even result in perverse incentives for keeping uncertainty high (Marland et al, 2014).[31] This may also result in the need for recalculating the base year emissions (GHP, 2020). However, this could be confusing to various stakeholders.

Obviously, one approach to address the issue of unreliable data is to mandate provision of more accurate data over time, both upstream and downstream, with clear timelines. This would send clear signals to the market that appropriate resources need to be engaged. In the context, (PCAF, 2020), takes a welcome first step in that it requires different sectors to at least start providing Scope 3 emissions data, based on the following deadlines:

- From 2020, at least energy (oil & gas), mining.
- From 2023, at least transportation, constructions, buildings, materials, and industrial activities.
- From 2025, every sector.

Furthermore, another welcome effort is by the Bank of America, which set emission reduction targets for 70% of its vendors (BOA, 2021).

However, despite this first step of simply reporting Scope 3 emissions data, the next key step would be in requiring these sectors to improve reliability of their reported Scope 3 emissions data over time. In this context, there needs to be recognition that estimated (i.e., lower quality) data is much less effective than reported (i.e., higher quality)

28 Both Lenzen (2000) and Takahashi (2003) document that process-based methods result in potentially underestimating supply chain emissions, due to truncation of system boundaries, which is inevitable given explosion of effort and time needed for a comprehensive analysis. Their process-based estimates for specific case studies are less than 50% from ones obtained from EEIO-based estimates.
30 Qin and Suh (2016) categorize uncertainty as stochastic (due to inherent randomness) and epistemic (due to lack of knowledge).
31 Marland et al (2014) provides three different examples of this, each leading to erroneous measurement and management of emissions.

data in identifying the worst emitters (Kalesnik et al, 2020),[32] and that estimated data has no predictive power in estimating future emissions, further strengthening the case for (a) mandatory and (b) audited carbon emissions disclosure, potentially using regulation (IOSCO, 2021; Shrimali, 2021).[33]

Nevertheless, in the interim, we need to figure out a couple of things: first, how to combine data of different reliability; and second, how to improve data reliability using advances in information technology and computer science. The latter would ideally use the artificial intelligence and machine learning techniques (SBTi, 2018),[34] such as ones used by GHGSAT, Climate TRACE (John, 2020) and CarbonChain (Shieber, 2020).[35] In this paper, we briefly cover the former to provide appropriate context as well background for the latter, which should be part of deeper investigations in future.

On the issues of how to combine data, one approach is by PCAF (2020) which, while combining Scope 3 emissions from multiple downstream entities to calculate the Scope 3 emissions of a financial institution, adds the central (i.e., expected) values; while also calculating a normalized reliability score, using the corresponding reliability scores (in the range 1-5) of constituent Scope 3 emissions, as defined in Section 3.1. This normalized reliability score is calculated using the amount of financed capital as weights.

However, this approach itself may have a couple of issues. To begin with, while weights are chosen as financed capital (e.g., as opposed to the total emissions themselves – see GHP (2020), or emission intensities) in PCAF (2020), given the focus of financial institutions on quantum of finance, it is not clear that they are the appropriate weights for our purpose. For example, using the emission intensity of financed capital (tons-CO2/$-financed) as weights may provide a more accurate measurement of the normalized reliability score in the sense that, to bring carbon emissions down quickly enough to meet stated climate targets, we should be focusing more on higher emission intensity activities. Furthermore, even if we use alternate weights, a key issue remains – the reliability scores do not directly indicate the magnitude of the underlying uncertainties in the constituent Scope 3 emissions.

To address this latter issue of signaling the underlying uncertainties appropriately (Schaubroeck et al, 2020), in this discussion paper, we describe the traditional approach used by the IPCC (GHP, 2020; IPCC, 1996),[36] based on directly quantifying uncertainties, such as parameter, scenario and model ones. While various approaches for propagating uncertainties are possible, including Monte Carlo simulations (Cai et al, 2019; Huijbregts, 1998; Lloyd and Ries, 2008; Super et al, 2020; Venkatesh et al, 2011); taking the PCAF (2020) example outline above, the basic idea here would be to denote Scope 3 emissions as random variables (Frey, 2007; IPCC, 2006; Ritter et al, 2019), with the well-known Gaussian distributions as a first order approximation.

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32 According to Kalesnik et al (2020), estimated data is approximately 2.5 times less effective than reported data in identifying worst emitters.
33 In this context, the International Organization of Securities Commissions (IOSCO) sees value in standardizing disclosure and suggests setting up of a Sustainability Standards Board, as a complement to the International Accounting Standards Board (IASB). To see more coverage of this, we refer the reader to the companion paper, Shrimali (2021).
34 There has been a lot of academic interest in the application of artificial intelligence (AI) and machine learning (ML) to problems in climate (Rolnick et al, 2019), environment (Ye et al, 2019), and governance (Nishant et al, 2020). However, it is still early days from the perspective of application of these techniques to emission measurement, in particular Scope 3. One of the potential issues in the application of these techniques would be the lack of high-quality big data to train underlying model, which may require identification of specific subproblems that are more amenable to AI/ML (SFI, 2021).
35 These organizations use satellite data and machine learning techniques to calculate emissions for various industries, including power generation, oil & gas, mining, manufacturing, and mining. CarbonChain claims to even calculate supply chain (i.e., Scope 3) emissions. However, it is not clear if these efforts are comprehensive enough, both from coverage (e.g., beyond power plants) and reliability perspectives (e.g., what is the improvement in data quality).
36 Again, while GHP (2020) provides various elements of the discussion of uncertainty in calculating Scope 3 emissions, our discussion paper provides a succinct summary.

We assume Gaussian distributions as a first order approximation because they are not only the most common distributions in presence of multiple uncertainties but also the most tractable analytically (IPCC, 2006; Frey, 2007). For example, Gaussian distributions allow straightforward conversion of the intuitive confidence intervals into variances and vice-versa. However, the Gaussian distribution assumption is appropriate only when related uncertainties are small (IPCC, 2006; Frey, 2007), and is not necessary to move forward with the treatment of emissions as random variables.[37]

Then, the reported values of the emissions from the downstream entities are still the expected values of these random variables; furthermore, the corresponding uncertainties (e.g., confidence intervals) can be translated into variances or standard deviations, and vice versa, depending on the underlying probability distributions. Now, the resulting sum of the random variables, i.e., the Scope 3 emissions of the financial institution in focus, is another random variable; with the expected value being the sum of the expected values of the constituent Scope 3 emissions random variables; and the variance being the sum of the Scope 3 emissions variances, assuming that the random variables are uncorrelated.[38]

The use of Scope 3 emissions as random variables automatically allows the emission intensities (e.g., tons-CO2/$-financed) to also be represented as random variables. Then, using the economic activity as weights (e.g., financed capital in $), the emission intensity of the financial organization under scrutiny is a weighted average of the constituent emission intensities; the expected emission intensity of the organization in focus is the weighted average of the expected constituent emission intensities; and, the variance of emission intensity of the organization is again a weighted average of the variance of the constituent emission intensities, again assuming that the random variables are uncorrelated.

3.3 Managing uncertainty in managing Scope 3 emissions

While accurate measurement of Scope 3 emissions remains an important problem and should remain a key area of focus (Section 3.2), given the goal of getting to our ambitious climate targets and the urgency surrounding it, there is an increasing recognition that we need to develop practical methods that allow real reductions of economy wide emissions in the interim. That is, now we tackle the following question: *How to reduce carbon emissions in the supply chains, in presence of uncertain (i.e., unreliable) emissions data?*

Not surprisingly, this question has not been tackled in a comprehensive manner. This is not to say it has not been examined at all. In fact, companies and coalitions have been using various qualitative and quantitative approaches, including hybrid approaches (Agez et al, 2019; BT, 2020; Finogenova, 2018; Jaber, 2020), where the top-down EEIO-based approach first is used to quickly identify so-called hotspots in the supply chain (Huang et al, 2009; Yang, 2017), allowing for deeper dives within the hotspots using the bottom-up process-based approach (SFI, 2021).

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37 The Gaussian distribution may be a first order approximation to the underlying probability distributions, which tend to involve various sub-uncertainties that themselves may belong to different types of probability distributions, such as uniform, triangular, beta, or even log normal (Cai et al, 2012; Abdi and Tahipour, 2018; Qin and Suh, 2016; Venkatesh et al, 2011). In case the Scope 3 emissions are eventually not best represented by Gaussian or log-normal distributions, we may need to resort to either Bayesian Methods (Abdi and Tahipour, 2018) or Monte Carlo simulations (Frey, 2007; Venkatesh et al, 2011) for establishing the final Scope 3 emission distributions.
38 To find the variance of the sum, the assumption of uncorrelated inputs is not necessary, given the ultimate tool of Monte Carlo simulations (Frey, 2007; IPCC, 2006).

BSR (2020) has taken an important first step in this direction,[39] by identifying a three-step process for the so-called carbon leaders,[40] to be implemented in collaboration with supply chain (and other) partners, as follows: (1) map the value chain and develop a reverse sourcing approach; (2) demonstrate emissions reductions through pilot projects; and (3) scale up through engaging value chain partners and peers. Step #1 goes beyond supply chain mapping to identifying emission hotspots as well as emission reduction opportunities, and then Steps #2 and 3# involve recursively assigning and managing the emission reduction responsibilities with suppliers that are increasingly upstream in the value chain. While this approach needs to be fine-tuned in practice, and many open questions remain, we examine these steps in more detail below.

In Step #1, supply chain mapping would involve identification of raw materials and process flows, including key geographies; and identification of emission hotspots and emission reduction opportunities would utilize best available information (e.g., using life cycle assessments, emission factors, etc.), even if it is uncertain, including at the sector as well as geography levels. In this context, the top-down EEIO-based approach can help in quickly identifying these hotspots (Yang, 2017), while recognizing sector specificity (Huang et al, 2009).[41] To ensure that the focus remains on hotspots, this information can be updated as it becomes more certain over time, including using the bottom-up process-based approaches (Ritter et al, 2019).

In Step #2 and #3, after the hotspots have been identified, there can be many ways to engage partners, including ones identified in Section 2.2, such as monitoring, information sharing, rewarding, and penalizing partners; and in WEF (2021), such as risk sharing via co-investing, offtake agreements, etc. Here, the game theoretic approaches, in presence of a carbon leader, using an internal carbon tax for rewarding (and penalizing) partners should be explored in more detail in practice. For example, this would be an extension of the internal carbon tax already being used in many firms, such as Microsoft (Smith, 2020).[42]

However, these steps leave some of the previously identified questions unanswered. For example, Step #1 leaves an open question around the possibility of focusing on non-hotspots in the interim due to the uncertain information (Section 3.2). Similarly, Step #2 and #3 leave an open question around how well these schemes would work in presence of uncertain information (Section 2.2). These open questions would require this process to be closely monitored and managed.

4 Path Forward

In this discussion paper, we have approached the key topic of Scope 3 emissions from the perspectives of not only measurement but also management. Both are made difficult due to the complexity of the processes as well as the lack of standards. Despite this, we have outlined approaches for the following:

- Measurement: In case the supply chain Scope 1 emissions are known with certainty, how to allocate these emissions towards Scope 3 emissions without double counting (Section 2.1 as well as Section 6.2).
- Management: Furthermore, in the same case (i.e., when supply chain Scope 1 emissions are known), methods for allocation of emissions and emission reductions, in presence of carbon leaders (Section 2.2).
- Measurement: In case the supply chain Scope 1 emissions are not known with certainty, how to represent them as random variables, and to calculate Scope 3 emissions as random variables (Section 3.2), while avoiding double counting.

We recognize that, while the broad contours of solutions are available, each of the above would require further fine tuning. On the other hand, the issue of management of uncertain supply chain emissions remains wide open. While we have provided some initial thoughts on this issue (Section 3.3), a lot more work needs to be done. Recognizing this, future work would need to be the following areas:

- Management: In case the supply chain Scope 1 emissions are known with certainty, applying the game theoretic methods presented in Section 2.2 to actual pilots in the field, with carbon leaders that are willing to take actions.
- Measurement: In case the supply chain Scope 1 emissions are not known with certainty, creating methods, including Scope 3 category specific hybrid methods (Agez et al, 2019; Perkins and Suh, 2019; Schaubroeck et al, 2020; SFI, 2021)[43] as well as standards potentially driven by regulation (IOSCO, 2021; Shrimali, 2021), that enable reduction in uncertainty of emission data over time. In this context, a pertinent investigation would be in comparing methods used by various commercial providers (Busch et al, 2018), understanding reasons for divergence in results, and developing solutions for harmonizing these estimates, potentially using an open-source approach (SFI, 2021). Another pertinent investigation would be in the application of AI/ML techniques in improving data quality, while overcoming related data quality issues (SFI, 2021).
- Management: Furthermore, in the same case (i.e., when Scope 1 emissions are not known with certainty) developing extensions of game theoretic methods presented in Section 2.2 for the case when emission data is uncertain.

43 Schaubroeck et al (2020) calls for various approaches for reducing uncertainty, including collaboration with other researchers, iterative refinements (Perkins and Suh, 2019), and even using qualitative scores.

5 References

Abdi A, Taahipour S, 2018. Uncertainty Analysis of Project Emissions. Proceedings of the IEEE Electrical Power and Energy Conference.

ADEME, 2016. Understanding the Issues Around Quantifying Emissions in the Financial Sector. Available at https://www.banktrack.org/download/understanding_the_issues_around_quantifying_ghg_emissions_in_the_financial_sector_1/fichier_v_1_eng_understanding_the_issues_around_quantifying_ghg_emissions_in_the_financial_sector.pdf

Agez M, Bettez G M, Margni M, Stromann A, Samson R, 2019. Lifting the Veil on the Correction of Double Counting Incident in Hybrid Lifecyle Assessments. Journal of Industrial Ecology, 24 (6): 517-533.

API, 2016. Estimating Petroleum Industry Value Chain Greenhouse Gas Emissions: Overview of Methodologies. Available at https://www.api.org/~/media/Files/EHS/climate-change/Scope-3-emissions-reporting-guidance-2016.pdf

Baker B, 2020. Scope 3 Carbon Emissions: Seeing the Full Picture. Available at https://www.msci.com/www/blog-posts/scope-3-carbon-emissions-seeing/02092372761

BHP, 2019. Scope 3 Emission Calculation Methodology. Available at https://www.bhp.com/-/media/documents/investors/annual-reports/2019/bhpscope3emissionscalculationmethodology2019.pdf?la=en

BNP, 2016. BNP Paribas Press Release. Available at BNP Paribas and PUMA launch innovative financing program for suppliers to reward social and environmental standards - BNP Paribas (group.bnpparibas)

BSR, 2020. Climate Action in the Value Chain: Reducing Scope 3 Emissions and Achieving Science-Based Targets. Available at https://www.bsr.org/en/our-insights/report-view/scope-3-emissions-science-based-targets-climate-action-value-chain

BT, 2020. BT's Supply Chain Emissions Reporting Approach and Methodology. Available at BT's supply chain carbon emissions reporting approach and methodology

Busch T, Johnson M, Pioch T, Kopp M, 2018. Consistency of Corporate Carbon Emissions Data. University of Hamburg Working Paper.

BOA, 2021. Bank of America Announces Actions to Achieve Net Zero Greenhouse Gas Emissions before 2050. Available at Bank of America Announces Actions to Achieve Net Zero Greenhouse Gas Emissions before 2050

Cai H, Wang A, Elgowainy A, Han J, 2012. Updates Greenhouse Gas and Criteria Air Pollution Emission Factors and their Probability Distribution Functions for Electric Generating Units. Argonne National Lab Working Paper, ANL-ESD-2.

Cai et al, 2019. China City-level Greenhouse Gas Emissions Inventory in 2015 and Uncertainty Analysis. Applied Energy, 253.

Caro F, Corbett C J, Tan T, Zuidwijk R, 2013. Double Counting in Supply Chain Carbon Footprinting. Manufacturing and Service Operations Management, 15 (4): 545-558.

CDP, 2016. Out of the Starting Blocks: Tacking Progress on Corporate Climate Action. Available at Tracking corporate climate progress 2016 - CDP

Chen J X, Chen J, 2017. Supply Chain Carbon Footprinting and Responsibility Allocation under Emission Regulations. Journal of Environmental Management, 188: 255-267.

Chen X, Benjaafar S, Elomri E, 2019. On the Effectiveness of Emission Penalties in Decentralized Supply Chains. European Journal of Operational Research, 274 (3): 1155-1167.

Cullenward D, Victor D G, 2020. Making Climate Policy Work. Polity.

Economist, 2020. Making Sense of Banks' Climate Targets. December 10.

EPA, 2020. Scope 3 Inventory Guidance. Available at https://www.epa.gov/climateleadership/scope-3-inventory-guidance

EY, 2015. Financing for a Better Future: Estimating the Environmental Benefits of Bank of America's Environmental Business Initiative. Available at Financing for a sustainable future Estimating the environmental benefits of Bank of America's Environmental Business Initiative

Fickling D, Elaine H, 2020. The Biggest Polluters Are Hiding in Plain Sight. Available at https://www.bloomberg.com/graphics/2020-opinion-climate-global-biggest-polluters-scope-3-emissions-disclosures/

Finegenova N, Bach V, Merger M, Finkbeiner M, 2018. Hybrid Approach for the Evaluation of the Organizational Indirect Impact. The International Journal of Lifecycle Assessment, 24: 1058-1074.

Frey H C, 2007. Quantification of Uncertainty in Emission Factors and Inventories. EPA Working paper. Available at Quantification of Uncertainty in Emissions Factors and Inventories (epa.gov)

Gallego B, Lenzen M, 2015. A Consistent Input-output Formulation of Shared Producer and Consumer Responsibility. Economic Systems Research, 17 (4): 365-391.

Granot D, Granot F, Sosic G, 2014. Allocation of Greenhouse Gas Emissions in Supply Chains. Working paper. Available at https://pdfs.semanticscholar.org/2c1c/90268ae4288f3b7cdf1d614c16744a1da1d6.pdf

GRESB, 2017. Whose Carbon Is It. Available at https://gresb.com/whose-carbon-is-it/

GHP, 2013. Guidance for the Financial Sector: Scope 3 Accounting and Reporting of Greenhouse Gas Emissions. https://ghgprotocol.org/sites/default/files/standards_supporting/New%20York%20Scoping%20Workshop%20Summary%20-%20GHG%20Protocol%20Financial%20Sector%20Guidance.pdf

GHP, 2015. Portfolio Carbon Initiative. Available at https://ghgprotocol.org/sites/default/files/standards_supporting/Concept%20Note%20-%20Portfolio%20Carbon%20Initiative.pdf

GHP, 2020. Corporate Value Chain (Scope 3) Standard and Technical Guidance. Available at https://ghgprotocol.org/standards/scope-3-standard as well as https://ghgprotocol.org/scope-3-technical-calculation-guidance

Gopalakrishnan S, Granot D, Granot F, Sosic G, Cui H, 2020. Incentives and Emission Responsibility Allocation in Supply Chains. Management Science.

GS, 2019. Climate Related Risks and Opportunities. Goldman Sachs 2019 TCFD Report. Available at tcfd.pdf (goldmansachs.com)

Hendrickson C, Horvath A, Joshi S, Lave L, 1998. Peer Reviewed: Economic Input-Output Models for Environmental Life Cycle Assessment. Environ Sci Tech, 34 (7): 184-191.

Hertwich E G, Wood R, 2018. The Growing Importance of Scope 3 Greenhouse Gas Emissions from Industry. Environmental Research Letters, 13.

Hetzner C, 2019. Volkswagen to Reward Green Suppliers. Automotive News Europe, February 23. Available at Volkswagen to reward green suppliers (autonews.com)

Holstrom B, 1982. Moral Hazard in Teams. Bell Journal of Economics, 13 (2): 324-340.

Huijbregts M A, 1998. Application of Uncertainty and Variability in LCA. The International Journal of Life Cycle Assessment, 3.

Huang H, Narayanan S, Swaminathan J M, 2020. Carrot or Stick? Supplier Diversity and Its Impact on Carbon Emission Reduction Strategies. Working paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3559770

Huang Y A, Weber C, Mathews H S, 2009. Categorization of Scope 3 Emissions for Streamlined Enterprise Carbon Footprinting. Environ Sci Tech, 43 (22): 8509-8515.

ICF, 2017. Whose Carbon Is It? Available at https://cdn.ymaws.com/www.realpac.ca/resource/resmgr/industry_sustainability_-_research_reports/ghgpublicationfinsp.pdf

IOSCO, 2021. Need for Sustainability Disclosure Standards. Available at IOSCO sees an urgent need for globally consistent, comparable, and reliable sustainability disclosure standards and announces its priorities and vision for a Sustainability Standards Board under the IFRS Foundation

IPCC, 1996. Evaluating the Uncertainty of Emission Estimates. Available at EIIP Vol VI, CH 4: Evaluating the Uncertainty of Emission Estimates (epa.gov)

IPCC, 2006. Uncertainties. Available at Microsoft Word - V1_Ch3_Uncertainty_final_V2.doc (iges.or.jp)

Jaber D, 2020. Why Simplified Approaches to Reducing Scope 3 Emissions Don't Always Work. Available at Why simplified approaches to reducing Scope 3 emissions don't always work | Greenbiz

John J S, 2020. Climate TRACE: Using Satellites and Machine Learning to Poinpoint Global Greenhouse Gas Emissions. Available at ClimateTRACE: Using Satellites and Machine Learning to Pinpoint Global Greenhouse Gas Emissions | Greentech Media

Kalesnik V, Wilkens M, Zink J, 2020. Green Data or Greenwashing? Do Corporate Carbon Emissions Data Enable Investors to Mitigate Climate Change? Working paper. Available at https://ioandc.com/wp-content/uploads/2020/11/3-Research-Affiliates-carbon-paper.pdf

Larsen H N, Solli C, Pettersena J, 2012. Supply Chain Management: How Can We Reduce Our Energy/Climate Footprint? Energy Procedia, 20: 354-363.

Lee C H, Ma H W, 2013. Improving the Integrated Hybrid LCA in the Upstream Scope 3 Emissions Inventory Analysis. International Journal of Life Cycle Assessment, 18: 17-23.

Lenzen M, 2000. Errors in Conventional and Input-Output-based Life Cycle Inventories. Journal of Industrial Ecology, 4 (4): 127-148.

Lenzen, 2007. Structural Path Analysis Ecosystem Networks. Ecological Modeling, 200 (3-4): 334-342.

Lenzen, 2008. Double Counting in Life Cycle Calculations. Journal of Industrial Ecology, 12 (4): 583-599.

Li T, Zhang R, Zhao S, Liu B, 2019. Low Carbon Strategy Analysis under Revenue-sharing and Cost-sharing Contracts. Journal of Cleaner Production, 212: 1462-1477.

Li M, Wiedman T, Hadjikakou M, 2020. Enabling Full Supply Chain Corporate Responsibility. Environ Sci Technol 54 (1): 400-411.

Lloyd S M, Ries R, 2007. Characterizing, Propagating, and Analyzing Uncertainty in Life Cycle Assessment. Journal of Industrial Ecology, 11 (1): 161-179.

Marland E, Cantrell J, Kiser K, Marland G, Shirley K, 2014. Valuing Uncertainty Part I: The Impact of Uncertainty in GHG Accounting. Carbon Management, 5 (1): 35-42.

Metcalf G E, Weisbach D, 2009. The Design of a Carbon Tax. Harvard Environmental Letters Review.

Nishant R, Kennedy M, Corbett J, 2020. Artificial Intelligence for Sustainability: Challenges, Opportunities, and a Research Agenda. International Journal of Information Management, 53.

PCAF, 2019. Harmonizing and Implementing a Carbon Accounting Approach for the Financial Sector in North America. Available at https://carbonaccountingfinancials.com/files/2019-10/20191028-pcaf-report-2019.pdf

PCAF, 2020. Public Consultation of the draft Global Carbon Accounting Standard for the Financial Industry. Available at https://carbonaccountingfinancials.com/consultation-signup

PCI, 2015a. Carbon Asset Risk: Discussion Framework. Available at https://www.wri.org/publication/carbon-asset-risk-discussion-framework

PCI, 2015b. Climate Strategies and Metrics: Exploring Options for Institutional Investors. Available at https://www.unepfi.org/fileadmin/climatechange/climate_strategies_metrics.pdf

PCI, 2015c. Exploring Metrics to Measure the Climate Progress of Banks. Available at https://www.wri.org/publication/exploring-metrics-to-measure-the-climate-progress-of-banks

Perkins J, Suh S, 2019. Uncertainty Implications of Hybrid Approach in LCA. Environ Sci Technol, 53 (7): 3681-3688.

Pflug G C, Pichler A, Wozabal D, 2012. The 1/N Investment Strategy is Optimal under High Model Ambiguity. Journal of Banking and Finance, 36 (2): 410-417.

Porter E, 2013. Rethinking How to Split the Costs of Carbon. New York Times, December 24.

PRI, 2020. Draft 2025 Target Setting Protocol. Available at https://www.unepfi.org/wordpress/wp-content/uploads/2020/10/Alliance-Target-Setting-Protocol_Final-Consultation-Draft.pdf

Qin Y, Suh S, 2016. What Distribution Function do Life Cycle Inventories Follows? The International Journal of Life Cycle Assessment, 22: 1138-1145.

Raynaud, 2020. The Alignment Cookbook. Available at https://gsf.institutlouisbachelier.org/publication/the-alignment-cookbook-a-technical-review-of-methodologies-assessing-a-portfolios-alignment-with-low-carbon-trajectories-or-temperature-goal/

Ritter K, Lev-On M, Shires T, 2019. Understanding Uncertainty in Greenhouse Gas Emission Estimates. Available at https://www3.epa.gov/ttn/chief/conference/ei19/session3/shires.pdf

Rolnick et al, 2019. Tackling Climate Change with Machine Learning. Working paper. Available at [PDF] Tackling Climate Change with Machine Learning | Semantic Scholar

SBTi, 2018. Best Practices in Scope 3 Greenhouse Gas Management. Available at https://sciencebasedtargets.org/wp-content/uploads/2018/12/SBT_Value_Chain_Report-1.pdf

SBTi, 2020. Financial Sector Science Based Target Guidance. Available at https://sciencebasedtargets.org/wp-content/uploads/2020/10/Financial-Sector-Science-Based-Targets-Guidance-Pilot-Version.pdf

Schaubroeck T, Baustert P, Igos E, Benetto E, 2020. Environ Sci Technol, 54 (4): 2051-2053.

SE, 2018. Scope 3 Methodology. Available at https://www.sustainabilityexchange.ac.uk/files/scope_3_methodology_guidance.pdf

Shieber J, 2020, Carbon Chain is using AI to Determine the Emission Profiles of the World's Largest Polluters. Available at CarbonChain is using AI to determine the emissions profile of the world's biggest polluters – TechCrunch

Smith B, 2019. We're Increasing Our Carbon Fee as We Double Down on Sustainability. Microsoft Blog. Available at https://blogs.microsoft.com/on-the-issues/2019/04/15/were-increasing-our-carbon-fee-as-we-double-down-on-sustainability

Smith B, 2020. Microsoft Will be Carbon Negative by 2030. Microsoft Blog. Available at https://blogs.microsoft.com/blog/2020/01/16/microsoft-will-be-carbon-negative-by-2030/

Shrimali G, 2021, Transition Bonds Frameworks, Stanford University Working Paper.

Suh S, Huppes G, 2005. Methods for Life Cycle Inventory of a Product. Journal of Cleaner Production, 13 (7): 687-697.

Suh S, Nakamura S, 2007. Five Years in the Area of Input-Output and Hybrid LCA. The International Journal of Life Cycle Assessment, 12.

Super I et al, 2020. Uncertainty Analysis of a European High-resolution Emission Inventory. Atmospheric Chemistry and Physics, 20: 1795-1816.

TCFD, 2017. Recommendations of the Task Force on Climate-related Financial Disclosures. Available at FINAL-2017-TCFD-Report-11052018.pdf (bbhub.io)

TPI, 2020. State of the Transition Presentation. Available at https://www.transitionpathwayinitiative.org/tpi/publications/54.pdf?type=Publication

Tuni A, Athanasios R, 2019. An Innovative Eco-Intensity Based Method for Assessing Extended Supply Chain Environmental Sustainability. International Journal of Production Economics, 217: 126-142.

UNFCCC, 2015. IFIs – Harmonization of Standards for GHG Accounting. Available at https://unfccc.int/climate-action/sectoral-engagement/ifis-harmonization-of-standards-for-ghg-accounting

US, 2020. Dealing with Scope 3. Available at https://isa.org.usyd.edu.au/research/InformationSheets/ISATBLInfo17_new.pdf

Venkatesh A, Jaramillo P, Griffin M, Matthews H S, 2011. Uncertainty in Life Cycle Greenhouse Gas Emissions. Environ Sci Technol, 45 (19): 8182-8189.

Williams E D, Weber C L, Hawkins T R, 2009. Hybrid Framework for Managing Uncertainty in Life Cycle Inventories. Journal of Industrial Ecology, 13 (6): 928-944.

WEF, 2021. Net-zero Challenge: The Supply Chain Opportunity. Available at [Net-Zero Challenge: The supply chain opportunity | World Economic Forum (weforum.org)]

Weidema B D, Wesnaes M S, 1996. Data Quality Management for Life Cycle Inventories. Journal of Clean Production, 4 (3-4): 167-174.

WRI, 2017. Methodology. Available at [Methodology | World Resources Institute (wri.org)]

Ye et al, 2020. Tackling Environmental Challenges in Pollution control using Artificial Intelligence. Science of the Total Environment, 699.

6 APPENDICES

6.1 A brief history of Scope 3 emissions protocols

6.1.1 The Financed Emissions Initiative (FII), 2014

In 2014, the Greenhouse Gas Protocol (i.e., GHP, a joint initiative of WRI and WBCSD) and UNEPFI partnered to investigate the need and potential scope for financial sector guidance on Scope 3 emissions. The focus was on banks, institutional investors, and advisory services.

This resulted in a couple of workshops, one in London and one in New York, with the following takeaways (GHP, 2013):

- The focus was on Scope 3 for the financial sector: with recognition that Scope 3 for lending would be useful, however for investments it should be explored further.
- There was recognition that Scope 3 is more useful across time (for a company); however, there was still interest in across company comparisons and benchmarking.

6.1.2 The Portfolio Carbon Initiative (PCI), 2015

In 2015, the GHP, UNEPFI, and 2dii partnered to make further progress on the recommendations of the above workshops of the FIIs (GHP, 2013): developing climate performance metrics for banks and asset owners as well as guidance on assessing and managing carbon asset risks.

The findings of the PCI were published in three different documents (PCI, 2015a; PCI, 2015b; PCI, 2015c), with the following takeaways:

- Carbon asset risk (i.e., Scoped emissions) is not the same as transition risk; and multiple metrics are needed to assess climate risk i.e. (1) carbon (i.e., Scope), (2) green vs brown (i.e., indicators distinguishing between climate solutions and climate problems), and (3) ESG metrics.
- There are multiple issues with Scope 3 emissions, such as the following: Meaning and practicality of (esp. Scope 3) emissions, annual vs lifetime values, consistency across Scopes, double counting, etc. At the end of the day, we would need Science Based Targets.

6.1.3 Partnership for Carbon Accounting Financials (PCAF), 2019/2020

PCAF, created in 2015, is specific to financial institutions, and is driven by financial institutions as opposed to NGOs. It is focused on guidance for measuring Scope 3 emissions. In its latest report, which is focused on North America (PCAF, 2019), the following are the takeaways:

- PCAF North America to quantify Scope 3 emissions for banks, based on GHP (2020).
- Goals of the effort: Consistent (across space and time), relevant for decision making, and assured.

The latest report (PCAF, 2020) is the output of the effort, and is referenced heavily in main text. The main contribution of PCAF (2020) is, if downstream Scope 3 emissions are available from financed entities, a comprehensive framework for assigning these downstream emissions to the financial institution in focus. Further, it not only allows for these downstream emissions to have different reliability scores but also provides a framework for combining these reliability scores as a normalized reliability score for the Scope 3 emissions of the financial institution in focus.

However, PCAF (2020) suffers from multiple drawbacks. The first one is that it appears to assume that the downstream Scope 3 emissions have been calculated while addressing across supply chains double counting, which is unlikely given the state of Scope 3 emission measurement and reporting.[44] The second one is that the method for calculating the normalized reliability score may not only be suspect but also it does not allow for appropriately addressing uncertainties around Scope 3 emissions. A third one is the use of enterprise value as a base to divide up a firm's emissions among various investors, but enterprise value can change based on market dynamics.

6.1.4 Science Based Targets (SBT), 2020

SBTi is a collaboration between CDP, the United Nations Global Compact (UNGC), WRI, and WWF. The basic idea to help companies set science-based emissions targets i.e., in line with what the latest climate science says is necessary to limit global warming to well-below 2°C above pre-industrial levels and pursue efforts to limit warming to 1.5°C.

44 E.g., HSBC says that climate-related data are provided by only 12% of its loan portfolio (Economist, 2020).

In its recent report (SBTi, 2020), the following are the key takeaways:

- It establishes absolute targets (2C/1.5C) as well as rates (4.2/2.5%) for Scope 1 & 2, but not Scope 3, which is the focus of this discussion paper.
- However, there are no specifics on approved vs non-approved activities, in connection with the SBTs.

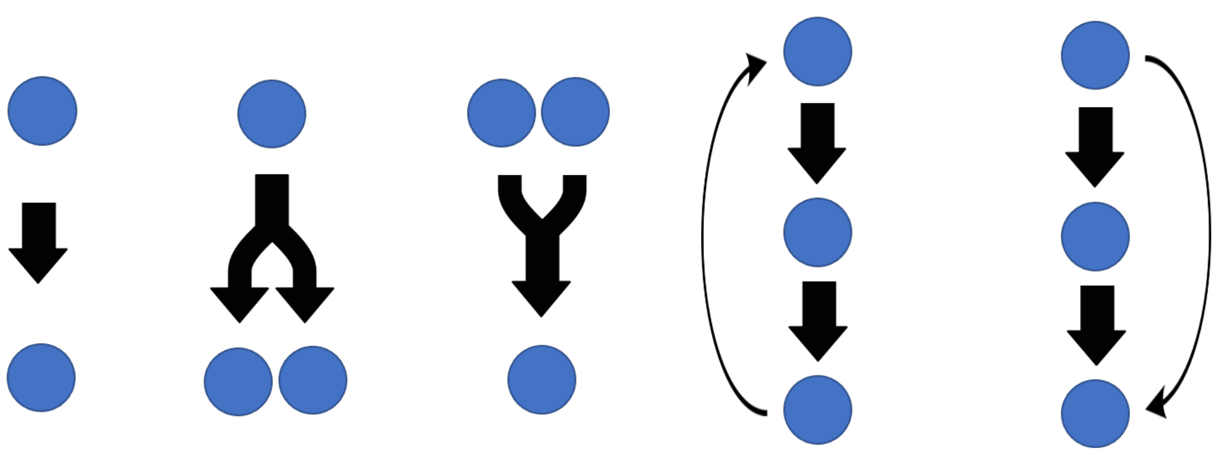
6.2 A recursive method for calculating Scope 3 emissions

In this section, we describe our recursive method for calculating Scope 3 emissions per product. The assumption is that the Scope 1 emissions per product are available throughout the supply chain.

We start with attribution of embedded carbon as we move downstream (Figure 3). We deal with three different cases, as follows:

- In a supply chain network, the problem is straightforward if there are no *splits* (i.e., single supplier selling to multiple buyers) or *joins* (i.e., multiple suppliers selling to single buyer) in the supply chain network. In this case, the embedded carbon flowing downstream from a business entity (i.e., the seller) to the downstream entity (i.e., the buyer) is simply the embedded carbon flowing into the seller plus the seller's Scope 1 emissions.
- However, in case of splits, where a seller is selling its products to multiple sellers, to avoid double counting, this total embedded carbon downstream from the seller would need to be split in proportion to the fractions of the corresponding physical quantity of products brought by the downstream entities (i.e., buyers). This assumes that the total embedded emissions for a product are homogenously distributed over the quantity of product produced, and that emissions across products are appropriately allocated.
- Similarly, in case of joins, where multiple sellers are selling their products to a buyer, the embedded carbon downstream from multiple sellers would need to be added together to become the embedded carbon flowing into the buyer.

Figure 3: Common cases in Scope 3 emissions allocation. Moving from left to right: (a) single seller, single buyer; (b) single seller, multiple buyers; (c) multiple sellers, single buyer; (d) feedback loops; (e) multiple levels.



These three cases are straightforward. However, they may leave out some corner cases, which requires special attention. These include feedback loops as well as connections to multiple levels. An example of the former is when a downstream entity provides a product to an upstream entity, whereas an example of the latter is when an upstream entity connects to downstream entities (or vice-versa) at multiple levels of the supply chain. While the latter is appropriately addressed via the basic methods around splits and joins, the former may require artificially breaking the feedback loops at the first instance they are encountered.

The attribution of latent carbon can be done in a similar way (Figure 4), except that now the flow of latent carbon is upstream as opposed to the downstream flow of embedded carbon. This means that, in the supply chain, the split of the downstream flow becomes the join of the upstream flow, and the join of the downstream flow becomes the split of the upstream flow. Then, we have the following cases:

- In case of no splits and no joins, the latent carbon flowing upstream from a buyer is simply the latent carbon flowing upstream into the buyer plus the buyer's Scope 1 emissions.
- Further, in case of splits, where a buyer is buying its products from multiple sellers, to avoid double counting, this total latent carbon upstream from the buyer would need to be split in proportion to the fractions of the corresponding products sold by the upstream entities (i.e., sellers).
- Similarly, in case of joins, where multiple buyers are buying their products from a seller, the latent carbon upstream from multiple buyers would need to be added together to become the latent carbon flowing into the seller.
- Finally, the corner cases of feedback loops as well as connections to multiple levels may need to be addressed in similar ways to the embedded carbon.

Figure 4: Common cases in downstream Scope 3 emissions allocation. Moving from left to right: (a) single seller, single buyer; (b) single seller, multiple buyers; (c) multiple sellers, single buyer; (d) feedback loops; (e) multiple levels.