Working Paper

Developing Climate Indicators for Small and Medium-Sized Enterprises using Product Information

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Structured Abstract:

Purpose: As double materiality gains prominence in sustainable finance, financial institutions increasingly require reliable climate data to assess their environmental impact and transition risks. Existing datasets overlook Small and Medium Enterprises (SMEs), contributing to 63% of emissions in the European Union. This paper introduces a method to generate climate indicators for SMEs, addressing this data gap.

Design/methodology approach: The approach requires only basic firm inputs—products, business type, and location—without needing sustainability expertise, ensuring SME suitability. Two firm-level indicators, the Relative Emission Reduction Potential and Transition Risk, are derived by integrating product-level Life Cycle Assessment (LCA) data with climate scenario models.

Findings: We showcase a dataset of about 50,000 firms applying our method and code, demonstrating the method's scalability. The product-level granularity enhances SME coverage beyond industry averages, while the methodology's transparency fosters trust in Environmental, Social and Governance (ESG) reporting.

Research limitations/implications: A key limitation is the focus on climate, which restricts its applicability to the environmental (E) dimension of ESG. However, LCA data support the future inclusion of broader environmental indicators.

Practical implications: Granular, scalable climate indicators for SMEs enable double materiality assessments without direct outreach, especially for financial institutions with large SME portfolios.

Social implications: The data allows financial institutions to identify SMEs with high emission reduction potential or transition risk based on products. Since SMEs are the backbone of our European economy, such targeted approaches are crucial for adequate transition financing.

Originality/value: To the best of the author's knowledge, they are the first to develop a transparent method for constructing climate indicators for SMEs at scale.

1. Introduction

The European Union's (EU's) goal of achieving climate neutrality by 2050 is a key ambition of the European Green Deal, impacting all sectors of the economy, including the financial industry (European Commission, 2019). Financial institutions like banks and asset managers can steer the low-carbon transition through investment and lending choices—for example, by financing transitioning firms or divesting from carbon-intensive ones. Rising carbon prices may further incentivize such actions (Edenhofer *et al.*, 2022). This relationship is called the *inside-out* or *impact perspective* (Adams *et al.*, 2021). At the same time, they might be vulnerable to climate-related risks, e.g., rising carbon prices potentially disrupting cash flows and increasing the risk of loan defaults (von Dulong *et al.*, 2023) – called the *outside-in* or *risk perspective*. This two-way relationship between finance and climate is called double materiality (Gourdel *et al.*, 2024; Abhayawansa, 2022) and is used in standards and regulations like the EU's Corporate Sustainability Reporting Directive (CSRD) (European Commission, 2025) or guidelines on Environmental, Social and Governance (ESG) risk management (EBA, 2025; 2022).

Financial institutions, researchers, and policymakers need climate data to assess double materiality. These climate data include climate footprints, ESG scores, and climate sector classifications. Despite the rise in climate data, significant gaps remain. First, climate data primarily focuses on large, listed firms, neglecting (unlisted) Small and Medium Enterprises (SMEs). For financial institutions with large SME portfolios, limited resources make it unfeasible to engage each firm individually for ESG data. Second, it lacks granular assessment because it relies on industry averages rather than product or firm-specific data. Third, it suffers from transparency due to proprietary methods and inconsistent standards.

To address these shortcomings, we developed the *tilt* method (transforming in a low-carbon transition). We construct two climate indicators - the relative emission reduction potential and the transition risk indicator. The *tilt* method requires only three essential firm inputs: products, business type, and location. This approach fits SMEs' needs by bypassing complex ESG questionnaires. Further, the method offers a more granular assessment than sector averages by focusing on product-specific information. Additionally, the process is transparent, enabling comparability and reliability assessment.

The *tilt* method matches firm-level inputs—such as products, business type, and location—with external climate data to generate climate indicators. It focuses on five high-level climate-relevant sectors, here defined as the high-level economic groups: industry, land use, metals, non-metallic minerals, and transport, each with more detailed subsectors (e.g. chemicals within the industry sector). The method links these inputs with datasets like life cycle assessments (e.g. ecoinvent provided by Wernet *et al.*, 2016), sectoral decarbonization targets (e.g. IEA, n.d.; IPR, n.d.), and climate action classifications (e.g. EIB, 2023), enabling product-level climate analysis. Importantly, the *tilt* method is data provider-agnostic: it can be applied flexibly to any dataset that contains the necessary input variables. To demonstrate this scalability, we showcase a cross-sectional dataset by Lepore *et al.* (2024) of applying the *tilt* method to about 50,000 firms from Austria, France, Germany, the Netherlands, and Spain.

The method is especially valuable for financial institutions with an extensive SME portfolio to identify the firms with a) the highest potential for emission reduction (*impact perspective*), helping the banks in planning transition financing and transition strategies and b) to assess transition risk (*risk perspective*) when financing certain firms. Furthermore, researchers can use the method to analyze whether financial institutions consider transition risk or emission reduction potential in their finance and lending decisions (to SMEs). When matched to other financial datasets, the dataset can help expand studies on larger firms and beyond equity and syndicated loans (e.g., Sastry *et al.*, 2024; Kacperczyk and Peydró, 2022; Bolton and Kacperczyk, 2022, 2021; Ehlers *et al.*, 2022; Carbone *et al.*, 2021 or see Dawar *et al.*, 2024 for a systemic literature review listing 372 papers analyzing the relationship between financial institutions and climate). The method also supports regional climate transition analysis and case study selection by exploiting locational data. Furthermore, the method can be applied wherever data on location, products, and business types are available, allowing for expansion beyond the initial scope of about 50,000 firms with our open-source GitHub code (see **supplementary material S3**).

The remainder of the paper is structured as follows: Section 2 summarises the method's contribution to the current climate data and method landscape, mentions its shortcomings, and provides an overview of the resulting *tilt's* guiding principles. Section 3 overviews the purpose of the climate indicators, constructs them, describes limitations and summarises further potential enhancements. Section 4 showcases a dataset that applied the method to about 50,000 firms. Section 5 concludes. The Annex overviews the calculation methods and the indicator's statistical properties. The **supplementary material S1-3** supports researchers with matching algorithms and other relevant GitHub links to reconstruct the climate indicators for their use.

2. The Current Climate Data Landscape, its Shortcomings and *tilt's* Guiding Principles

In addition to the CSRD and Voluntary Reporting Standard for SME (VSME) (EFRAG, 2024) in the EU, various 'market standards' such as the Global Reporting Initiative (GRI, n.d.), or the Sustainability Accounting Standards Board (IFRS Foundation, n.d.) identify ESG data needs for accurate reporting and set new standards (Afolabi *et al.*, 2023). To fulfil these standards climate data is required ranging from environmental scores (Pástor *et al.*, 2022; van der Beck, 2021to emission levels (scope 1, 2, and 3) (Bolton & Kacperczyk, 2020, 2021), emission intensities (Ardia *et al.*, 2022; Aswani *et al.*, 2024), assessments of alignment with environmental taxonomies (Bassen *et al.*, 2022), and sector classifications that emphasize technological data (Battiston et al., 2017) as categorized by Fliegel (2024).

Numerous climate data and software providers offer these climate data points. **Table I** gives an overview of the current climate data landscape and shows that current data are often proprietary (Institutional Shareholder Services (ISS), Morgan Stanley Capital International (MSCI), Sustainable Platform, Climate Disclosure Project (CDP), Intercontinental Exchange (ICE), Bloomberg, Trucost), on sector-level (Partnership for Carbon Accounting Financials (PCAF)), and focus on listed firms only (ISS, Sustainable Platform, CDP, MSCI, ICE, Bloomberg, Trucost). **Table I** also indicates software tools to capture climate data methodologies suitable for SMEs. These tools primarily use extensive questionnaires that demand significant time and resources from the SMEs (e.g., Greenly, ESG2Go) or have not been widely implemented yet (e.g., Ozkan *et al.*, 2023).

This overview of the current climate data and methodology landscape emphasizes three challenges: First, current climate data primarily focuses on large firms, often neglecting SMEs. Major climate rating agencies like ISS, MSCI, Bloomberg, and Sustainalytics assess fewer than 50,000 listed firms, leaving 26.1 million SMEs (Statista, 2024) in the EU without evaluation. Further, the software focusing on SMEs is based on lengthy ESG questionnaires (SME Climate Hub, Greenly, ESG2go) or standards like VSME, SASB, and GRI requiring comprehensive environmental reporting. Such standards demand resources and expertise SMEs may not have (SME Climate Hub, 2023; Koirala, 2019), making comprehensive ESG reporting impractical (Ozkan *et al.*, 2023). Second, the PCAF-financed emissions approach shows that while covering SMEs, the data relies on 3-digit ISIC codes rather than firm-specific or product-specific data (Carbone *et al.*, 2021). This approach overlooks the diverse environmental impacts within the same industry (Kalesnik *et al.*, 2022). Third, current climate data face transparency issues. Transparency is limited as most rating methodologies are proprietary, complicating validation (Dimmelmeier, 2023; Cakir *et al.*, 2023). The lack of transparency also challenges comparability, exemplified by the low correlation (0.38 to 0.71) in ESG ratings from different providers for the same firm (Berg *et al.*, 2022).

Following these shortcomings, we have defined three principles (following the approach of Dietzenbacher *et al.* (2013) guiding the development of the *tilt* method. The first is the *SME-centric* principle. The principle implies that the method should simplify data collection, benefitting the SMEs as it requires minimal data, resources and expertise from firms. Such an approach recognizes that SMEs have different resources and expertise than larger firms (D'Angiò *et al.*, 2024, or see Stubblefield Loucks *et al.,* 2010 for emphasizing the differences between larger firms and SMEs in sustainable development). A simplified data collection process also promotes scalability, making an extensive SME portfolio assessment for banks easier. The principle is important as to achieve the EU Green Deal, SMEs must be included in banks' impact and risk assessment analyses, but without data, there is limited inclusion. 48% of EU SMEs rely on bank financing (ECB, 2021), emphasizing that banks can influence SME's investment decisions with the potential for transition finance. Since SMEs in the EU account for 99% of businesses contribute over half of the economic value-added, produce 63% of emissions (European Commission, 2024, 2023, 2022), and employ over 100 million people, their transformation is critical for climate and economic stability (European Commission, 2023).

The second principle is the *product-centric analysis*. The principle balances reducing SME reporting burdens (aligned with the first principle) with the desire for detailed firm-specific assessments. Ideally, firm-specific, assured and accurate ESG data from all SMEs would be best, but many firms lack the capacity for such thorough reporting. Therefore, we chose product-centric analysis because it provides more detail than the 3-digit ISIC codes used by PCAF. At the same time, SMEs can easily report on their products. However, this principle implies a limitation. We use regional average emission intensities from LCA to obtain climate information regarding the products, i.e. our climate data is not firm-specific but a product proxy.

The third principle is about *transparency*. Inspired by Berg *et al.'s* (2020) call for transparent ESG scores, we make our methods and algorithms for constructing the data openly accessible on GitHub (**supplementary material S3**). This transparency allows stakeholders to understand, verify, and engage with our indicators, enhancing trust and accountability.

3. The Construction of Climate Indicators for Impact and Risks Assessment

We develop two climate indicators following the SME-centric, product-centric, and transparency principles - the Relative Emission Reduction Potential Indicator (Section 3.1) and the Transition Risk Indicator (Section 3.2). **Figure 1** outlines the steps for constructing the two climate indicators. This section includes the **purpose and scope of the indicator**, the **construction** of the indicator, **potential usage** and **limitations, and an analysis of statistical properties with future enhancement**.

3.1. The Impact Perspective with the Relative Emission Reduction Potential Indicator

The **purpose and scope** of the Relative Emission Reduction Potential Indicator are to help banks identify firms with a relatively high emission reduction potential compared to other peer firms. These firms are then suitable for transition financing. Two pieces of information are needed for this: identifying the firms with the highest *relative emission-intensive products* and identifying the firms with the highest *emission reduction capacity*.

Figure 1 overviews the steps to **construct** these two indicator components. We first gather firm information for both components—the product, business type, and location **(Figure 1, step 1, in green).** See the **supplementary material S1.1** for details on potential data sources.

The two indicator components differ for the second step. As the *relative emission intensity indicator* compares the emissions intensity of one product (measured in CO2e kg/kg) to other products, we match firm-specific data (products, location, and business type) with an LCA database **(Figure 1, step 2, in green).** See **supplementary material S2.1** for our NLP-based matching algorithm for matching different data sources.

As an LCA database, we chose Ecoinvent v3.10 (Wernet *et al.*, 2016), which provides LCA data on over 20.000 activities across various sectors (for alternative sources, see **supplementary material S1.2**). The database represents average production conditions in specific geographical locations rather than company-specific data. Specifically, we used the indicator “Global Warming Potential (GWP 100)” according to the IPCC 2021 method, giving us the emission intensity of products.

In the third step, the users can decide between different *grouping choices* for the relative emission intensity indicator **(Figure 1, step 3, in green)** to categorize products into specific groups. We then use these groups to construct the indicator. After selecting a group, each activity from our LCA database is compared to other activities within the same group in terms of their emission intensity to calculate the rank of each activity. The relative emission intensity for each product is then calculated by dividing its rank by the total number of products (n) in that group. “1” indicates the highest emission intensity within the group, and “1/n” represents the lowest (see detailed equation in **Annex A1.1**). The idea is that high emission intensity typically reflects energy-intensive processes, long transport distances, or carbon-heavy inputs. Assuming cleaner alternatives exist, higher intensity signals greater emission reduction potential across the value chain. Please note that a higher relative emission-intensive product does not mean that the product can be substituted with a lower relative emission-intensive product.

There are two available groups the user can choose from:

- *Unit*: This grouping compares the emission intensity of each activity in our LCA database to activities with the same unit. For this application, we chose to limit the grouping only to the unit “kg”, as it is the most common unit and to reduce the complexity of the different choices (see number of products per group in **Table II**). For instance, this group implies that the emission intensity of 1 kg of apples is compared to the production of 1 kg of cement. A higher relative emission intensity of cement reflects higher emission processes in cement production throughout its lifecycle.
- *Tilt subsector unit*: This grouping compares each activity in our LCA database to activities within the same tilt subsector and unit (see **Table II** for a list of the tilt sectors and subsectors). For example, choosing this group means comparing 1 kg of cattle production to 1 kg of apple production, as both are in the agriculture and livestock subsector. This approach benefits banks that have prioritized specific sectors for steering but need help determining which firms within the sector to approach first. For the application in this paper, we limited this grouping only to products measured in kg across different tilt subsectors to reduce the number of groups to the most relevant ones. We considered the unit "kg" the most applicable as most products are measured in this unit.

We aggregate product-level emission indicators to the firm level **as a fourth step (Figure 1, step 4 in green).** For the relative emission intensity indicator, we average all relative emission intensity indicators for a firm's products (see **Annex A1.2** for equations). Please note that this aggregation is only meaningful if all firm products refer to the same group (e.g., they have the same unit or the same unit and tilt subsector). This restriction ensures that the average value indicates a firm's actual emission intensity because otherwise, it would eventually mask different emission levels between groups. For example, an industrial product with a low rank could emit more, in absolute terms, than a high-ranked agricultural product. Hence, an aggregation across these two different products could cause misleading conclusions. The average value, ranging from 0 to 1, indicates the firm's average emission intensity relative to others in the selected group, with values closer to 1 suggesting relatively higher emissions. One of the most significant limitations of our method is that the production volume or product's revenue share is unknown, leading to potential inaccuracies about which products are most important to the firm. To address this data gap, we calculate the lower and the upper bound to express the uncertainty of the relative emission intensity indicator:

- Lower bound: Assumes the firm only produces the lowest emission-intensive product.
- Upper bound: Assumes the firm only produces the highest emission-intensive product.

Based on the lower and upper bounds, we can calculate the spread, which indicates the uncertainty of the calculation (see **Annex A1.3).** Financial institutions can choose beforehand which spread they would accept.

Figure 2 shows the results for Farmer Lena. The average relative emission intensity rank comparing Farmer Lena's products to others in the same tilt subsector, measured in kg, lies between 0.6 and 0.8. Therefore, it has a spread of 0.2.

Now, we turn to the second component of the relative emission reduction potential indicator – *the emission reduction capacity indicator*. A high relative emission intensity does not guarantee a firm can reduce emissions across its entire value chain. Not all materials or processes have viable low-emission alternatives. For instance, cattle emissions mainly come from methane (by-product), which a farmer cannot change. Thus, we complement the relative emission intensity indicator with the emission reduction capacity indicator, indicating if the potential to reduce emissions is under the firm's control or, in other words, if a firm can reduce emissions by implementing climate actions. As a first step **(Figure 1, step 2, in red)**, we use ecoinvent to identify the drivers of the product's emissions, which can be (i) direct emissions, i.e. by-products of the process, or (ii) inputs, i.e. products used for the production (e.g., raw materials or machinery used for production) that contribute to emissions. As the firm cannot control the byproducts, we exclude byproducts and only focus on inputs. To construct the indicator, we take a standardized list of climate actions – in our case, inspired by the European Investment Bank (EIB, 2023), detailing over 40 climate actions firms can undertake and potentially qualify for EIB-funded intermediated debt products or guarantees. The list includes upgrading agricultural machinery, enhancing energy systems with sustainable fuels, and reducing resource use. If a firm's production includes components listed by the EIB as substitutable with greener alternatives, it shows significant potential for emissions reduction. For instance, if an agricultural firm uses tractors and produces wheat, one option on the EIB list is replacing old machinery with more efficient machinery. We then match these inputs with the EIB's climate actions list; if an input aligns, it is assumed that the firm can reduce the emission of the input to its maximum. Through ecoinvent, we can further quantify each input's share of total CO2e emissions. With the calculation rule in **Annex A1.4,** we calculate that for Farmer Lena, the emission reduction capacity to reduce emissions for cattle is 20% and for wheat and grain, 60% **(see Figure 3).**

We finally need to aggregate the *emission reduction capacity indicator* on the firm level **(Figure 1, step 4 in red and calculation method in Annex A1.5).** We take the weighted average of emission reduction capacity indicators on a product level, assuming cattle, wheat and grain are produced equally. Since cattle have a higher emission intensity than wheat and grain, cattle are weighted more than wheat and grain products. We then again calculate the lower and upper bounds with **Annex A1.6** to understand the uncertainty around the weighted average. For Farmer Lena, we finally receive the results of 0.33 as the emission reduction capacity indicator on the firm level, with a lower bound of 0.2 and a higher bound of 0.6, which makes a spread of 0.4 **(see Figure 3)**.

We suggest using a matrix to combine the two indicator components—the relative emission intensity and the emission reduction capacity indicator **(Figure 1, step 5)**. On the x-axis, we see the relative emission intensity indicator, and on the y-axis, the firm's capacity to reduce emissions.

The matrix helps banks identify firms with the highest emission reduction capacity. Each institution can set its threshold to determine which firms to prioritize, allowing for the creation of quadrants. Firms in the top quadrant are well-suited for transition finance (see **Figure 4**). Once identified, banks can analyze these firms' products and climate action potential using the reduction capacity indicator. Such analyses can support transition planning that is aligned with frameworks like the EBA or VSME standard. While financial metrics such as loan size and default risk are still missing for a financial product, the climate data offered here is a first step for integrating sustainability into lending decisions.

The approach has several **limitations**. This indicator measures emission intensity per product, focusing on production inefficiencies rather than total emissions. While total emissions help distinguish environmentally friendly firms, we aim to spotlight inefficiencies. For instance, Company A emits 50,000 kg CO_2e, producing 1 million units (0.05 CO_2e/unit), while Company B emits only 10,000 kg CO_2e for 100,000 units (0.1 CO_2e/unit). Although Company B emits less overall, the firms' products' higher emission intensity per unit signals higher inefficiencies in their production processes. Identifying such inefficiencies is essential for meeting the Green Deal's 2050 net-zero goal as it highlights an opportunity for improvement.

Furthermore, while our method minimizes SME burden by requiring minimal input per our SME-centric principle, total emissions are also valuable information. If SMEs can provide production volumes, these amounts can be multiplied by the emission intensity per product unit to derive absolute emissions. Further, our data also allows to estimate scope 1, 2, and 3 emissions in addition to total emissions. Such calculations could also work with revenue data from SMEs or financial institutions based on market price data from ecoinvent.

Another limitation of the indicator is that it is based on product averages from ecoinvent, building on, e.g. regional energy mixes, not firm-specific estimates. LCA data account for firm location and business type and consider regional energy mixes and practices. The indicator will treat firms that produce the same products similarly, even though a firm may already implement some climate action. While this is a limitation, the purpose of this indicator is to identify potential candidates in the first step, given that banks need a starting point with many SMEs in their portfolio. After the identification, banks should further enhance the indicator through firm-specific questions.

The developed method only allows for comparing firms with products in the same group to draw meaningful conclusions. This restricts the number of firms to which the approach is applicable. Alternatively, we could compare products' emission intensity per revenue (CO_2e kg/EUR) (Greenhouse Gas Protocol, 2013). While useful for financial analysis, it can misrepresent actual emission improvements when biased by market prices.

Finally, the method is prone to group size effects: smaller groups tend to have higher average ranks. For example, a 3-product group has an average rank of 0.67, while a group of 11 approaches 0.5 (average rank: 0.545). To ensure ranking consistency, we set a minimum group size of 11 to mitigate this bias, excluding smaller groups. This resulted in the exclusion of 1 out of 12 groups in the "tilt subsector" unit (kg), while no exclusions were necessary for the grouping unit with unit = kg **(see Table II)**.

3.2. The Risk Perspective with the Transition Risk Indicator

The Transition Risk Indicator helps banks assess the risk of financing their clients' products. According to the IPCC (2014), climate risk results from the interaction of hazards, exposures, and vulnerabilities. For example, a firm located in a flood zone is exposed to the hazard, but effective flood defences reduce its vulnerability—together, these factors determine its overall risk.

Following Campiglio (2023), we adapt the climate impact framework to transition risks (see **Table III**). In this context, political targets—such as net zero by 2050—represent hazards that pressure firms to cut emissions. A firm's exposure depends on its sector and the emission intensity of its products. For instance, the EU Green Deal targets sectors like automotive and shipping (European Parliament, 2024). Products with higher emissions also face steeper cost increases under carbon taxes or EU ETS policies. While the EU ETS initially focused on energy-intensive and aviation sectors, its influence extends broadly through rising energy costs (Böning et al., 2023). In short, higher emission intensity translates into higher production costs under transition policies.

The Transition Risk Indicator combines relative emission intensity (indicating a product's exposure within its sector) with a sector decarbonization indicator (representing the hazard from political pressure to cut emissions). We use relative emission intensity rather than reduction potential, as carbon pricing mechanisms like the EU ETS affect entire value chains. For instance, a company using steel will face higher input costs due to emissions priced at the production stage, regardless of its own emissions or efficiency gains.

The first step in constructing the sector decarbonization indicator **is gathering firm-specific information** (**Figure 1**, step 1, in blue). The indicator regarding the sector decarbonization target encompasses products, business type, and, optionally, the sector in which the firm operates. **In the second step** (**Figure 1**, step 2, in blue)**,** we match these firm-specific data with climate scenario data, modelling the potential pressure of a firm to transition. Climate scenario providers simulate future CO2 emissions at the sector level to meet specific climate goals. For instance, the targets indicate the required CO2 emission reductions by 2030 compared to 2020 to align with a 1.5° scenario for 2050. If policymakers enforce the essential policies to attain these political objectives, the reduction targets for each year reflect the pressure a firm faces when operating in a specific sector. The higher the reduction target, the higher the pressure. Please see **Annex A1.7** for the exact calculation of such reduction targets. We allocate each product to a target by assigning the product to the appropriate tilt subsector (please see the **supplementary material S2.2** for more detail if reconstructing the data). The **third step is a methodological choice** (**Figure 1**, step 3, in blue). The users can configure the sector decarbonization indicator based on a *scenario choice*. The user can choose (for more details, see **supplementary material S1.3**):

- *Scenarios*. Users can choose between the IPR 1.5°C RPS scenario and the IEA WEO NZE 2050 scenario (IEA, n.d.). The IPR (n.d.) scenario forecasts sector-specific decarbonization pathways based on national policies and expert likelihood assessments, such as Germany's 2030 coal phase-out. In contrast, the IEA scenario models sectoral decarbonization requirements to reach net zero by 2050 based on assumptions about economic growth, population, energy use, and technology costs.
- *Year*. Users can choose between the target years 2030 and 2050. The models show a sector decarbonization target for different years. Selecting 2030 in the IEA scenario gives the user a sector decarbonization target that should be achieved by this year compared to 2020 to achieve net zero in 2050.

Table IV gives an overview of the final sector decarbonization targets per tilt subsector.

For step 4 (Figure 1, step 4, in blue), **we aggregate the product-level information to assess the firm level.** For the average transition risk on a firm level, we calculate the average of the transition risk of all products. Similar to the relative emission intensity indicator, one challenge is that we do not have any product revenue shares or production amounts. To address this, we introduce the following lower and upper bounds:

- Lower bound: Assumes the firm only produces products with the lowest emissions.
- Higher bound: Assumes the firm only produces the highest emitting products.

Figure 5 shows the results for Farmer Lena**.** Farmer Lena's products are both in the Agriculture and Livestock tilt sub-sector, which, under the 1.5 RPS scenario from IPR (2022), has a decarbonization target of 61% in 2030. There is no spread, as both products are exposed to the same decarbonization targets. After constructing the sector decarbonization indicator, we combine the information (**Figure 1, step 5)** with the relative emission intensity indicator constructed in Section 3.1 in a matrix **(Figure 6)**.

The financial institution can use the matrix to compare firms. The y-axis shows exposure to sector decarbonization targets. In **Figure 6**, we compare Farmer Lena to firms within the same tilt subsector, all of which share the same hazard value of 0.61—meaning each must reduce emissions by 61% by 2030 to align with the 1.5 °C goal for 2050. The x-axis displays the relative emission intensity indicator, reflecting each firm's exposure to those targets. The lower the value, the lower the exposure.

The **limitation** of the transition risk indicator is that we use global scenarios for the transition risk indicator. However, licensed country-specific scenarios may offer greater accuracy for local conditions. Users can substitute global targets with regional ones to better reflect local realities.

Further, the sector decarbonization targets used in this analysis do not consider the varying degrees of adaptability among different industries. Some industries might be better equipped to manage these transitions than others. Even if the automotive and cement industries have the same reduction target, their transition risks can vary. For example, the automotive sector can adopt low-carbon technologies, such as electric vehicles, to help it meet reduction targets more easily. In contrast, the cement industry, which has fewer readily available low-carbon alternatives, may find it much harder to adapt, resulting in higher transition risks. Incorporating industry-specific adaptive capacities may be a valuable enhancement of the *tilt* method.

Additionally, we lack data on firm-specific vulnerabilities, such as transition plans, which are essential for accurately gauging transition risks, which would require additional outreach to the firm.

4. Illustrative Application of the Method

The dataset provided by Lepore *et al.* (2024) applies the *tilt* method to 48,180 firms, demonstrating the feasibility of generating an extensive SME database. **Figure 7** provides an overview of its coverage. The data is sourced from a B2B platform (please see **supplementary materials S1.1** for alternatives) and reflects higher representation from German firms—likely due to more active usage—compared to EU SME estimates. Most firms operate in the industry and land use sectors, which is consistent with B2B marketing. Most firms are manufacturers or producers, followed by wholesalers and distributors. While many did not report employee numbers, those that did are mostly under 200 employees, aligning with the SME definition.

We use this data to illustrate how banks can use the data to identify firms for transition planning. In this example, a bank targets the most transition-risk-exposed firms in its Netherlands portfolio. It focuses only on firms with zero uncertainty (no spread in relative emissions or decarbonization targets) and compares firms with products measured in kilograms (the reference unit). The bank treats sector decarbonization targets above 20% by 2030—in line with the IEA Net Zero 2050 scenario—as indicative of significant transition risk and prioritizes these firms for engagement.

After applying these thresholds, 42 firms remain (each dot in **Figure 7** representing one firm). Looking at these firms, all are active in the automotive subsector (with a decarbonization target of 40%), iron & steel (with a decarbonization target of 23%), other industries and other metals (both 22%). Please note that the agriculture and livestock sector is not included, as the IEA WEO scenario does not cover this sector. Looking into the emission reduction capacity indicator in the second step of these products will help the bank identify which firms they can target for transition financing.

5. Conclusion

We developed a method to generate climate indicators suitable for SMEs, requiring minimal data: product type, business category, and location. We illustrated the data by Lepore *et al.* (2024) that applied the *tilt* method across 50,000 firms in Austria, France, Germany, the Netherlands, and Spain. While this proves the method's feasibility and scalability, it is essential to note that it is universally applicable to any firm with access to the required data and operating within the *tilt* sectors and is, therefore, data-source agnostic.

With the indicators, banks can enhance steering strategies and portfolio assessments by automatically identifying and grouping firms based on their potential climate impact and risk. This enables targeted, effective outreach and risk management within loan portfolios and supports the double materiality assessment for financial institutions. For researchers, the indicators allow for analyses of economic practices and regional trends. They further allow for selecting relevant firms for detailed case studies, particularly within specific sectors. The data can be used for all business and economic questions when matched with other data sources, such as firm or loan data sets.

Looking ahead, the work on *tilt* proves the feasibility of an automated product-based climate data assessment and analysis of SMEs. While focused on emission data, this approach is not limited to climate. Ecoinvent's impact assessment for other areas can also include nature-related questions, such as water depletion. When implemented in software, the method could also help SMEs fulfil the VSME reporting standard (at least for the 'E' in ESG reporting) and successfully reduce the reporting burden.

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Technical Annex

A1. Calculation rules

A1.1 Calculating the relative emission intensity on product-level

The relative emission intensity indicator at the product level is calculated with the relative emission intensity rank defined as follows.

$relative\ emission\ intensity = rank(x_i)/n$

Rank is defined as follows: First, we define $X = \{x_1, x_2, x_3, \ldots, x_n\}$ as all emission intensity observations (CO2e (kg/kg)) of all products in one group. We arrange X in ascending order, i.e., if x_i is the ith element in X, then for any $i < j$, $x_i \leq x_j$. After that, we assign a rank to each element in x_i in X. For the first element, $rank\ (x_1) = 1$, i.e. the lowest emission intensity (CO2e kg/kg) in the group has rank one, and the highest emission intensity (CO2e kg/kg) in the group has rank n, i.e. $rank\ (x_n) = n$.

After having the rank defined in the first step, we divide the rank by n which is the number of products in this specific group. We do so to receive a number between 0 and 1, which reflects the percentile of the product's emission intensity (CO2e kg/kg) in the group's distribution. A product having a relative emission reduction rank of 1/n indicates that the product has the lowest emission intensity (CO2e kg/kg), and a 1 (i.e. n/n) indicates that the product has the highest emission intensity CO2e kg/kg in the group.

To further understand the properties of the CO2e kg/kg, we conducted an analysis of their distribution by plotting a boxplot for the relevant groups, such as for all subsectors with unit = kg (grouping tilt subsector unit) and for all activities with unit = kg (grouping unit). In **Figure 9**, one can get an indication of the variance within and across groups.

A1.2 Aggregation of the relative emission intensity on firm-level

The formula to compute the average relative emission intensity indicator for a reference group g for a firm F, considering only products with a defined REI, is:

$$Average\ Relative\ Emission\ Rank_{g,F} = \frac{1}{n_{g,F}} \sum_{i=1}^{n_{g,F}} REI_{i,g}$$

Where:

- $REI_{i,g}$ is the relative emission intensity of the i-th product within a reference group g

- g: The reference group can be either the tilt subsector unit or the unit, depending on the users' choice. The reference group must be uniformly the same for all products i of the firm.
- $\sum_{i=1}^{n_{g,F}} REI_{i,g}$ sums the relative emission intensity of only those products within firm F under a selected reference group g and that have a defined emission rank REI.
- $n_{g,F}$ is the number of products in firm F that are compared according to the same reference group g and that have a defined REI.

A1.3 Expressing uncertainty of the relative emission intensity indicator with calculating the spread

As we do not have revenue shares or production amount the assumption that any product is equally important for the firm is limited. Therefore, we calculate the spread of each firm.

$$Spread\ REI_{g,F} = \max(REI_{i,g}) - \min(REI_{i,g})$$

Where:

- $REI_{i,g}$ is the relative emission rank of product i within reference group g

A1.4 Calculating the emission reduction capacity indicator on product level

The Emission Reduction Capacity Indicator is calculated as:

$$ERCI_i = \frac{\sum_{j=1}^{m} CO2e_j}{CO2e_i}$$

Where:

- $ERCI_i$ is the emission reduction capacity indicator for product i
- $CO2e_j$ is the CO2e per input j where a climate action is defined contributing to $CO2e_i$
- $CO2e_i$ is the total emissions of one product i
- m Number of input products with defined climate actions

A1.5 Aggregation of emission reduction capacity indicator on firm level

To aggregate the emission reduction capacity indicator on product level we take the weighted average:

$$ERCI_F = \frac{\sum_{i=1}^{n}(ERCI_i * CO2e_i)}{\sum_{p=1}^{n} CO2e_i}$$

- $ERCI_F$ is the emission reduction capacity indicator for Firm F
- $ERCI_i$ is the emission reduction capacity indicator for product i
- $CO2e_j$ is the CO2e per input j where a climate action is defined contributing to $CO2e\ _i$
- $CO2e_i$ is the total emissions of one product i
- n Number of products with defined ERCI values

A1.6 Expressing uncertainty of emission reduction capacity indicator with calculating the spread

As we do not have revenue shares or production amount the assumption that any product is equally important for the firm is limited. Therefore, we calculate the spread of each firm.

$$Spread\ ERCI\ _F = \max(ERCI_i) - \min(ERCI_i)$$

Where:

- $ERCI_i$ is the emission reduction capacity indicator of product i

A1.7 Calculating the sector decarbonization indicator on product level

Using this data, we calculate the required reduction targets, which are detailed in the final column, "sector decarbonization targets", according to the specified equation:

$$Sector\ Decarbonization\ Target\ (SDT) = 1 - (\frac{CO2\ value_{target\ year}}{CO2\ value_{2020}})$$

A1.8 Aggregation of the sector decarbonization indicator on firm level

The formula to compute the average sector decarbonization target for under a scenario s in a year y for a firm F, considering only products with a defined sector decarbonisation target, is:

$$Average\ Sector\ Decarbonization\ Target_{s,y,F} = \frac{1}{n_{g,F}} \sum_{i=1}^{n_{s,y,F}} SDT_{i,s,y}$$

Where:

- $SDT_{i,s,y}$ is the sector decarbonization target of the i-th product within a scenario s for a year y
- s: The scenario s can be either the IPR RPS 1.5° in 2050 or the IEA NZ in 2050 scenario.
- y: The year can be 2030 or 2050 indicating how many emissions need to be reduced by this year to achieve the scenario targets chosen with s.
- $\sum_{i=1}^{n_{s,y,F}} SDT_{i,s,y}$ sums the sector decarbonization targets of only those products within firm F that are defined under s and y.
- $n_{g,F}$ is the number of products in firm F that have a sector decarbonization target under s and y.

A1.9 Expressing uncertainty of sector decarbonization indicator with calculating the spread

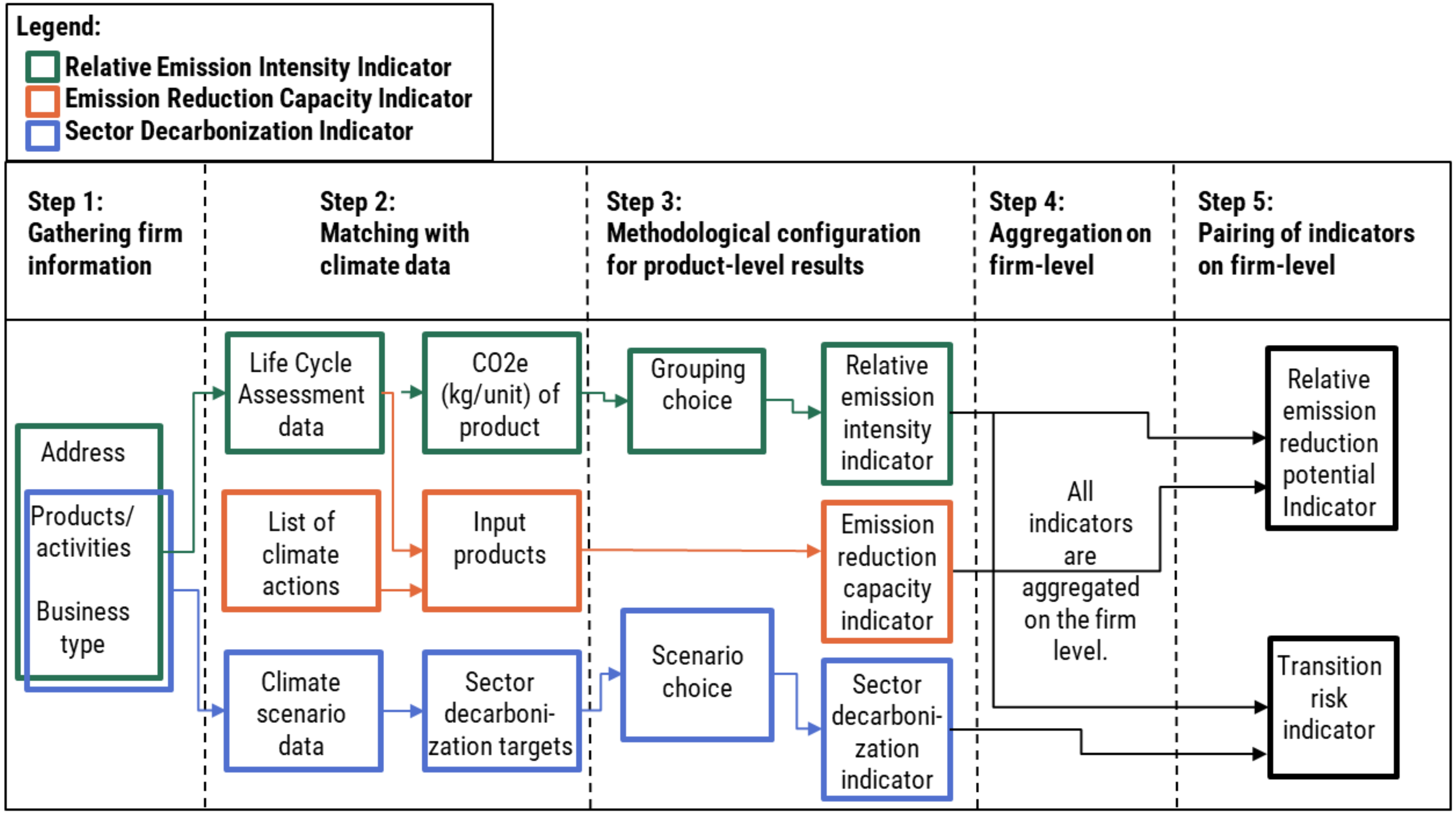
As we do not have revenue shares or production amount the assumption that any product is equally important for the firm is limited. Therefore, we calculate the spread of each firm.

$$Spread\ SDT_F = \max\left(SDT_{i,y,s}\right) - \min\left(SDT_{i,y,s}\right)$$

Where:

- $SDT_{i,y,s}$ is the sector decarbonization indicator of product i under a scenario s and year y.

Figure 1: Overview of the steps involved in constructing the indicators.



The critical firm-specific data required includes the firm's products/activities, business type, and location. Although our methodology is product-focused, details on location and business type are essential. This is because the emission intensity measured in CO2e (kg/unit) depends on the production location, as relevant LCA variables vary cross-country (e.g. the renewable share of the electricity), as well as on the business type (producer or trader) of the firm.

Source: Author's own.

Figure 3: Results of the emission reduction capacity indicator for Farmer Lena (all values and inputs/byproducts are illustrative).

Step 1: Gathering firm information

Step 2: Matching with climate data

Step 3: Results product-level results

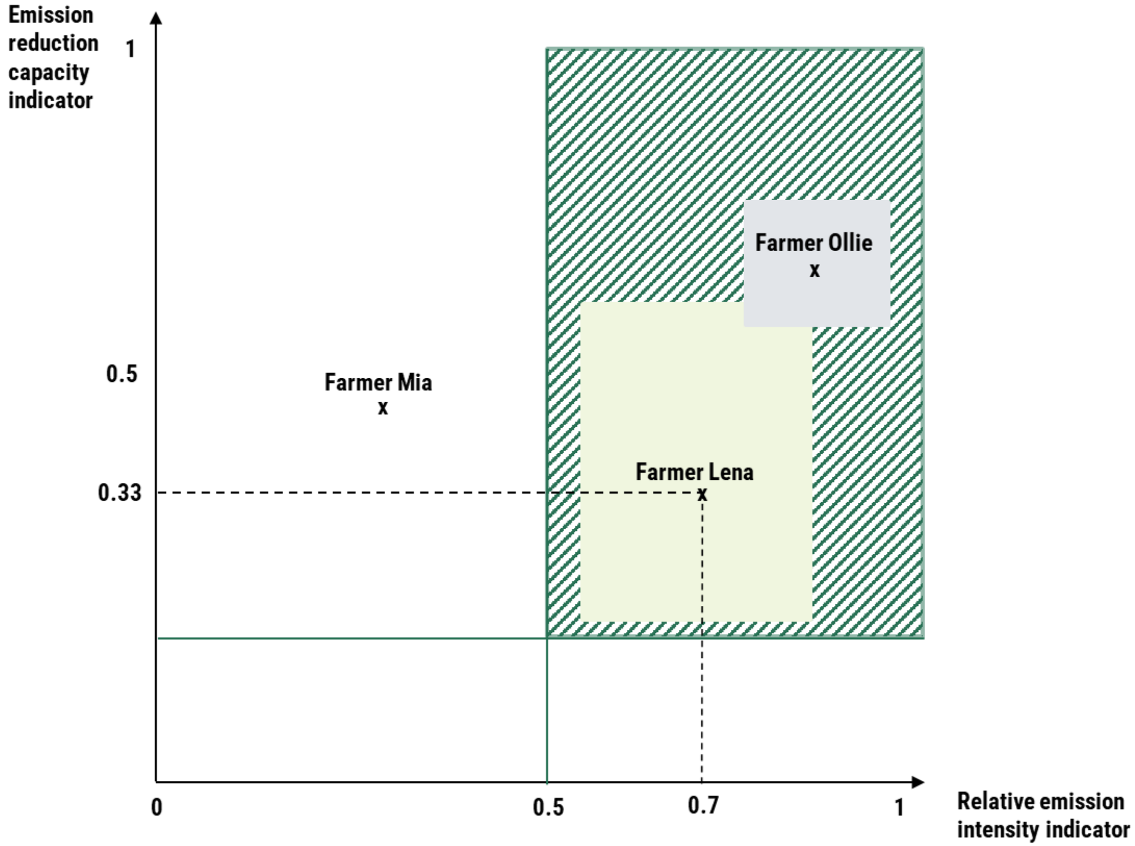
Firm	Location	Products/ services	CO2e (kg/ output unit)	Name of input or byproduct	Input / Byproduct	CO2e (kg/ output unit) per input/ byproduct	Climate Action	Emission reduction capacity indicator
Farmer Lena (producer)	GER	Cattle	20	Methane	Byproduct	12	NA	**0.2** *(=4/20)*
				Dinitrogen monoxide	Byproduct	4	NA	
				Fertiliser	Input product	**4**	**Decreased Resource Input Requirements**	
		Wheat and grains	10	Dinitrogen monoxide	Byproduct	4	NA	**0.6** *(=(4+2)/10))*
				Fertiliser	Input product	**4**	**Decreased Resource Input Requirements**	
				Tillage and harvesting with tractors	Input products	**2**	**Replacement of self-propelled or traction agricultural machinery with more efficient alternatives, including tractors and harvesters.**	

Step 4: Aggregation on firm-level

Firm	Emission reduction capacity indicator lower-bound	Emission reduction capacity indicator equal weight	Emission reduction capacity indicator higher bound	Spread of Emission Reduction Capacity
Farmer Lena	0.2 *(only cattle)*	0.33 *(weighted average of emission reduction capacity indicators on product level)*	0.6 *(only wheat & grain)*	0.4

Source: Author's own.

Figure 4: Matrix – combining the relative emission intensity indicator and emission reduction capacity indicator with an illustrative decision criteria for a financial institution to derive at the emission reduction potential indicator.



The financial institution decides to engage with Farmer Ollie and Farmer Lena as it has the decision rule to engage with all firms that have at least a relative emission intensity of 0.5 and an emission capacity indicator of at least 0.2. Farmer Mia most likely only produce one product as there is no spread. Farmer Ollie produces product that are very similar in its emission intensity and the emission reduction capacity. Even with a higher spread the financial institutions decide to engage with Farmer Lena due to its individual decision rules. Source: Author's own.

Figure 5: Results of the sector decarbonization indicator on the product level for Farmer Lena for IPR (n.d.) scenario data under the 1.5 RPS, 2030 scenario.

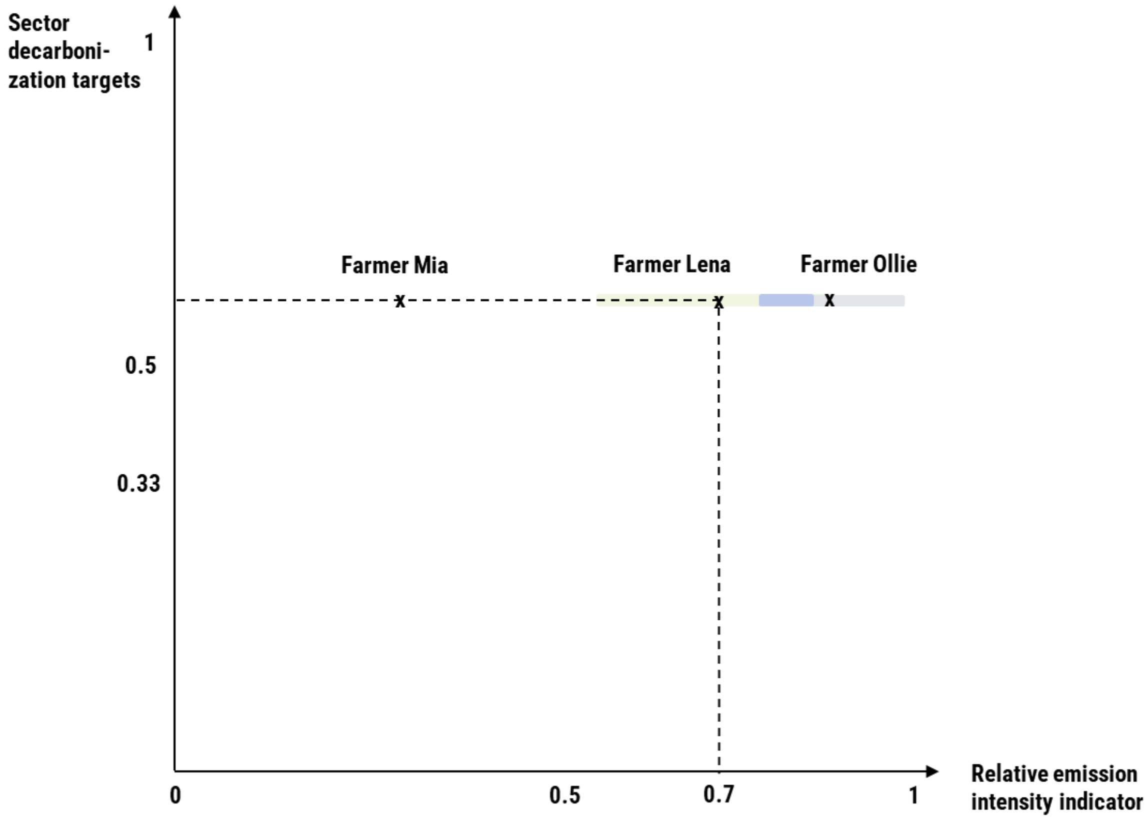
Step 1: Gathering firm information			**Step 2: Matching with climate data**			**Step 3: Methodological configuration for product-level results**		
Firm	**Location**	**Products/ services**	**Matched tilt sector**	**Matched tilt subsector**	**Matched to scenario subsector (IPR)**	**Scenario**	**Year**	**Sector decarbonization target**
Farmer Lena (producer)	GER	cattle	Land Use	Agriculture & Livestock	Land Use	1.5 RPS	2030	0.61
		wheat and grains	Land Use	Agriculture & Livestock	Land Use	1.5 RPS	2030	0.61

Step 4: Aggregation on firm-level

Firm	**Emission reduction capacity indicator lower-bound**	**Emission reduction capacity indicator equal weight**	**Emission reduction capacity indicator higher bound**	**Spread of Emission Reduction Capacity**
Farmer Lena	0.61 *(only cattle)*	0.61 *(average of cattle and wheat & grain)*	0.61 *(only wheat & grain)*	0

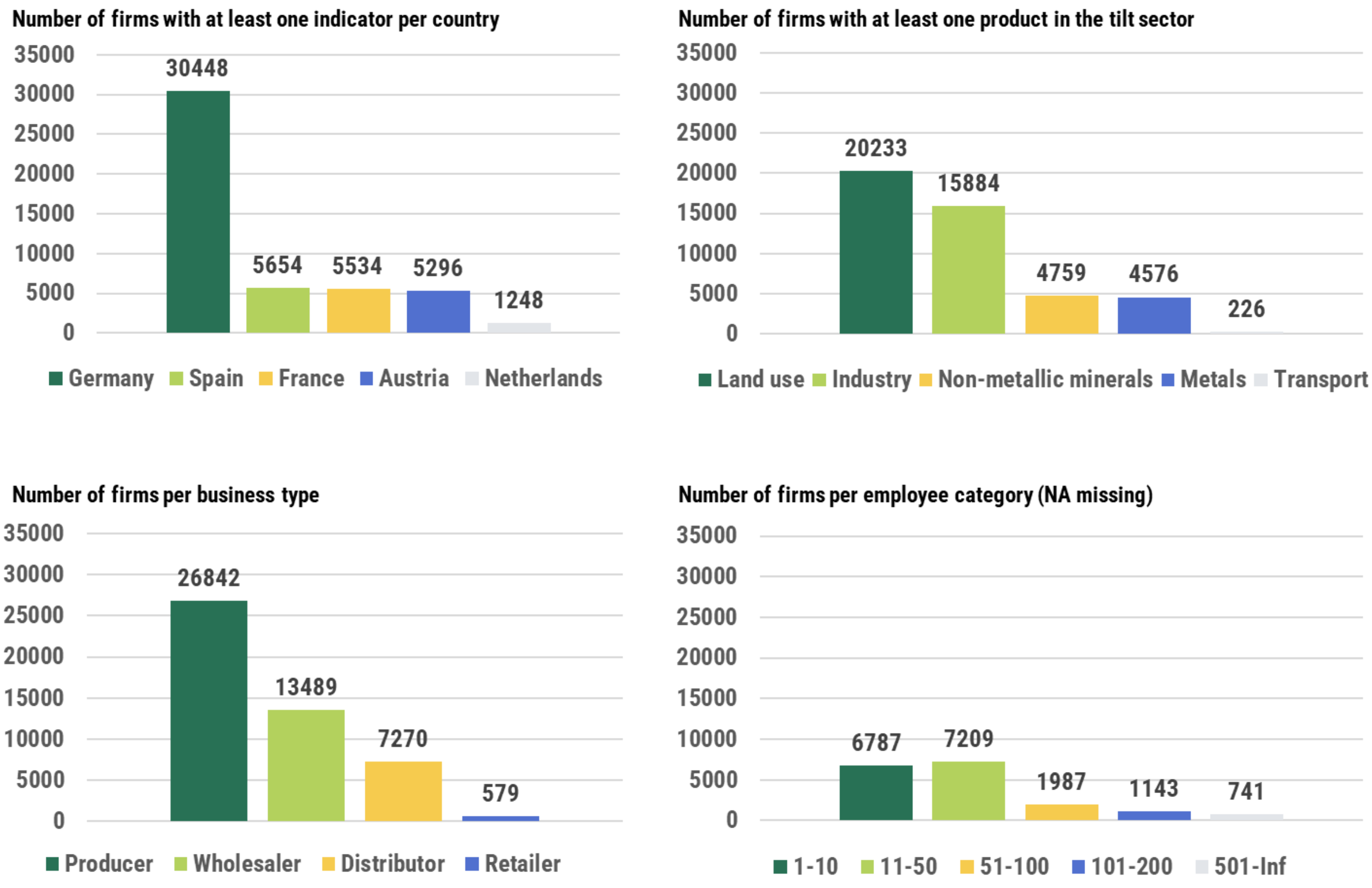
Source: Author's own.

Figure 6: Matrix – combining the relative emission intensity indicator and sector decarbonization targets to derive at the transition risk indicator.



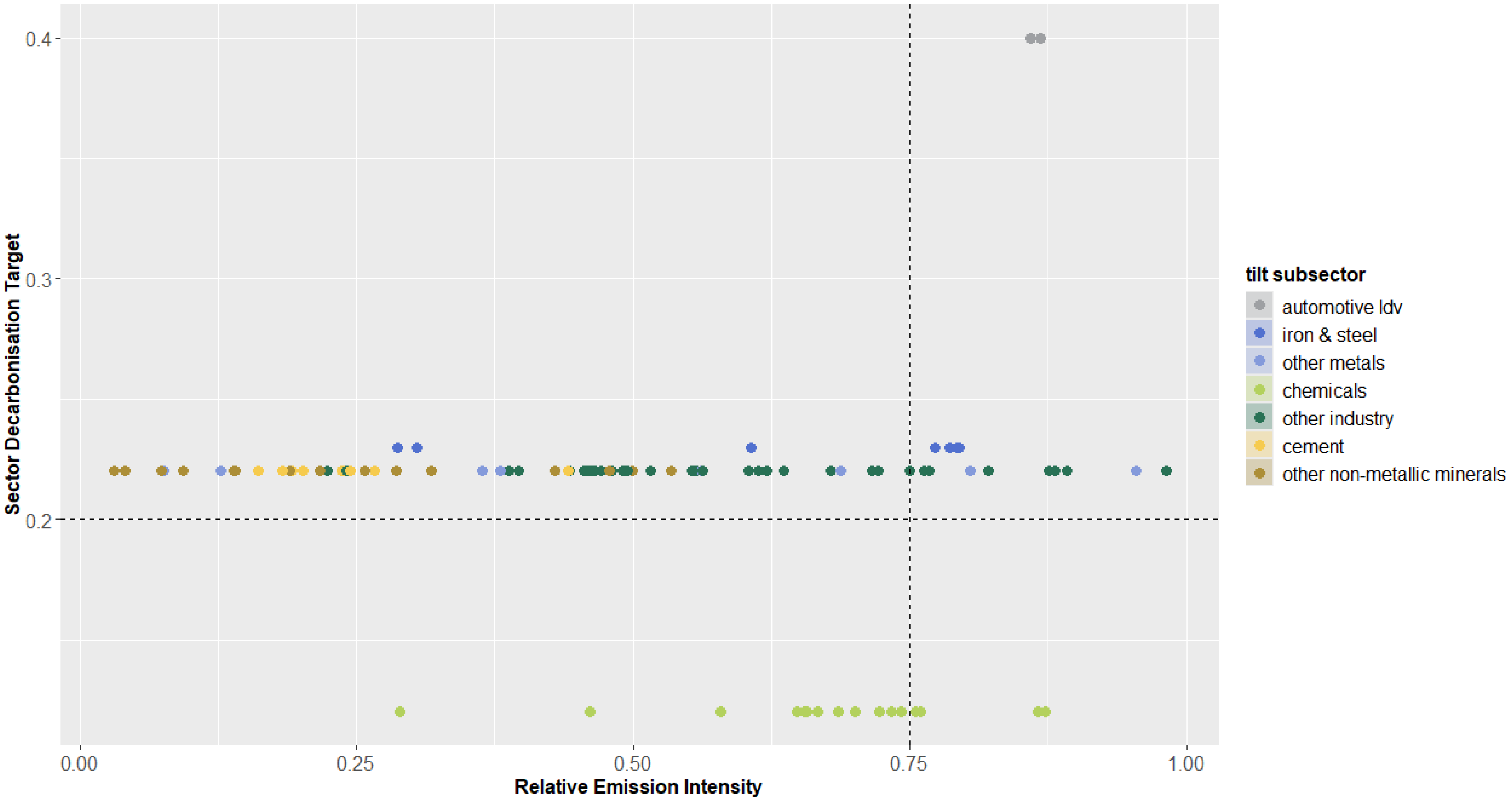
All farmers operate in the agriculture and livestock sector and thus share the same sectoral decarbonisation target, resulting in no spread on the y-axis. Therefore, the financial institution can rank them based on their average relative emission intensity (assuming equal product weights). Farmer Mia has the lowest transition risk, followed by Farmer Lena, and Farmer Ollie has the highest. The light green and grey lines represent the spread in relative emission intensity for Lena and Ollie, respectively. In contrast, the light blue line overlaps, indicating that Lena may have a higher transition risk in some scenarios than Ollie. The bank can define its own tolerance for such a spread. Source: Author's own..

Figure 7: Descriptive Analysis of dataset from Theia Finance Labs applied the tilt method to around 50,000 firms.



Calculations are based on Lepore et al., 2024. Available on request. Source: Author's own.

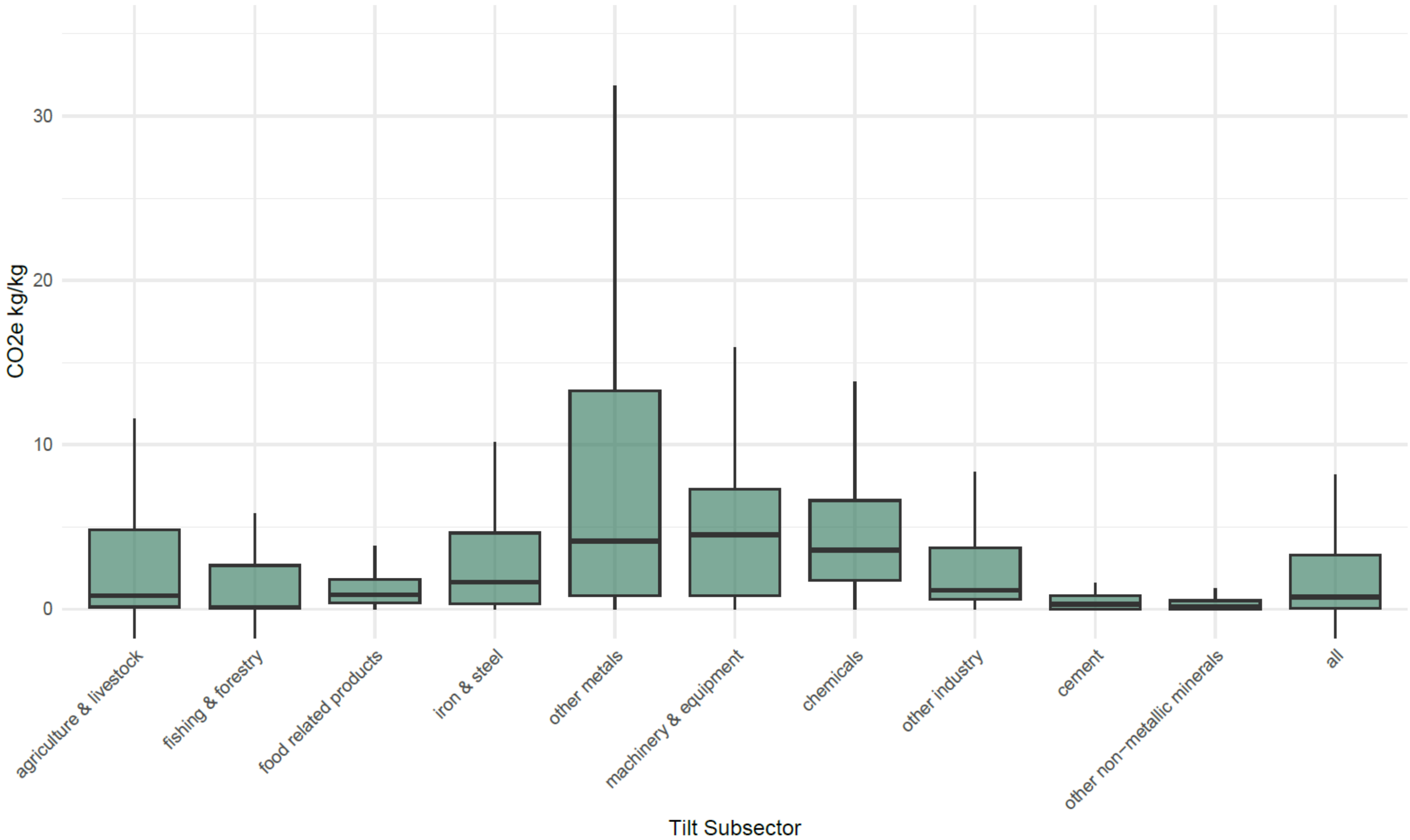
Figure 8: Transition Risk Analysis for Firms in the Netherlands.



Analysis for a financial institution focusing on firms with a relative emission intensity above 0.75 (4th quartile, in kg) and a sector decarbonisation target above 0.2 under a 2050 net-zero scenario (for 2030). Only firms with zero uncertainty (spread = 0) are considered, based on Lepore et al., 2024.

Source: Author's own.

Figure 9: Distribution of relative emission intensity in CO2e kg/kg for grouping tilt subsector unit and unit, with unit = kg.



This boxplot shows the median (black line inside the boxes), the 1st quartile (25th percentile, bottom line), the 3rd quartile (75th percentile, upper line) and the whiskers (min/max within 1.5 x IQR). The grouping applied is the tilt subsector unit grouping with unit = kg for the 10 subsectors (agriculture & livestock to other non-metallic minerals) and the unit grouping with unit = kg across all subsectors, referenced as "all" in the figure.

Source: Author's own.

Table I: Overview of existing databases and software providers.

Name	Coverage	What	Type	SMEs included	Methodology open source
Data providers					
Institutional Shareholder Services (ISS, n.d.)	25,000 listed corporates worldwide	TCFD data, carbon footprint data (scope 1-3), scenario analysis, transition risk, stress testing, physical risks	Reported and estimated	No	No
Sustainable Platform Pty Ltd (n.d.)	33,000 corporates worldwide	Physical risk, transition risk, climate alignment, and regulatory risks	Reported	Yes	No
Carbon Disclosure Project Worldwide (CDP, n.d.)	13,500 firms (firms in the MSCI country world index)	Absolute scope 1 + 2 GHG emissions, total fuel consumption, and purchased steam, heat, electricity, and cooling, emissions revenue intensity	Reported and estimated	No	No
Morgan Stanley Capital International (MSCI, n.d.)	10,000 firms	Low carbon patent analysis, current green revenues, climate risk management, sovereign, fossil fuel screens, emissions (scope 1-3, either reported or estimated), Implied Temperature Rise metric	Reported and estimated	Yes (listed SMEs)	No
Intercontinental Exchange (ICE, n.d.)	30,00 firms	Scope 1, 2, 3, absolute and intensive values, outlier detection, regional and country-level analysis, emission reduction targets	Reported and estimated	No	No
Bloomberg (n.d.)	130,000 global public and private firms	ESG firm reported sustainable debt, ESG scores, carbon emissions (scope 1,2,3), implied temperature rise, climate risk exposure indicators, EBA pillar 3 climate risks, government climate score, EU taxonomy SFDR, European ESG template	Reported and estimated	No	No
Truecost (n.d.)	750 firms	Database to identify upstream oil and gas opportunities and compare the firm's portfolio performance against the industry.	Reported and estimated	No	No
Sustainalytics (n.d.)	7,500 disclosed firms, coverage to 16,00 firms	15 climate data	Reported and estimated	No	No
Climate Action 100+ (n.d.)	170 firms	Emission reduction, governance, disclosure and implementation of net-zero transition plans	Reported	No	Yes
Partnership for Carbon Accounting Financials PCAF (2022)	Emission factor for 3-digit ISIC codes	Applicable to any firm with 3-digit ISIC information, Listed equity and corporate bonds, Commercial real estate, Business loans and unlisted equity, Mortgages, Motor vehicle loans, Project finance, Sovereign debt	Estimated	Yes	Yes
Software providers					

SME climate hub (n.d.)	software	Rather a tool than a data source	Questionnaire	Yes	Yes
Greenly (n.d.)	software	Rather a tool than a data source	Questionnaire	Yes	No
Cakir *et al.* 2023	software	Rather a tool than a data source	Questionnaire	Yes	Yes
Ozkan *et al.* 2023	Methodology, tested for ten firms	ESG scores extrapolated from larger firms based on satellite data and neural networks	Estimated	Yes	Yes

Source: Authors' own, inspired by Dimmelmeier (2023). The Table covers the most prominent providers but does not claim to be exhaustive. Ozkan et al. (2023) are included as a methodology provider since they tested their approach with only ten firms. Table is based on desk research in September 2024.

Table II: Number of unique activities per different groupings (tilt subsector unit and unit, where unit = kg)

Tilt sector	Tilt Subsector	Unit	Unique activities
Group 1: tilt subsector unit			
Land Use	agriculture & livestock	kg	1,852
	fishing & forestry	kg	253
	food-related products	kg	263
Transport	automotive ldv	kg	12
Industry	machinery & equipment	kg	79
	chemicals	kg	2,599
	other industry	kg	1,359
Non-metallic Minerals	cement	kg	468
	other non-metallic minerals	kg	295
Iron & Steel	iron & steel	kg	107
	other metals	kg	1,034
Group 2: unit			
all	all	kg	12,419

Source: Author's own. Activities from ecoinvent (Wernet et al., 2016).

Table III: Conceptual design of the transition risk indicator –a combination of the relative emission intensity and sector decarbonisation indicators.

Stage	**Risk concept (IPPC AR 5)**	**Applying the risk concept to transition risk**	**Operationalising the concept**
Hazard	*Triggered by an event or trend related to climate change*	*Policymakers have established climate objectives, including achieving net-zero CO2 emissions by 2050. To meet these goals, firms will encounter market and policy pressures, such as carbon taxes or EU ETS schemes, making their production processes more costly.*	*Sector decarbonisation indicator: Identifies the pressure on a firm to lower its emission intensity based on the sector decarbonisation targets to which the product belongs.*
Exposure	*People, assets, or ecosystems at risk*	*Firms that produce more emission-intensive products will be more at risk as they are more exposed to the hazards. Policy pressures through the EU ETS or carbon taxes will increase the production costs of a product per unit.*	*The relative emission-intensive indicator compares a firm's product emission intensity to other products' emission intensity within the sector. If the emission intensity of one product is higher than that of others, it is also more exposed to sector decarbonisation targets.*
Vulner-ability	*Susceptibility to harm*	*Firms that prepare for the transition might not be vulnerable despite high exposure and hazards. They might currently have high emission footprints, but they already have transition plans to reduce these emissions.*	*It is not included in the automated assessment, which is based on product averages. However, if firm-specific data is available, specific climate transition plans can be added.*

Source: Author's own inspired by Campiglio (2024) and the risk definition of the IPPC (2014).

Table IV: tilt sector and subsector categorisation plus the reduction targets per subsector for all four scenarios

Group	Tilt sector	Tilt subsector	IPR_2030	IPR_2050	WEO_2050	WEO_2050
Tilt subsector unit	Land Use	Agriculture & Livestock	0.62	1.32	NA	NA
		Fishing & Forestry	0.62	1.32	NA	NA
		Food Related Products	0.62	1.32	NA	NA
	Industry	Chemicals	0.12	0.93	0.12	0.97
		Machinery & Equipment	0.09	0.95	0.22	0.96
		Other Industry	0.09	0.95	0.22	0.96
	Metals	Iron & Steel	0.22	0.96	0.23	0.94
		Other Metals	0.09	0.95	0.22	0.96
	Non-metallic Minerals	Cement	0.13	0.80	0.22	0.97
		Other Non-metallic Minerals	0.13	0.80	0.22	0.96
		Automotive LDV	0.15	0.99	0.40	0.98

Source: Sector Decarbonization Targets can be calculated with IEA (n.d.) and IPR (n.d.) data set. Matching the scenario sectors with tilt sector and tilt subsector can be found in the supplementary material S2.2.

Supplementary Material - Support in applying the *tilt* method to construct a database

S1 Potential Other Data Inputs and Sources

S1.1 Firm data

We require the firm's business type, location, and products. When this information exists, our method can be applied. Illustrative data sources for firm-specific data can be, for example, Kompass, Open Corporates, and trade registries with granular data. Lepore *et al.* (2024) applied our method to europages, which Visible GmbH operates. Europages is an international B2B platform with around 2.6 million firms from Europe, where firms self-report the required information. After comparing coverage, benefits, limitations, costs, and data collection processes, Lepore *et al.* (2024) chose europages for its comprehensive, free access and product-level data. They collected data on firms in Austria, Germany, France, the Netherlands, and Spain. The dataset includes approximately 280,000 firms across these countries with 31,383 products.

S1.2 Life cycle impact assessment data

Before choosing ecoinvent, we considered four other data providers:

- Idemat: Offers accurate LCI data for specific sectors, but is a paid platform with infrequent updates.
- Nationale Milieu Database: A paid Dutch platform focused on construction products, limited to Dutch activities.
- Exiobase: Provides open-source global data, but has variable quality and coverage.
- World Steel Association LCI Database: This database offers detailed, open-source data on global steel production, but its scope is limited to the steel industry.

After evaluating various LCA data providers, ecoinvent was the most comprehensive and accurate source, covering multiple sectors and geographies.

S1.3 Climate Scenario data

The tilt method requires sector-level GHG reduction targets to create the climate data for the sector decarbonisation indicator. We sourced this data from climate scenario providers.

According to the IPCC (2022), a climate scenario is a "plausible description of how the future may develop" based on consistent assumptions, not a forecast. These scenarios provide sectoral decarbonisation targets needed to achieve specific temperature outcomes.

There are many scenario data providers. We chose two:

- Inevitable Policy Response (IPR, n.d.): Led by Vivid Economics and Energy Transition Advisors, IPR offers two scenarios—Forecast Policy Scenario (FPS) and 1.5°C Required Policy Scenario (1.5°C RPS), modelling the impact of policies and pathways to limit global warming to 1.5°C by 2050. IPR asks policy experts in specific countries how likely certain policies will be implemented at a particular time. For example, experts could be asked which year by which policy delivers significant nationwide market incentives to encourage farmers to reduce emissions from crop production and livestock. The experts' answers are then taken in a model-to-model analysis of potential future scenarios of CO2 pathways.
- World Energy Outlook (WEO, n.d.): Provided by the International Energy Agency (IEA), WEO offers three scenarios: the Stated Policy Scenario (STEPS), the Announced Pledges Scenario (APS), and the Net-Zero Emissions Scenario (NZE), the latter modelling a pathway to Net Zero by 2050.

We applied the IPR 1.5°C RPS and WEO NZE scenarios in *tilt* due to their comprehensive sector coverage and WEO's high market reputation, notably used by the European Central Bank. Although other scenarios could be used, we limited our selection to these for simplicity.

Table S1 below summarises key parameters used to evaluate these scenario providers and highlights critical differences between the WEO and IPR scenarios relevant to our work. Both cover similar regions, offering global aggregates and European data, though with slight variations in European geography. To maintain comparability, we selected the global aggregates for this application.

Table SI: Summary of key parameters used to evaluate the scenario providers

Regional granularity of projected GHG Emissions	The sectoral granularity of projected GHG Emissions	Time intervals	Period	Costs	Emissions Variable	Average global temperature target	Over-shoot	Source + Documentation	Updates
Inevitable Policy Response (IPR), 1.5°C RPS									
Western Europe (WEU); Global	14 sector-subsector combinations, including transport, construction, industry, power, energy, and Land Use	1 year	2021-2050	Free	CO2	1.5°C by 2050	low overshoot before 2050	NPR's "Supporting Key Documents" (Link)	Annually
World Energy Outlook (WEO), by International Energy Agency (IEA), NZE Scenario									
Free dataset: Global Extended dataset: EU	28 sector-subsector combinations, including transport, construction, industry, power, and energy.	5 year	2010-2050	Free / Extended: 640€ per user	CO2	1.4°C by 2100 (50% probability)	No overshoot before 2050	WEO 2023 Documentation and data (Link)	Annually

Source: Author's own.

WEO provides greater sector granularity, with 28 sector-subsector combinations, including detailed breakdowns of the energy and power sectors, though it does not cover land use. In contrast, IPR offers 14 land-use combinations but lacks detailed energy sector breakdowns.

IPR provides annual GHG emission projections, while WEO offers them in 5-year intervals. Both scenarios extend projections to 2050, enabling tilt to calculate indicators for 2030 and 2050. Regarding pricing, IPR's data is completely free, while WEO offers a free subset with a more detailed version available for purchase. The free WEO data was sufficient for our needs.

S2 Matching of different Data Sources

S2.1 Relative emission intensity indicators: Product Matching of different Data Sources with NLP

To construct the relative emission intensity indicator, we first need to match the firm-specific products with ecoinvent products to obtain the emission data needed for constructing the relative emission intensity rank (see **Section 3.1**). For this, an NLP matching algorithm was developed (**see code in S3**). The matching algorithm is openly accessible. This matching process involves identifying potential matches and confirming accurate matches.

In the first step, we use a Dense Passage Retriever (DPR) model to generate 10 potential ecoinvent matches for each europages product. Unlike traditional string comparisons, the DPR model uses semantic similarity matching, embedding product descriptions into a higher-dimensional space to assess deeper linguistic and semantic relationships. To train this model, we created a dataset using a BERT model, which identified five potential matches for each of 1,000 randomly selected europages products. This process resulted in 5,000 candidate matches, which were then manually labelled as "high," "medium," or "no match" by two reviewers.

A "high match" indicates very similar products, such as matching "necklace" to "necklace." A "medium match" involves relevant attributes affecting the emission intensity of a product, like matching "gold necklace" to "necklace." "No match" is assigned when products differ significantly, such as "chalk" not matching "limestone" despite their relationship as raw material and product. The labelling process included a review to ensure consistency, and this dataset was used to train the DPR model.

To train the model, we needed firm-specific data. After training, the DPR model provided 10 ecoinvent activities for each europages product. We then used a GPT-3.5 model, trained on our dataset, to categorise these matches as "no match," "high match," or "low match."

To validate the model, we tested it on 297 random europages products, generating 1,485 candidate matches. The manual review found 61 matches, with 52 correct and 9 false positives, resulting in a coverage rate of 20.5% and a false positive rate of 15%. The review process identified the false positives. The table below shows these 9 false positives.

Table SII: Matching of europages and ecoinvent Products – an Example of False Positives

europages_prod_DPR	**ecoinvent_prod_DPR**
anhydrous acids	adipic acid
glass mosaics	ceramic tile
gold ingots	gold, unrefined
iron, special grade	steel, chromium steel 18/8
photovoltaic panels	photovoltaics, electric installation for 3kWp module, at building
polyethylene	polyethylene pipe, corrugated, DN 75
pulp (cellulose)	cellulose fibre
salt substitute	salt
sowing machines	sowing

Source: Author's own.

Matching europages products with ecoinvent products is only the first step in linking europages to ecoinvent's LCA data. Product Life Cycle Assessment varies based on factors like region and whether the product is produced, traded, or sold. Therefore, after the initial product match, we also consider the firm's business type and location.

We use a business type mapper to align business types, as both data sources categorise them differently. For location, we apply a GEO filtering system. In total, we matched 3,144 europages products to 1,201 unique ecoinvent activities.

So many products fall out of the matching process for several reasons. First, the 31,383 products include services, like consultancy, which are not traditional products and therefore not included in ecoinvent. Second, some products are particular and may not align with the 20,000 ecoinvent activities. Third, the data quality from web scraping may not identify similar products, as broad categories like "equipment and accessories" can cover many items, making it hard for the algorithm to match accurately. Finally, the matching algorithm is conservative in prioritising data quality, which limits coverage.

We validated the data quality for the 136 firms and their 393 products. From these 393 products, we matched 198 products to ecoinvent activities, so the coverage was about 50%. From these 50% matches, 18.56% were false positives, and 84.34% were correct positives. In these cases, the coverage rate was higher as the selection of firms was biased, and we only picked firms that had at least one match with ecoinvent. However, the error rate is similar to what we have seen when testing our NLP model.

Table A9: Matching quality of activity name with product,

Does the activity name (ecoinvent) fit the product?	Answer
Yes	167 (84.34%)
No	31 (18.56%)
Total matched	198

Source: Author's own.

We performed an outlier analysis better to understand the spread of the absolute emission intensity values. As part of the outlier analysis, we applied the Interquartile Range Method (IQR) to identify outliers that lay beyond the maximum, defined through the following equation:

$$Maximum = 3rd\ Quartile + 1.5 * 3rd\ Quartile$$

This approach delivered a list of the highest 260 unique CO2e (kg/unit) values, ranging up to a CO2e (kg/unit) of 73,942,674,121. As a next step, we analysed the corresponding ecoinvent activities and the company products to which they matched. With that approach, we identified that many of the largest emission intensive products relate to activities in the field of construction, often the construction of whole infrastructure projects. For example, the highest emission intensity value mentioned above relates to constructing a whole port. While the matched product from the firm also corresponded to the construction of harbours, that firm offered as a service the construction of elements of a harbour instead of the whole harbour.

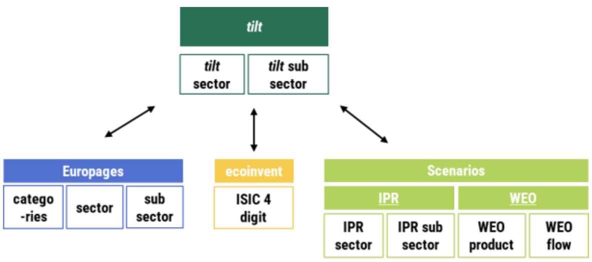
Similarly, we analysed all matches from the list of outliers and identified that the top 102 emission intensity values related to constructing whole infrastructures. We decided to exclude these values because SMEs cannot be made responsible for the emissions of a whole infrastructure project.

S2.2 Sector decarbonisation indicator: Mapping different sectors

As step 2 in constructing the sector decarbonisation indicator, our methodology involves mapping different sector classifications. There are two methods for assigning products to sectors. The first method involves mapping via ecoinvent. Suppose a product matches an activity in the ecoinvent LCA database. In that case, we use ecoinvent's sector information (4-digit ISIC code) and map it to the scenario sectors using our sector mappers (if you need the mappers, please contact us). If no ecoinvent match exists, we apply the second method, known as sector resolving, using Natural Language Processing (NLP). The NLP model identifies the most suitable sector information from the europages database, which is then mapped to a scenario sector.

To align products with scenario sectors, we developed a tilt sector classification that serves as an interface, allowing us to map each data source—europages, ecoinvent, WEO, and IPR—to *tilt* sectors. This approach simplifies the mapping process by avoiding the need for direct mappers between every combination of data sources. The schema below illustrates the mapping process across these different sources.

Figure A1: Overview of making different sector categorisations to the tilt sector categorisation



Source: Author's own

The figure above illustrates the relationships between the different mappers. We developed the following sector mappers:

- The europages-tilt sector mapper aligns each combination of europages' "category," "sector," and "subsector" to a unique "tilt sector" and "tilt subsector."
- The ISIC-tilt sector mapper links each 4-digit ISIC code to a unique "tilt sector" and "tilt subsector."
- The WEO-tilt sector mapper connects each combination of WEO's "product" and "flow" to a unique "tilt sector" and "tilt subsector."
- The IPR-tilt sector mapper maps each combination of IPR's "sector" and "subsector" to a unique "tilt sector" and "tilt subsector."

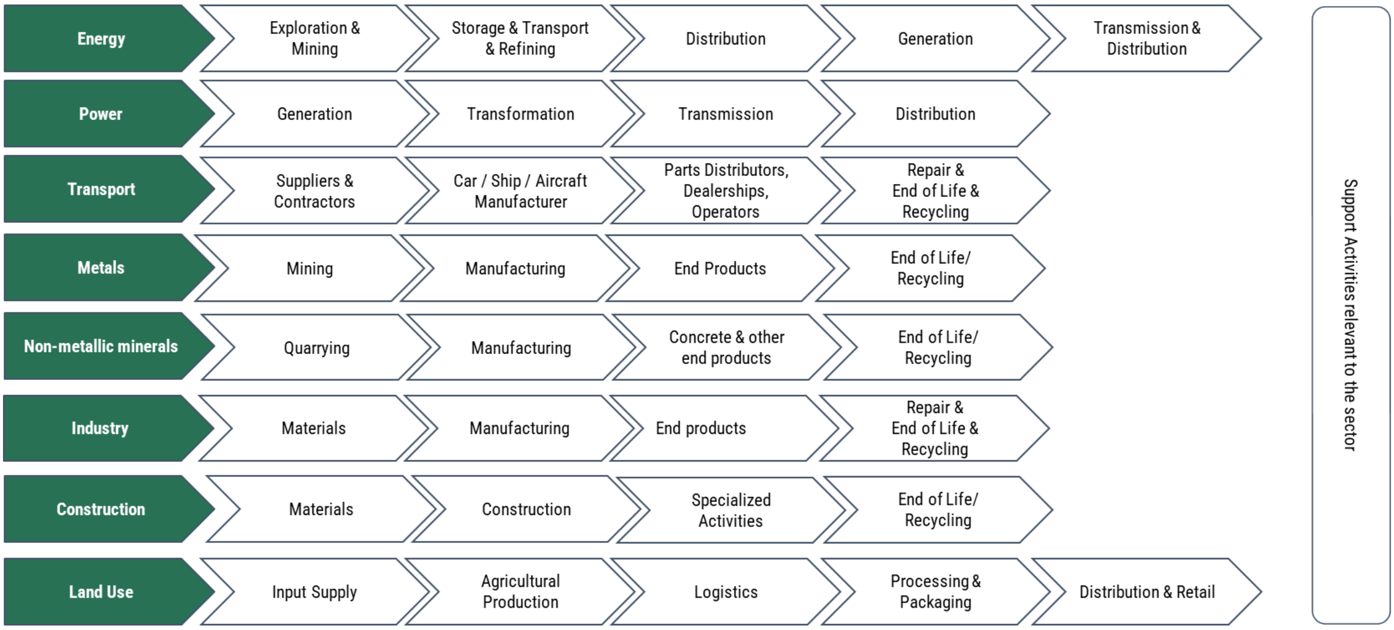
Several vital challenges arose during the development process of the sector mappers and the new tilt sector classification.

First, understanding which economic activities are included in different sectors was particularly challenging for the scenario sectors, as the documentation did not always provide transparent information. Extensive desk research and interviews with climate scenario experts overcame this challenge.

Second, mapping extensive and granular industry classifications, such as 4-digit ISIC codes, to other sector mappers required significant manual effort and a high degree of consistency in decision-making. This challenge was overcome through detailed decision rules and a 6-eye-principle to ensure consistency.

It was third, determining how risks and responsibilities from the transition to a low-carbon future would affect different supply chain segments. For example, assessing how transition risks in the automotive industry might impact suppliers required methodological decisions about whether manufacturers of essential electronic components for cars are more influenced by trends in the automotive sector, such as the shift to electric vehicles, or by broader trends in the industry sector, such as the trend towards more energy-efficient production. We decided that each sector covers the whole supply chain to overcome this challenge. That means a product/industry segment is assigned to the sector it originates from, not necessarily where it is used. E.g., “tractor manufacturing” is part of the sector “Other Industry” and not “Land Use”. For more details, please see **Figure S1** below.

Figure S1: The Value Chain of tilt sectors



Source: Author's own

This comprehensive supply chain coverage assigns responsibility for decarbonisation to the entire sector, especially the most emission-intensive elements. For instance, if the automotive industry must decarbonise by replacing internal combustion engines (ICEs) with electric vehicles (EVs), the sector decarbonisation target not only applies to the transportation segment but also extends to suppliers and manufacturers, who must adapt to new technologies to contribute to the sector's overall decarbonisation.

S3 Code to support constructing a dataset based on the *tilt* method

- NLPTiltMatch: NLP based data matching for tilt.
- tiltIndicatorBefore: Create input datasets for the tilt ecosystem.
- tiltIndicator: Implement the core business logic of the tilt indicators.
- tiltIndicatorAfter: Process indicator results so that they are closer to the user-facing outputs. It depends on multiple other "tilt" packages. To discover each dependency see the Remotes section of its DESCRIPTION file.
- tiltTransitionRisk:
- tiltCompanyMatch: helps users match tilt data with other sources based on a firm's name and address. The algorithm provides a similarity probability between firms, and if this similarity is below 0.98, we recommend manual validation to confirm the match.