Carbon Footprint of FDI and Multinational Enterprise Activities: Emission Intensities and Insights for France and the Netherlands

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Executive Summary

Foreign Direct Investment (FDI) plays a crucial role in global economic development and policy-making and can serve as a key mechanism for policymakers seeking to tackle climate change. While FDI promotes the international transfer of low-carbon technologies, it can also introduce challenges by allowing companies to circumvent stringent emissions regulations. This occurs when firms shift carbon-heavy production to countries with looser environmental rules—a process referred to as carbon leakage—and subsequently export the goods to other markets, making it vital for policymakers to thoroughly assess FDI's environmental impacts.

A key aspect of accurately estimating the carbon footprint associated with FDI is understanding the ownership dimension—distinguishing between domestic and foreign-owned enterprises. Incorporating ownership data allows for more granular analysis of emission sources and consumption patterns across global value chains (GVCs). Emissions stem not only from the operational activities of foreign-controlled firms but also from assets acquired through FDI, such as new buildings, infrastructure, and machinery. These investments, captured by Gross Fixed Capital Formation (GFCF), significantly contribute to the host country's economic growth but also generate emissions during both construction and operation. This underscores the need for comprehensive indicators covering both capital formation and ongoing business activities.

Methodological approaches to estimating the carbon footprint of FDI and of multinational enterprise (MNE) activities range from basic models requiring minimal data to advanced frameworks that incorporate detailed information on ownership structures, FDI composition, and international supply chains. More sophisticated models enable a clearer differentiation between emissions attributable to domestic and foreign-owned firms, providing richer insights for policy analysis and enhancing comparability across countries. This increased granularity improves the accuracy of footprint estimates and supports targeted interventions.

Recent research, including Borga et al. (2023), illustrates the complex impact of FDI on host economies. While FDI can drive economic growth, diversify exports, and foster structural transformation, emissions from foreign-owned enterprises add complexity to policy design. Isolating these emissions requires detailed ownership and activity data, which can be achieved through global input-output models that integrate ownership information. This approach enhances policymakers' ability to craft targeted interventions, such as coordinated strategies and green investment incentives.

The importance of integrating ownership data is highlighted by findings from France and the Netherlands. In France, private emissions data reveal clear differences in emissions intensity between domestic and foreign-owned firms, with foreign multinationals showing higher carbon footprints in certain sectors, guiding sector-specific policies. In the Netherlands, national statistics allow estimation of MNEs' emission intensities, showing significant contributions in key industries. Incorporating ownership details improves accuracy, uncovering patterns otherwise hidden in aggregate data.

In conclusion, integrating the ownership dimension into carbon footprint estimation is essential for capturing the true environmental impact of FDI and multinational enterprises. This enables policymakers to identify major emission sources, design effective coordinated responses, and encourage sustainable investments. While data gaps and enterprise heterogeneity remain as challenges, ongoing methodological improvements and harmonized data initiatives offer promising pathways forward.

Introduction

Foreign Direct Investment (FDI) policies are a crucial tool for policymakers in addressing climate change. FDI not only facilitates the transfer of low-carbon technologies across borders (see Gill et al. (2018)) but also poses challenges, as it can enable firms to bypass stricter emissions standards by relocating carbon-intensive production processes to countries with more lenient regulations, a phenomenon known as carbon leakage, and then exporting the production to other economies.

To fully understand these dynamics, it is essential to incorporate the ownership dimension into carbon footprint estimates, distinguishing between domestic and foreign-owned firms. This additional context regarding FDI, Multinational Enterprises (MNEs), and Global Value Chains (GVCs) enhances the understanding of emission sources, ownership structures, and consumption patterns, ultimately providing policymakers with vital information to develop coordinated climate-related strategies. Improvements can be made by including data on the type of assets involved in FDI and related MNE emissions. These indicators would reflect the emissions from both capital formation financed by FDI and the emissions generated by the operations of foreign-controlled firms within the host economy.

According to Borga et al. (2023), one benefit of FDI for host countries is the expansion of production capacity through greenfield investments and enhancements to existing operations, such as new buildings, infrastructure, machinery, and equipment. FDI has also been associated with technological know-how and skills' spillovers to the domestic economy (Sugiharti et al., 2022) and with exports diversification (Tadesse and Shukralla, 2013). These investments contribute to Gross Fixed Capital Formation (GFCF), which captures the total value of a producer's acquisitions of fixed assets, minus disposals, along with certain specified expenditures that enhance the value of non-produced assets. However, the GFCF process also generates carbon emissions. The FDI carbon footprint indicator aims to estimate the total carbon emissions arising from GFCF created by foreign investments in the host economy.

Furthermore, Borga et al. (2023) highlight that FDI can stimulate economic activity, diversify exports, and foster structural changes by introducing new industries. Nevertheless, the production activities of foreign-owned enterprises contribute to carbon emissions in the host economy. Isolation of these operations is challenging without detailed ownership data. Information on MNE activities allows for the identification of a subset of FDI enterprises where direct investors exert control. By employing a global input-output model that incorporates the ownership dimension, it becomes feasible to estimate the carbon footprint associated with MNE activities effectively.[1]

This paper is organized as follows: the next section highlights the importance of considering the heterogeneity among different types of enterprises, particularly foreign multinationals and domestic enterprises, in estimating the carbon footprint related to FDI and MNE operations. This is followed by a section on the methodology used to estimate the carbon footprint of FDI and the activities of MNEs. The paper then discusses the estimation process in different data situations, using toy input-output models to illustrate possible estimation approaches, and emphasizes the importance of incorporating firm heterogeneity and ownership in supply, use, and input-

[1] The ideal estimation of the MNEs emissions intensities will be based on data of the total emissions and output of the MNEs in the host economy.

output tables for policy analysis—particularly in the context of this work. A subsequent section provides an overview of harmonized databases available from international organizations that can be used in this work.

In estimating the FDI impact on global emissions, a key component is estimating the emissions of MNEs and their intensity by industry. Among the possible approaches is the estimation of these emissions using private data. Accordingly, the following discussion presents the methodology of this approach as applied to France, with its results used in the section discussing the carbon footprint of foreign MNEs' activities in France, see Genre et al. (2025). Another possible approach relies on data from national statistical offices; here, emission intensity estimates for the Netherlands by Van Rossum et al. (2014) and Statistics Netherlands (2024) are used to estimate the carbon footprint of MNE activities in the Netherlands.

The final section offers concluding comments and discusses the way forward.

Heterogeneity

This section explains that different types of enterprises, such as foreign-owned multinationals and domestically owned micro enterprises, are different in many aspects. This heterogeneity has consequences for estimates of the carbon footprint related to FDI or to the operations of MNEs as well. Therefore, it is necessary to take this heterogeneity into account. Otherwise, assuming that all enterprises in an industry produce the same goods and services and use the same products from the same sources (domestically and abroad), the results will be biased. Subsequently, the section explains how to do this in general terms, referring to a handbook that provides extensive guidance in compiling the necessary data. The section ends with the remaining data gap, emissions by MNEs and non-MNEs, mentioning two projects which tackled this issue.

Heterogeneity and the literature

It is well-known that different types of enterprises have different characteristics; the literature on enterprise heterogeneity is large. We mention a few stylized facts. Comparing MNEs to non-MNEs in the same industry, on average an enterprise in the first group:

- imports more
- exports more
- is larger in terms of revenue and employment
- is more productive

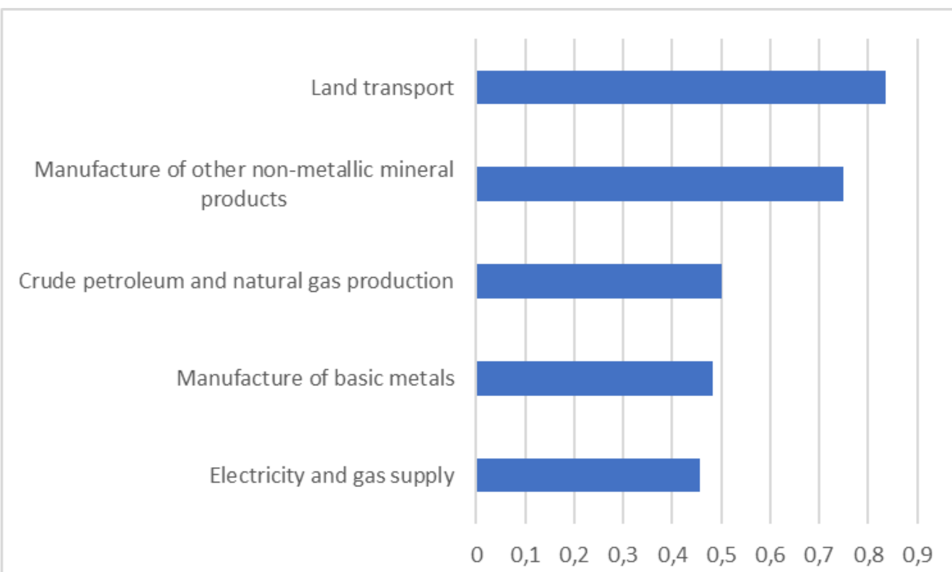
Size, ownership, and age are the most important characteristics that make enterprises differ (Wagner, 2007, 2012; Bernard et al., 2007, 2012). This leads to massive dispersion in enterprise outcomes, such as revenue, employment, exports, and Total Factor Productivity (TFP) (Bernard et al., 2022). Since MNEs import relatively more intermediate goods than domestic enterprises, they integrate more foreign (and less domestic) value added into their production (De Backer et al., 2019). Another explanation for the differences is that MNEs and non-MNEs might have very different production processes ("how") and that they might produce very different goods and services ("what"). Foreign-owned MNEs generate more income from intangible assets, relatively often related to R&D and sales, whereas domestically owned enterprises concentrate on fabrication tasks (Cadestin et al., 2021).

Relevance for carbon footprint related to FDI and MNEs

The previous paragraph provided the insight that MNEs and non-MNEs are different in what they produce and how they produce. Furthermore, note that even with the same production process, if the MNE imports relatively more of its intermediate inputs, its emission intensity in the country of production will be smaller. And even when MNEs and non-MNEs import the same amount but from a different source country, the different supply chains will lead to different carbon footprints. Sillen and Jaarsma (2014) and Antràs et al. (2024) show that foreign-owned enterprises trade relatively more with the parent country. Altogether, it is expected that one unit of production of MNEs will have a different carbon footprint than one unit of production of non-MNEs.

As a consequence of all these differences, the emission intensities of MNEs and non-MNEs can be very different in the country where they are producing. This is confirmed in the following example from the Netherlands. Figure 1 shows that in the same industry, several domestically owned enterprises emit less CO_2 per unit of production than foreign-owned enterprises. This could have all kinds of causes. For example, consider the industry of electricity and gas suppliers. The Dutch-owned enterprises might be relatively more focused on supplying gas (relatively few emissions per unit of production) and the foreign-owned enterprises might be relatively more focused on generating electricity using coal (relatively many emissions per unit of production).

Figure 1 Domestic CO_2 emissions by unit of production, ratio of domestically versus foreign-owned enterprises in the Netherlands, 2008



Source: Authors' calculations based on Van Rossum et al. (2014) and Statistics Netherlands (2024).

How to compile the necessary data

The common way to estimate the carbon footprint of an industry is using a Multi-Country Input-Output Table (MCIOT). This shows, for example, how much the metal industry in the Netherlands produces for the car industry in Germany. One fixes an industry in a country, considers all its suppliers, the suppliers of the suppliers and so on. One of the assumptions in this approach is that every (type of) enterprise in this industry has the same production structure: everybody uses the same inputs from the same sources (industries and countries) and produces the same outputs from the same sources. The previous paragraphs showed that this assumption is not valid when comparing MNEs and non-MNEs.

To take heterogeneity properly into account, it is necessary to make the distinction between MNEs and non-MNEs in the country under concern in the MCIOT. If one is only interested in the carbon footprint related to operations of foreign-owned MNEs in a specific country, it is sufficient to disaggregate each industry in that country into a foreign-owned part and a domestically owned part and embed the results in an MCIOT. For example, estimate how much the metal industry in the Netherlands produces for the foreign-owned car industry and for the domestically owned car industry in Germany. However, when one is interested in more countries, it is advised to disaggregate each industry in each country in two parts and embed the results in an MCIOT. For example, estimate how much the domestically owned metal industry in the Netherlands produces for the foreign-owned car industry in Germany.

Both approaches have advantages and disadvantages. The advantage of a single-country approach is that one might have access to very detailed data, and that one can choose the MCIOT according to the particular research questions at hand, e.g., to have more or less countries and industries, to be more recent and so on. The disadvantage is that one has to disaggregate the national input-output table and embed it into an MCIOT oneself. The advantage of the multi-country approach is that there is already a fully disaggregated MCIOT, namely the Analytical Activity of Multinational Enterprises (AAMNE) of the OECD (Cai et al., 2023). The disadvantage is that choosing this disaggregated MCIOT does not provide any flexibility with respect to countries, industries, and timeliness.

The *Handbook on Extended Supply and Use Tables and Extended Input-Output Tables* (OECD/European Union, 2025) provides extensive guidance on how to compile a national disaggregated input-output table. It also explains in detail how the result can be embedded into an MCIOT, building on OECD and Statistics Denmark (2017), Michel et al. (2018) and Yamano et al. (2022).

A remaining data gap

Although there is much information about production, value added, imports and exports by MNEs and non-MNEs, by industry and by country, there is hardly any information available about their emissions at this macro level. Van Rossum et al. (2014) compiled such data for the Netherlands, reporting year 2008, using a three-step approach that is described later in this paper. Genre et al. (2025) use a different approach. They use firms' greenhouse gas (GHG) reports and model the remaining gaps.

Methodology for estimation of FDI and activities of MNEs carbon footprints

This section discusses the methodology used for the estimation of carbon footprint indicators related to capital formation financed by FDI, and to the operations of foreign-controlled firms, i.e., carbon footprint from MNEs incorporated in trade and final demand.

The next 2 subsections below will delineate the methodologies for estimating the carbon footprint of FDI and the activities of MNEs, respectively. As discussed in the previous section on heterogeneity of the firms, integrating ownership dimensions into input-output tables can markedly improve the precision of estimating FDI carbon footprints and enhance the analytical capabilities of the results. Consequently, the last subsection will provide a detailed overview of the structure of a global input-output table incorporating ownership dimensions.

FDI carbon footprint

The methodology that is used to estimate the carbon emissions arising from the supply of GFCF funded by FDI involves, first, to determine the amount of GFCF, by type of asset, funded by a given industry FDI, e.g., the GFCF expenditure on buildings and structures, land improvements, machinery, transport equipment, ICT equipment, etc., made by the Electronic Industry with the resources coming from FDI. For example, FDI in the Electronic Industry is used to buy a machine that is produced in the Machine Industry.

Let's define the GFCF of an industry FDI as the vector k_i, specifying the expenditures in GFCF, by type of asset, made by industry i.
Following the methodology presented by Guilhoto (2021), Yamano and Guilhoto (2020), and Yamano et al. (2023), the estimation of the carbon footprint of FDI is done as follows:

Industry emission intensities, in metric tons of CO_2 per USD millions of output, are defined as the ratio between emissions and associated output:

$$\text{Industry emission intensities (e) = Industry emissions / Industry output} \tag{1}$$

To estimate carbon footprint of FDI one needs to take into consideration not only the direct emissions necessary for production but also the indirect emissions, i.e., the upstream emissions included in the inputs used in the production process. For example, to manufacture the GFCF demanded by FDI, direct emissions are produced by the industries producing these capital goods, while indirect emissions are produced by the upstream industries (both domestic and foreign) that supply the inputs required to produce these capital goods. Thus, the footprint of FDI is the sum of direct and indirect emissions. Given the complexity and fragmentation of production processes, this estimation requires the use of models based on IO analysis. In brief, this methodology requires the estimation and use of a "total requirements matrix," which shows in a given column the direct and indirect inputs needed from the different industries to produce one unit of the final product, known as the Leontief inverse matrix of total requirements.

From the emission intensities estimated in Equation 1 and the use of the Leontief inverse matrix it is possible to obtain the *carbon footprint of FDI*.

The *carbon footprint of FDI* of industry i is defined by the vector m_i, which links final GFCF demanded by industry i FDI, k_i, with the input requirements and the associated industry emission intensities:

$$\boldsymbol{m_i} = \hat{e}Bk_i \qquad (2)$$

Where $\hat{e}$ is a diagonal matrix with the industries' emissions intensities (as defined in Equation 1) in the main diagonal and B is the Leontief inverse matrix. As can be seen in Equation 2, the independent variable on the right side is the GFCF by industry i FDI (k_i) and the dependent variable are emissions (m_i), so it is possible to estimate for a basket of capital goods what are the carbon footprints and what are the source industries and source countries of these emissions.

Activities of MNEs carbon footprints

To estimate the carbon footprints of MNEs activities - namely, the total emissions from foreign-owned enterprises included in final demand and exports - a similar approach to that presented above can be employed. However, it is essential that both industry emissions intensities and the input-output table incorporate an ownership dimension, delineating industry breakdowns based on domestic and foreign-controlled enterprises. This ensures a comprehensive estimation process, as outlined below.

Industry emission intensities, in metric tons of CO_2 per millions USD of output, are now defined as the ratio between industry i emissions and associated output according to ownership w, i.e., domestically and foreign-owned enterprises:

$$\textit{Industry emission intensities } (e_{wi}) = (\textit{Industry emissions})_{wi} \,/\, (\textit{Industry output})_{wi} \qquad (3)$$

The carbon footprint emissions by ownership, M_w , are obtained by multiplying the emissions intensities by ownership, e_w , the Leontief inverse by ownership, B_w , and production for final use by ownership, Y_w :

$$M_w = \hat{e}_w B_w Y_w \qquad (4)$$

The matrix Y_w shows the production for final use of goods and services according to the ownership dimension of the supplying industry *i*, by specifying the ownership origin of the product being used, i.e., sourced by a domestic or foreign-owned enterprise. The carbon footprint emissions matrix, M_w , shows the carbon emissions emitted by industry *i*, according to ownership, to meet the final demand of the products produced by domestic and multinationals enterprises.

Using the same idea presented in equation (4) above, but, replacing the final demand matrix with a matrix of exports by ownership, it is possible to estimate the emissions embodied in exports produced by domestic and foreign-owned multinational enterprises.

$$C_w = \hat{e}_w B_w T_w \qquad (5)$$

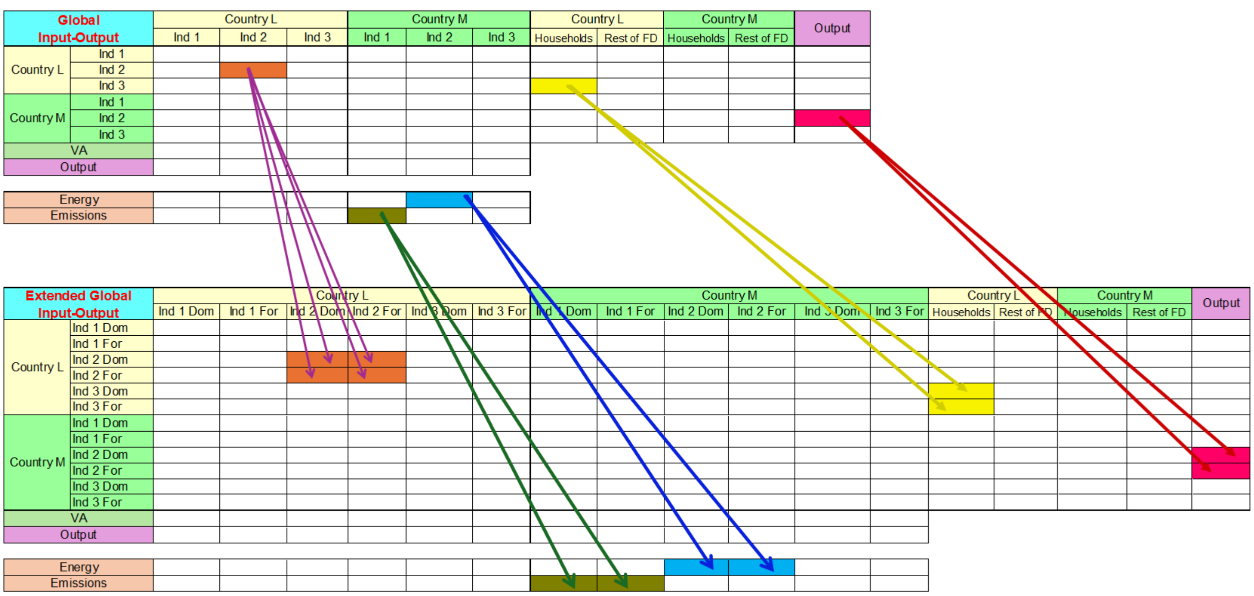
where C_w is a matrix of carbon footprints, by source industry split by ownership, associated with the exports, and T_w is a matrix of exports by domestic and foreign-owned enterprises. For example, the emissions in country L that produces something that is used in country M by a domestic enterprise to export.

The input-output table with the ownership dimension

The input-output table with the ownership dimension (domestic and multinational enterprises) splits the national industries production according to the technology of production of these industries.

Adapting the description in Cadestin et al. (2018)[2], Figure 2 illustrates how each cell of the intermediate consumption matrix in the global input-output table is divided into four cells corresponding to the inputs used by domestic-owned and foreign-owned firms. The final demand matrix is split only across rows to reflect the final demand of products from domestic-owned and foreign-owned firms. The value-added and gross output vectors are split across columns to indicate the value-added and gross output of domestic-owned and foreign-owned firms in each country and sector. With the resulting global input-output, we can for instance calculate the input requirements of a foreign-owned firm operating in industry 2 and country L from a domestic-owned firm operating in industry 1 of country M.

Figure 2 Splitting a global input-output table by ownership



Source: Authors' elaboration

[2] In this subsection we use the description for a global input-output table, however, the same idea can be applied to national tables.

Estimating Carbon Footprints in different data situations

This section presents a structured progression of approaches for estimating the carbon footprint associated with Foreign Direct Investment (FDI) and the activities of Multinational Enterprises (MNEs). The methods range from simplified models requiring minimal information to advanced frameworks incorporating detailed data on ownership, FDI composition, and the global fragmentation of production. As data availability increases, estimates become more accurate and better suited for analytical and policy purposes.

Estimating these emissions depends on data availability and countries' analytical capacity. Figure 3 summarizes the different cases, with sample results shown using toy models. Data in these toy models, for example about value added, imports and emission intensities at foreign owned and domestically owned enterprises, are based on real world observations. All related tables and estimates are available in the supplementary Excel file.

Table 1 presents the main results that will be discussed in the following sections, with the precision of the results increasing as more information is added to the analysis, as illustrated in Figure 3. Note that the results from the various approaches differ substantially. The first three columns summarize the results for Case 1, minimum data approach, while columns 4 to 9 refers to Case 2, refinement through FDI composition and SPE exclusion, and the results in the final 3 columns refer to the more comprehensive results, where more granular data is used in the estimation, as presented in Case 5 with full integration of FDI, ownership, and global IO data.

An example of the results: columns 4-6 present the results when only incoming Greenfield FDI is considered, which amounts to 495 in country L. The corresponding carbon footprint is 77.3 and the carbon footprint per unit of incoming FDI is 0.156. The results are available by industry and by country.

Table 1 Summary results for the carbon footprint of FDI, for countries L and M

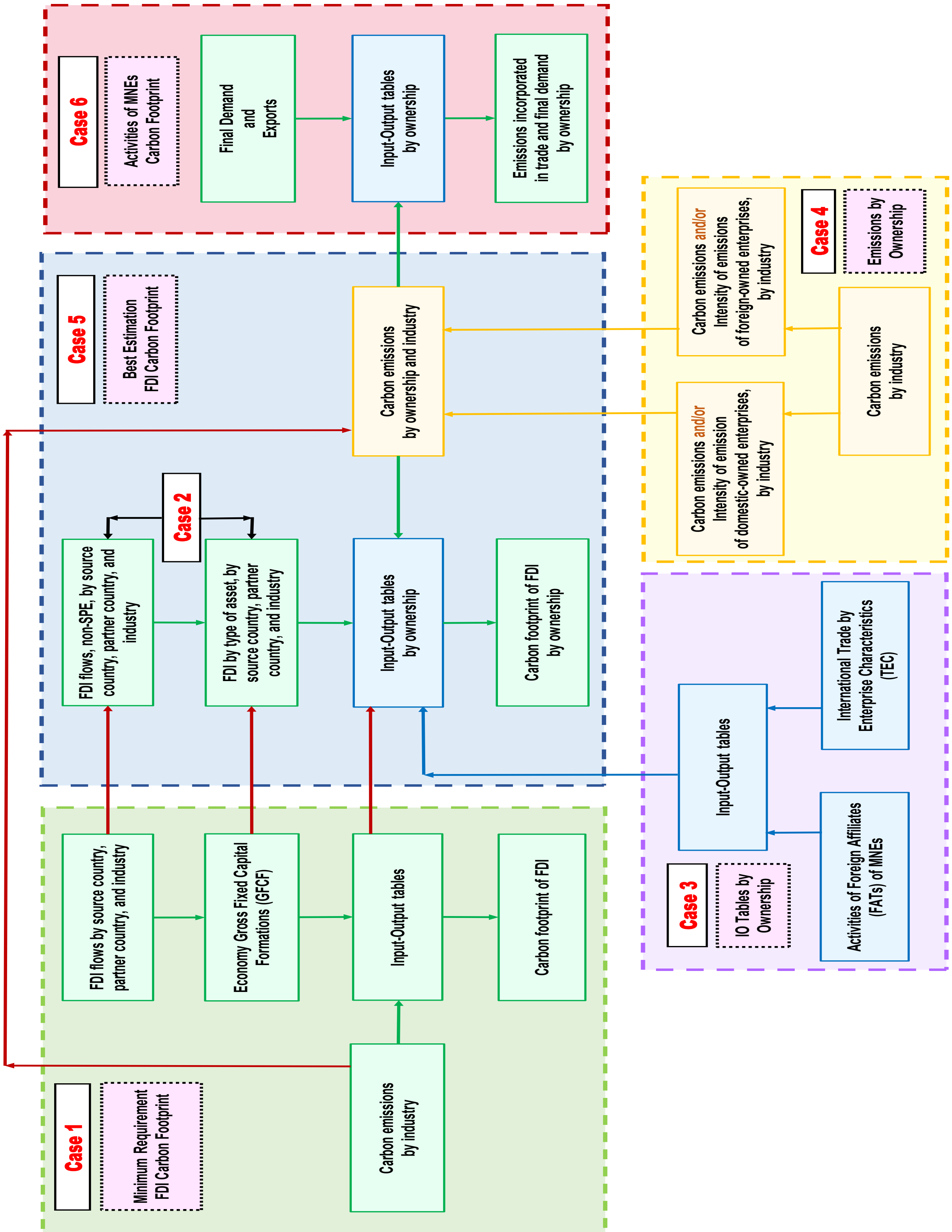
Country L		FDI Total Using GFCF Structure			FDI Greenfield			FDI Greenfield			FDI Greenfield		
		National I-O - No imports			National I-O - No imports			Global I-O			Global I-O Ownership		
		1	2	3	4	5	6	7	8	9	10	11	12
		Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value
Country L	Ind 1				35.0	9.1	0.261	35.0	23.3	0.665	35.0	22.4	0.640
	Ind 2				300.0	51.2	0.171	300.0	269.8	0.899	300.0	242.8	0.809
	Ind 3				160.0	17.0	0.107	160.0	136.2	0.851	160.0	127.4	0.796
Total		800.0	174.0	0.217	495.0	77.3	0.156	495.0	429.3	0.867	495.0	392.6	0.793

Country M		FDI Total Using GFCF Structure			FDI Greenfield			FDI Greenfield			FDI Greenfield		
		National I-O - No imports			National I-O - No imports			Global I-O			Global I-O Ownership		
		1	2	3	4	5	6	7	8	9	10	11	12
		Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value	Value	C-FP	C-FP / Value
Country M	Ind 1				230.0	174.5	0.759	230.0	194.2	0.844	230.0	182.8	0.795
	Ind 2				1,100.0	1,007.6	0.916	1,100.0	1,059.1	0.963	1,100.0	974.4	0.886
	Ind 3				140.0	92.2	0.659	140.0	122.1	0.872	140.0	114.2	0.815
Total		2,800.0	2,503.1	0.894	1,470.0	1,274.3	0.867	1,470.0	1,375.3	0.936	1,470.0	1,271.3	0.865

Note: Value = value of incoming FDI, C-FP = Carbon Footprint, C-FP/Value = carbon footprint per unit of incoming FDI

Source: Authors' elaboration

Figure 3 Estimation overview of FDI and activities of MNEs carbon footprint



Source: Authors' elaboration

Minimum data approach

The most basic methodology, Case 1, relies on aggregate FDI inflows, national or global input–output (IO) tables, and industry-level emissions. This approach requires strong assumptions: all FDI is treated as funding new capital formation, and the composition of FDI-financed investment is assumed to mirror the average structure of the host economy. It also assigns all upstream emissions to domestic producers when national IO tables are used, since imported capital goods cannot be traced. These simplifications typically lead to an overestimation of the domestic carbon footprint of inward FDI and provide only a broad approximation of the relationship between foreign investment and emissions.

Let's assume first that little is known about FDI inflows, and the only information available is that the total FDI inflows for countries L and M are 800 for country L and 2800 for country M. Given this information, and assuming that all these inflows are greenfield and aimed at creating new capital in the economy, and that their investment structure follows the same pattern as the average GFCF of these economies, using a national input-output table and corresponding emissions yields a total domestic carbon footprint of FDI—i.e., not considering the carbon footprint of imported GFCF—of 174.0 for country L and 2,503.1 for country M (see Table 1). This represents an overestimation of the domestic carbon footprint, given that not all FDI is greenfield and not all FDI is aimed at creating new capital.

Refinement through FDI composition and SPE exclusion

A more detailed approach, Case 2, becomes possible when Special Purpose Entities (SPEs) are excluded and additional information on FDI composition is introduced. Once FDI inflows are broken down by partner country, industry, and category—such as greenfield projects, mergers and acquisitions, or capacity expansions—the allocation of carbon emissions becomes more precise. Further granularity is achieved by distinguishing FDI by asset type, including structures, machinery, ICT equipment, and transport equipment. When this information is combined with global IO tables, the model captures the international fragmentation of production and can allocate emissions not only domestically but also to the countries where capital goods are manufactured. These refinements often lead to substantially different emission profiles, especially for economies highly integrated into global supply chains.

With this more detailed information, we observe in Table 1 that the carbon footprint of 77.3 for country L and 1,274.3 for country M using a national IO table and considering emissions in the domestic economy only, and 429.3 for country L and 1,375.3 for country M using a global IO table and taking all worldwide emissions in the global value chain into account (thus including emissions in the domestic economy). These results highlight the importance of having more detailed information for FDI, as well as the benefits of using a global IO table. In this example, of the emissions of 429.3 from greenfield capital investment in country L, 80.2 units of emissions occur in country L, while the remaining 349.1 come from country M. In the case of country M, of the total emissions of 1,375.3, the majority (1,300.5) occur in country M, with only 74.8 imported from country L.

Incorporating Enterprise Heterogeneity

A major improvement arises from explicitly accounting for the heterogeneity between domestic enterprises and foreign-owned MNEs, Case 3 in Figure 1. Firms with different ownership structures typically exhibit distinct production processes, technology adoption, size, productivity, and sourcing strategies, all of which influence emission intensities. Integrating data from Foreign Affiliates Statistics (FATS) and Trade by Enterprise Characteristics (TEC) enables the construction of ownership-disaggregated IO tables in which industries are split into domestic and foreign-owned components. This structure reveals meaningful differences in emission intensities and supply chain patterns that aggregate models cannot capture, thereby reducing distortions that stem from assuming identical production technologies across all firms.

Some key indicators by industry, for the economy as a whole and for the industry breakdown by ownership, resulting from the estimation process using information from the FATS and TEC databases, are presented in Table 2. It can be observed that the coefficients for value added and imports of intermediate consumption (by unit of production) differ considerably from the average coefficients of the economy. For example, in the case of value added for industry 2 in country M, the average coefficient is 0.54, while the coefficient for domestic enterprises is 0.46 and for foreign MNEs is 0.72.

Table 2 Key indicators by industry for the economy as a whole and for the industry breakdown by ownership

<table>
<tr><th colspan="2" rowspan="3">Global Input-Output</th><th colspan="4">Key Indicators by Industry Economy and Ownership</th></tr>
<tr><th colspan="2">Coef of VA</th><th colspan="2">Coef of imports IC</th></tr>
<tr><th>Econ</th><th>Own</th><th>Econ</th><th>Own</th></tr>
<tr><td rowspan="6">Country L</td><td>Ind 1 D</td><td rowspan="2">0.58</td><td>0.57</td><td rowspan="2">0.100</td><td>0.083</td></tr>
<tr><td>Ind 1 F</td><td>0.67</td><td>0.250</td></tr>
<tr><td>Ind 2 D</td><td rowspan="2">0.45</td><td>0.39</td><td rowspan="2">0.171</td><td>0.158</td></tr>
<tr><td>Ind 2 F</td><td>0.62</td><td>0.211</td></tr>
<tr><td>Ind 3 D</td><td rowspan="2">0.61</td><td>0.60</td><td rowspan="2">0.100</td><td>0.099</td></tr>
<tr><td>Ind 3 F</td><td>0.74</td><td>0.123</td></tr>
<tr><td rowspan="6">Country M</td><td>Ind 1 D</td><td rowspan="2">0.55</td><td>0.51</td><td rowspan="2">0.009</td><td>0.006</td></tr>
<tr><td>Ind 1 F</td><td>0.72</td><td>0.020</td></tr>
<tr><td>Ind 2 D</td><td rowspan="2">0.54</td><td>0.46</td><td rowspan="2">0.011</td><td>0.006</td></tr>
<tr><td>Ind 2 F</td><td>0.72</td><td>0.021</td></tr>
<tr><td>Ind 3 D</td><td rowspan="2">0.66</td><td>0.65</td><td rowspan="2">0.010</td><td>0.008</td></tr>
<tr><td>Ind 3 F</td><td>0.79</td><td>0.030</td></tr>
</table>

Source: Authors' elaboration

Ownership Specific Emission Intensities

To fully incorporate ownership into the estimation of carbon footprints, emissions must also be allocated between domestic enterprises and MNEs, Case 4 in Figure 1. The resulting ownership-specific emission intensities offer a more accurate depiction of how domestic and foreign firms contribute to national emissions. When these intensities are used to evaluate the carbon footprint of FDI financed capital goods, the estimates frequently fall below those produced by aggregate industry averages. This occurs because MNEs, in many cases, operate with cleaner technologies or more efficient input mixes than the typical domestic firm.

Table 3 presents the coefficients of emissions by industry for the economy as a whole and for the breakdown by ownership. For example, in the case of industry 2 in country M, the average coefficient of emissions is 0.75, while the coefficient for domestic enterprises is 0.86 and for foreign MNEs is 0.50.

Table 3 Coefficients of emissions by industry for the economy as a whole and for the industry breakdown by ownership

Global Input-Output		Coef of emissions	
		Econ	Own
Country L	Ind 1 D	0.25	0.26
	Ind 1 F		0.20
	Ind 2 D	0.47	0.51
	Ind 2 F		0.38
	Ind 3 D	0.10	0.11
	Ind 3 F		0.08
Country M	Ind 1 D	0.35	0.39
	Ind 1 F		0.21
	Ind 2 D	0.75	0.86
	Ind 2 F		0.50
	Ind 3 D	0.16	0.17
	Ind 3 F		0.11

Source: Authors' elaboration

Full Integration of FDI, Ownership, and Global IO Data

The most advanced estimation method incorporates detailed FDI data—including industry and asset breakdowns—into a global ownership-disaggregated IO framework with ownership-specific emission intensities, Case 5 in Figure 1. This allows for a comprehensive mapping of emissions embodied in FDI-financed capital formation, tracing both domestic and imported emission contributions. The method also supports the estimation of emissions embodied in final demand and exports for domestic and foreign-owned firms separately. This integrated perspective highlights how foreign-owned MNEs often export a larger share of emissions, reflecting their deeper participation in global value chains, and how consumption in one country can drive emissions in another.

The results in Table 1 show a carbon footprint of 392.6 from greenfield capital investment in country L and 1,271.3 for country M. These results indicate a smaller carbon footprint of FDI compared to the results obtained without considering firm heterogeneity—8.6% less for country L and 7.6% less for country M. This suggests that the capital goods are produced by firms with a lower carbon footprint, specifically the MNEs in this example, compared to the average firm in the economy. Consequently, the production of consumer goods will have a higher carbon footprint than the average industry in the economy. The total carbon footprint by industry per monetary unit of production—i.e., including direct and indirect emissions—is presented in Table 4, which shows that the overall total intensity of MNEs (foreign companies) is smaller than that of domestic enterprises in both countries, L and M.

Table 4 Carbon footprint by industry per monetary unit of production of domestically and foreign owned enterprises in countries L and M

Carbon footprint by industry per monetary unit of production		
Country	Industry	Cabron FP
Country L	Ind 1 D	0.493
	Ind 1 F	0.445
	Ind 2 D	0.827
	Ind 2 F	0.617
	Ind 3 D	0.285
	Ind 3 F	0.225
Country M	Ind 1 D	0.771
	Ind 1 F	0.431
	Ind 2 D	1.343
	Ind 2 F	0.752
	Ind 3 D	0.361
	Ind 3 F	0.226

Source: Authors' elaboration

Carbon footprint of the activities of MNEs

The carbon footprint of MNE activities (Case 6) is measured by estimating emissions linked to trade and final demand, categorized by ownership, using previously collected data. This approach reveals how emissions are allocated throughout production and consumption stages across industries and countries, factoring in whether firms are domestic or foreign owned. By including both trade and final demand emissions, this method delivers a more complete global carbon footprint picture, supporting more precise mitigation efforts.

Table 5 demonstrates how emissions from various industries in countries L and M are allocated based on ownership (domestic vs. foreign) and final demand (domestic vs. foreign). The data show that foreign-owned MNEs tend to export a larger share of their emissions compared to domestic firms, highlighting their deeper involvement in global value chains. Specifically, a greater proportion of emissions from domestic enterprises stays within their own countries, while foreign-owned MNEs have a higher percentage of emissions linked to foreign consumption. Country L is characterized as a smaller, more trade-open economy with lower emission intensity than country M.

Concluding Remarks

The analysis demonstrates that the quality and policy relevance of carbon-footprint estimates depend critically on the availability of detailed, harmonized data. Basic models provide only coarse approximations, while methods incorporating FDI composition, ownership structures, micro-level emissions, and global supply-chain linkages yield more precise and meaningful results. As global production networks continue to expand, improving statistical coverage—particularly regarding MNE activities and emissions—will be essential for understanding the environmental implications of international investment and for designing effective climate-policy interventions.

Table 5 Carbon emissions incorporated in Final Demand by source country and industry, by ownership, and by Final Demand country, for countries L and M

Carbon Emissions in FD by Ownership		Carbon Emissions				
		Emissions			Shares (%)	
		Country L	Country M	Total	Country L	Country M
Country L	Ind 1 D	118.3	19.7	138.0	85.8	14.2
	Ind 1 F	8.9	3.1	12.0	74.10	25.90
	Ind 2 D	1,212.5	227.5	1,440.0	84.20	15.80
	Ind 2 F	289.1	70.9	360.0	80.30	19.70
	Ind 3 D	1,079.8	72.2	1,152.0	93.73	6.27
	Ind 3 F	43.1	4.9	48.0	89.72	10.28
	Dom	2,410.6	319.4	2,730.0	88.30	11.70
	For	341.1	78.9	420.0	81.20	18.80
	Total	2,751.6	398.4	3,150.0	87.35	12.65
Country M	Ind 1 D	117.3	2,962.7	3,080.0	3.81	96.19
	Ind 1 F	23.2	396.8	420.0	5.52	94.48
	Ind 2 D	683.8	23,316.2	24,000.0	2.85	97.15
	Ind 2 F	253.4	5,746.6	6,000.0	4.22	95.78
	Ind 3 D	125.0	7,315.0	7,440.0	1.68	98.32
	Ind 3 F	25.1	534.9	560.0	4.48	95.52
	Dom	926.1	33,593.9	34,520.0	2.68	97.32
	For	301.6	6,678.4	6,980.0	4.32	95.68
	Total	1,227.7	40,272.3	41,500.0	2.96	97.04

Source: Authors' elaboration

Harmonized Data Sources in Monetary Values

The estimation of the carbon footprint associated with FDI relies on standardized data collection methods. This process includes developing consistent templates and definitions for gathering necessary information. Currently, organizations such as the OECD, Eurostat, UNCTAD, and the IMF are already collecting relevant monetary data and producing harmonized estimates that contribute to FDI carbon footprint analysis. This section provides an overview of the databases managed by these institutions, which supports the ongoing discussion about data definitions, international collaboration, and template selection.

OECD

In the OECD case, the 4 main databases related to FDI and MNEs are:

1. Foreign Direct Investment (FDI) Statistics.[3]
1. International trade statistics by enterprise characteristics.[4]
2. Activities of Multinational Enterprises (AMNE).[5]
3. Analytical AMNE (AAMNE).[6]

[3] https://www.oecd.org/investment/statistics.htm
[4] https://www.oecd.org/sdd/its/trade-by-enterprise-characteristics.htm
[5] https://www.oecd.org/sti/ind/amne.htm
[6] https://www.oecd.org/industry/ind/analytical-amne-database.htm

Eurostat

In the Eurostat case, the 3 main databases related to FDI and MNEs are:

1. European Union FDI flows, by country and economic activity.[7]
4. Foreign affiliate statistics (FATS) by activity of MNE and country of control.[8]
5. Trade in goods statistics by enterprise characteristics (TEC).[9]
6. Services trade by enterprise characteristics (STEC).[10]

UNCTAD

UNCTAD provides three main sources of information:

1. The UNCTAD FDI dataset[11].
7. The UNCTAD World Investment Report[12].
8. Bilateral and sectoral FDI statistics, which can be obtained upon request.

The UNCTAD FDI dataset offers basic FDI information, including flows and stocks, inward and outward, by country, for the years 1990 to 2023. It covers more countries and economies than the OECD, totaling around 206 economies.

Moreover, the UNCTAD World Investment Report provides annex tables in Excel format that include additional details not found in the main report. This data extends to 2023 and includes information on M&A and greenfield FDI. The data on FDI and M&A come from UN sources, while greenfield FDI projects and non-financial MNEs are derived from third-party sources. Additionally, UNCTAD releases bilateral and sectoral FDI statistics, which can be obtained upon request.

For internal use, UNCTAD regularly collects both published and unpublished national official FDI stock data from central banks, statistical offices, and national authorities for its FDI/MNE database. This data, which accounts for over 90% of reported FDI figures, is supplemented by information from other international organizations that have partial data availability or use the asset/liability principle.

[7] https://ec.europa.eu/eurostat/databrowser/bookmark/e94c0beb-9a3d-4451-a1c9-bef5569a60bf?lang=en (reference years 2013-2023) and
https://ec.europa.eu/eurostat/databrowser/bookmark/f6d6e4c8-9382-4532-be8e-a9d2b1f55f00?lang=en (reference years 2008-2012)

[8] https://ec.europa.eu/eurostat/databrowser/view/fats_activ/default/table?lang=en&category=gbs.fats (reference years 2021-2022) and
https://ec.europa.eu/eurostat/databrowser/bookmark/b6e21780-f6c9-433e-bc80-7cf63b45451f?lang=en (reference years 2008-2020)

[9] https://ec.europa.eu/eurostat/databrowser/bookmark/9c5684fb-7420-4940-b9d4-1353714f1502?lang=en (reference years 2012-2023)

[10] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Services_trade_by_enterprise_characteristics_-_STEC

[11] https://unctadstat.unctad.org/datacentre/dataviewer/US.FdiFlowsStock

[12] https://unctad.org/topic/investment/world-investment-report

IMF

The International Monetary Fund (IMF) provides data on Foreign Direct Investment (FDI) through several key databases. Each of these resources can assist in the estimation and analysis of FDI flows. In particular,

1. The Balance of Payments (BOP).[13]
2. Special Purpose Entities (SPE).[14]
9. Direct Investment Positions by Counterpart Economy dataset (DIP) (collected on the Coordinated Direct Investment Survey, or CDIS).[15]

The BOP records a country's economic transactions with the rest of the world over a specific period, detailing both inflows and outflows of FDI under the financial account, however it does not provide partner country detail. The DIP enhances the quality and comparability of FDI statistics by collecting detailed data on FDI positions from participating countries. This survey provides insights into the sources and destinations of FDI, allowing for cross-country comparisons that reveal investment patterns across economies. Additionally, the SPE database focuses on entities established primarily for managing investments, highlighting their significant impact on perceived FDI flows. By understanding the role of these entities, analysts can adjust statistics to reflect genuine investment activities more accurately.

Estimating France Foreign Direct Investment's GHG footprint with granular data

This section describes an enhanced version of the methodology developed by Genre et al. (2025). who allocate consolidated group's GHG emissions to their foreign affiliates. They consider Greenhouse Gas (GHG) emissions, expressed in tons of CO_2e equivalent (CO_2e). The method consists of the following steps:

- Identify groups' entities involved in FDI relationships (DIEs and their parent(s)).
- Estimate GHG emissions of the group.
- Allocate a part of the group's total GHG emissions to its DIEs.
- Aggregate DIEs' GHG emissions by common breakdowns, such as activity sectors and countries.
- Compile GHG intensities among the same breakdowns.

These steps are now described in more detail.

GHG emissions data is available according to the Corporate Accounting and Reporting Standard breakdown from the Greenhouse Gas Protocol (GHG Protocol), that is:

- Scope 1 emissions are direct emissions from owned or controlled sources of the company.
- Scope 2 emissions are indirect emissions from the generation of purchased energy.

[13] https://data.imf.org/en/datasets/IMF.STA:BOP
[14] https://data.imf.org/en/datasets/IMF.STA:SPE
[15] https://data.imf.org/en/datasets/IMF.STA:DIP

- Scope 3 emissions are all indirect emissions that occur in the value chain (out of scope 2). It includes both upstream and downstream emissions.

Note that scope 1 emissions of a firm producing energy are part of scope 2 emissions of other firms. With scope 3 emissions, overcounting becomes more complex to deal with (Charpentier et al., 2023), although summing up the three scopes of emissions draws a picture of what emissions a firm is responsible for. However, we focus on scopes 1 and 2 for two reasons. First, results on scope 3 are less accurate due to data availability and quality. Second, the breakdown between upstream and downstream emissions is not available. Then, when compiling carbon intensities that we can define as the ratio between GHG emissions and various economic variables, using scopes 1 and 2 emissions is more representative of firms' output activities. Indeed, we can compute intensities relative to FDI equity in "mixed value" (market value for listed direct investment enterprises (DIEs) and Own Funds at Book Value (OFBV) for unlisted DIEs), value added, production, revenue or employees for instance.

The GHG Protocol also provides guidance to organizations for consolidating GHG emissions of its entities and reporting the data at group level. We assume companies follow this guidance, leading to homogeneous data.

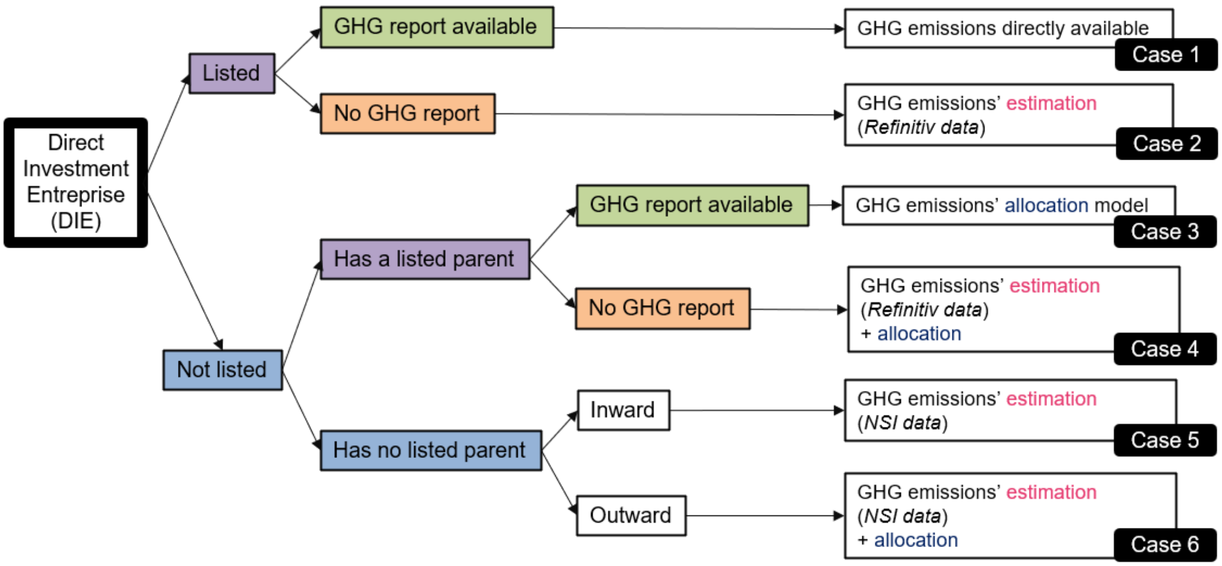
In France, since 2010, big companies (either more than 500 employees or more than 250 M€ of revenue) must report their GHG emissions on a yearly basis. In practice, such companies have been increasingly reporting their emissions in recent years, but not all of them do. Private data providers, such as Institutional Shareholder Services (ISS) and Refinitiv, collect this data from companies' reports in certain cases (~ 20%) and estimate GHG emissions for non-reporting companies in most cases (~ 80%), not always with a fully transparent methodology. The data is always consolidated at a group level and available for listed MNEs only, while most DIEs are unlisted (~ 85% in France, considering both inward and outward FDIs). To achieve sufficient coverage, it is thus key to estimate the GHG emissions of unlisted DIEs. The decision tree below sums up the approach, with each case representing a different combination of MNE status (listed or not) and GHG data availability.

This work is in line with Genre et al. (2025). Since then, two major improvements have been made:

- Improved performances of the estimation model in case of missing GHG emissions data (cases 2 and 4 on Figure 4) by using a random forest instead of a Generalized Linear Model (GLM) and extending the scope of predictive variables.
- Extension of model coverage to cases 5 and 6, by estimating the emissions of affiliates that do not have any listed parent in their holding chain. On average, those represent 85% of FDI transactions but 28% of their value.

Compared to Genre et al. (2025), in which authors use a model based on macro data when there is no listed entity in the holding chain (cases 5 and 6), we can now restrict the approach to only two models based on granular data. This leads to greater harmonization of estimation approaches between cases. This work covers years from 2019 to 2022.

Figure 4 Decision tree for choosing the GHG emissions estimation method



Source: Authors' elaboration

GHG emissions estimation model

Genre et al. (2025) use reported GHG emissions of listed entities for estimating a GLM based on sectoral and financial variables (cases 1 and 3). This model is then applied to estimate GHG emissions of listed companies that do not report GHG emissions (cases 2 and 4). We extend this approach along two dimensions:

1. We consider a broader set of predictive algorithms, including both regression-based and tree-based methods, in order to assess whether more flexible models better capture the high dimensionality of the feature space, particularly due to detailed sectoral classifications.
2. We establish a mapping between the predictive sectoral and financial variables available for listed and non-listed companies, allowing the model trained on listed firms to be applied to non-listed firms and thereby to cover cases 5 and 6. This extension necessarily relies on the assumption that relationships learned from listed companies generalize to unlisted companies. Since GHG emissions data is not available for unlisted groups, there is no bypass. One shall however bear in mind this uncontrolled potential bias.

All the data is annual, and we estimate the FDI carbon footprint of France over the period 2019-2022.

Data used for listed entities for which there is no GHG emissions data (cases 2 and 4)

The unit of observation is the ISIN identifier (listed group), per year. The table used for prediction includes 65 000 observations, of which cases 1 and 3, and 35 variables. Compared to Genre et al. (2025), this dataset also concerns some groups with no entity in France, making it larger and better suitable to machine learning algorithms.

- The target variables are the annual emissions (scope 1 and/or scope 2) of listed companies, retrieved from ISS (Institutional Shareholder Services). The explanatory variables are selected based on their relevance and their coverage in the database, with Refinitiv as the source. Refinitiv is a financial platform providing access to financial and economic data, used for analyzing companies, financial markets, offering both fundamental and historical data. The retrieved data are:Full time employees,
- Net income including extraordinary items before distributions,
- Total revenue,
- Total debt,
- Net debt including preferred stock with the minimum interest,
- Long term investments,
- EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization),
- Property, Plant, and Equipment Total Net.

Missing financial data is processed with MICE method (Multivariate Imputation by Chained Equations). This statistical technique is used for multivariate imputation of missing data. It relies on chained equations, which allows for multiple imputations. The algorithm uses a method where each variable with missing values is imputed using a separate model based on the other variables in the dataset. MICE is great for keeping variables' statistic distributions.

Imputed information is flagged as such, to allow the model to differentiate imputed values from others in prediction.

Sectoral and geographical variables with no missing values are added to these accounting and financial data:

- NAICS (North American Industry Classification System) sector dummies.
- NAICS subsector dummies.
- Country of incorporation.

Data used for DIEs that are part of unlisted groups (cases 5 and 6)

The unit of observation is the French business identifier (SIREN), per year. Since the same model is applied to unlisted entities, explanatory variables must match the ones used for listed entities. As Refinitiv only covers listed groups, we use ESANE database (Elaboration of Annual Statistics of Companies), provided by INSEE (French National Statistical Institute) for unlisted entities. The ESANE scheme allows the production of structural business statistics while combining administrative data with specific statistical surveys to generate comprehensive and accurate sector-based statistics. Most ESANE variables are the same as in Refinitiv, such as turnover, added value and employment. For the others, we can combine several ESANE variables to retrieve them. For instance, we rebuild EBITDA from its components:

$$\begin{aligned}\text{EBITDA} = \text{Operating income} + \text{Depreciation, amortization and provisions} \\ - \text{Reversal of amortization and provisions}\end{aligned}$$

FDI data compilers collect NACE activity sectors for French entities involved in the direct investment. We then map these to NAICS classification for consistency with listed groups.

Estimation of the GHG emissions predictive model

We considered a range of predictive models to estimate firm-level GHG emissions. These include penalized linear regressions (ridge, lasso, and elastic net) and tree-based algorithms (CART, random forest, gradient boosting, and XGBoost).

The target and explanatory variables described above were used in the baseline specifications. Although the models considered accommodate high-dimensional feature spaces, the inclusion of categorical variables with very high cardinality—sometimes exceeding 100 categories for some sectoral classifications and with sparse representation for some countries—raised concerns under one-hot encoding, as it substantially increases dimensionality. We therefore investigated a target encoding strategy, whereby each category is replaced by summary statistics of the target variable conditionally on that category (e.g. sector-level means, standard deviations, interquartile ranges and sample shares). For example, if firms in the agricultural sector emit on average XXX tons of equivalent CO_2 in the training data, the encoded feature assigns the value XXX to all agricultural firms (and sectoral information itself is discarded from the model). To prevent information leakage, target encoding is computed exclusively on the training sample and then applied unchanged to validation and test samples, including within cross-validation folds.

Given the absence of performance gains, however, we ultimately retained the unmodified categorical sectoral classifications. Following 10-fold cross-validation, the **random forest** algorithm consistently outperformed the alternative models across all scopes (Scope 1, Scope 2, and combined Scope 1 & 2 emissions). Its main performance metrics are reported in Table 6, while feature importance measures are presented in Figure 5.

For interpretation, a mean absolute error (MAE) of 0.95 in predicting log Scope 1 & 2 emissions implies that, on average, predicted emissions differ from observed values by a factor of: $e^{0.95} \approx \mathbf{2.6}$. While this level of accuracy is insufficient for firm-level decision-making, it appears adequate to capture cross-firm heterogeneity for aggregate statistical and analytical purposes. Compared to Genre et al. (2025), who report an MAE of 1.2, this leads to reducing the differences between predicted emissions and observed values by **25%.**

The model is then applied to both DIEs that are part of listed groups (cases 2 and 4) and DIEs that are not (cases 5 and 6). For cases 5 and 6, the below performance metrics are less reliable, as they have been computed for listed groups.

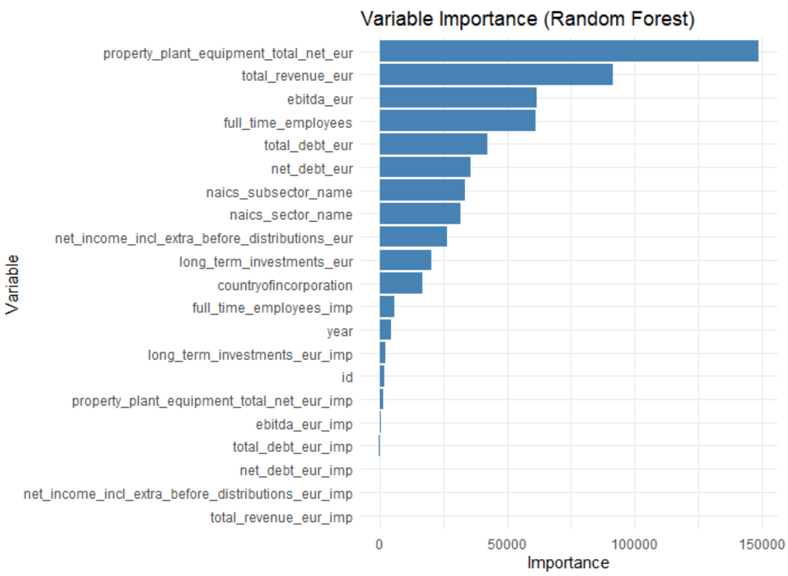
Table 6 Performance metrics of the better performing algorithm (Random Forest)

Target variable	**Mean absolute error (MAE)**	**Root mean standard error (RMSE)**
Log (scope 1 emissions + 1)	1.15	1.61
Log (scope 2 emissions + 1)	0.99	1.49
Log (scope 1&2 emissions + 1)	0.96	1.34

Source: Authors' elaboration

Figure 5 shows the most contributing variables to GHG emissions' estimates is property plant equipment; followed by firm financial performance and size: total revenue, EBITDA and employees.

Figure 5 Feature importance in the better performing algorithm (Random Forest)



Source: Authors' elaboration

GHG allocation model

We adopt the conceptual framework from Genre et al. (2025) to allocate yearly GHG emissions within an MNE (see cases 2, 4 and 6 on Figure 4), at the entity level. It works in three steps:

Initial allocation of emissions:

$$e_i = \frac{C_i}{C_{group}} \times E \tag{6}$$

Where e_i represents GHG emissions allocated to the affiliate i in the first step and E the total GHG emissions of the group. We note n the number of entities in the group ($i = 1, 2, \dots, n$). C_i (resp. C_{group}) is the affiliate's tangible long-term assets (resp. group's). In line with scopes 1 and 2 definitions, we assume that tangible long-term assets are directly linked with GHG emissions. Results of the estimation model tend to confirm this (see Figure 5).

However, neither tangible long-term assets nor any good proxy (total assets, employees…) are widely available for unlisted affiliates. Indeed, the only systematically collected data is the direct investor's shareholding, that is a portion of DIEs' equity which, in turn, includes tangible assets. When consolidating data at a group level, the direct investor includes all the assets of its DIEs in the assets side of its own balance sheet. We then have equations 6 & 7':

$$e_i = \frac{FDI_i}{C_{group}} \times E \tag{7}$$

$$e_i = \frac{FDI_i}{TA_{group}} \times E \tag{7'}$$

Where TA_{group} is the group total assets and FDI_i is the direct investor's share of capital in a DIE (NB: because emissions must be positive, we exclude negative equities for now).

This step assumes a 'pollution halo' effect, presuming identical production technology within the same productive structure. To balance this, the second step is based on a 'pollution haven' assumption by considering sector and country-level environmental efficiency.

Adjustment for sector/country environmental efficiency

$$e_i^* = \alpha_{c_i s_i} \times e_i \tag{8}$$

Where the carbon footprint $\alpha_{c_i s_i}$, expressed in tCO_2e/Million LCU per international dollar, is defined as the ratio between the total emissions of the DIE's sector s in country c, and the added value. It enables to consider the average environmental efficiency of sector / country.

Normalization

$$E_i = \frac{e_i^*}{\sum_{i=1}^{n} e_i^*} \times E \tag{9}$$

This last step ensures that the emissions allocated to each entity are consistent with the group's total emissions, thereby maintaining the integrity of the overall emissions data. We introduce here a fictitious "missing" affiliate to address the issue of missing data on either French entity for outward FDI or unknown affiliates for inward FDI – since we neither collect data about subsidiaries owned in other countries nor about entities in the investing country. Overall, the fictious affiliate represents the collective impact of entities that are not part of FDI data collection, ensuring that the total group GHG emissions are fully allocated without overburdening the known entities. The emissions for this fictitious affiliate are calculated based on the residual assets and average environmental efficiency of the known entities.

As in Genre et al. (2025), data for listed MNEs is consolidated at the group level and sourced from Refinitiv (cases 2 and 4 on Figure 4). Compared to Genre et al. (2025), we rebuild here consolidated data for unlisted French MNEs (long-term tangible assets C_{group} and total assets TA_{group}) thanks to firm-level data coming from ESANE, as described above. Then, we can apply the allocation model to outward DIEs that are part of unlisted French groups (case 6).

We face several challenges and limitations in applying this model. This lack of data necessitates adjustments and assumptions that may affect the accuracy of the emissions allocation. For instance, the model may underestimate the emissions of subsidiaries in labour-intensive industries if the direct investor's shareholding is lower than the invested company's tangible long-term assets.

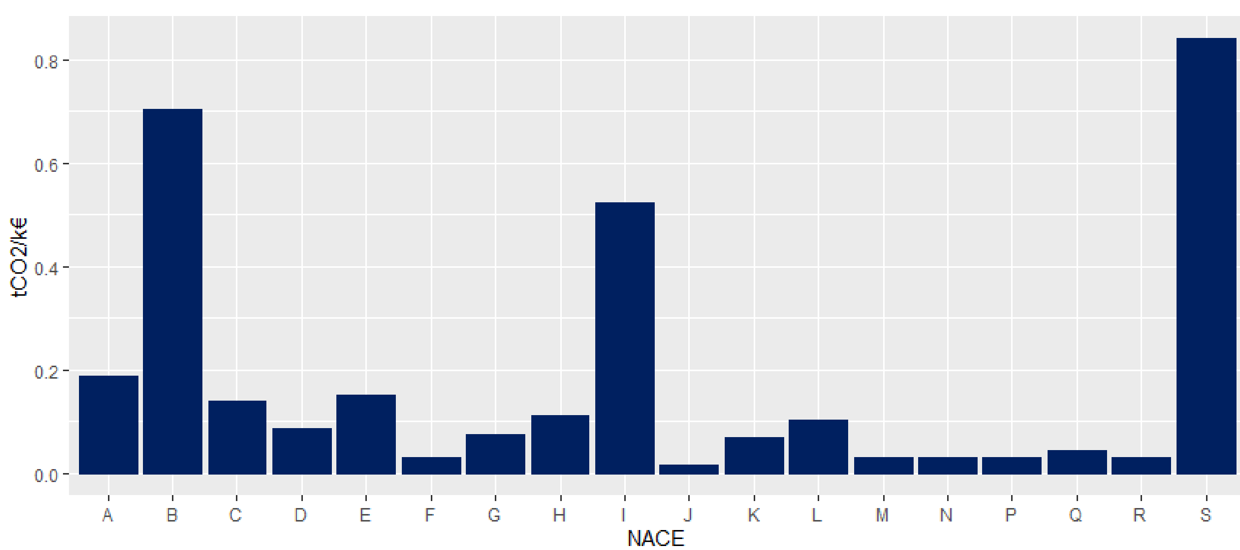
Results

Once GHG emissions are estimated for every French or foreign DIE, we aggregate the results by activity sector and country. GHG intensities are computed by dividing GHG emissions to value added over the same perimeters. Currently, no public data distinguishes GHG intensities between domestic and foreign-owned enterprises. This output from the micro approach then well integrates as an input for the macro approach. Figure 6 shows inward FDI GHG intensities broken down by activity sectors.

Intensities are highest in S (Other service activities), B (Mining and quarrying) and I (Accommodation and food service activities). These results contrast with total GHG emissions of foreign-owned entities in France, where C (Manufacturing) dominates, see on Figure 7. Indeed, the higher intensity in S (Other service activities) reflects its relatively low FDI equity. Foreign-owned entities emit more GHG in C (Manufacturing) and H (Transporting and storage).

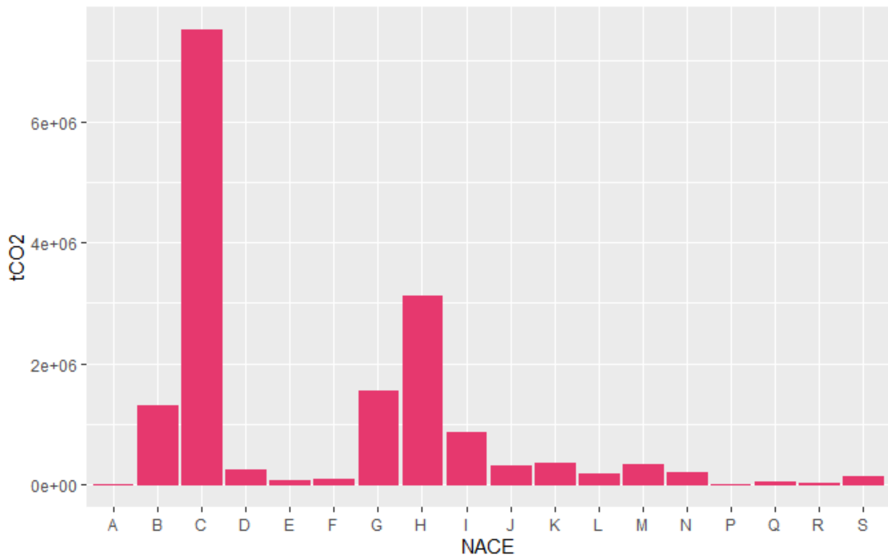
We also break down the results by country (Figures 8 and 9) representing the GHG footprint of FDI liabilities and assets in 2022.

Figure 6 Inward FDI GHG intensities by value added broken down by activity sectors – Scopes 1 & 2



Source: Authors' elaboration

Figure 7 Inward FDI GHG emissions broken down by activity sectors – Scopes 1 & 2



Source: Authors' elaboration

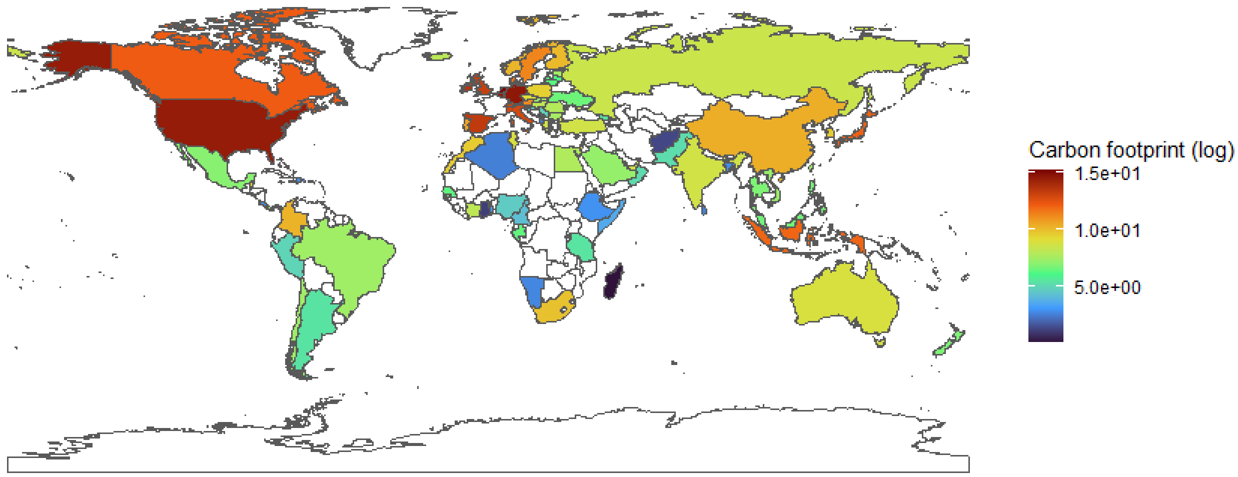
Figure 8 shows that the highest foreign carbon footprint in France comes from the United States, which is also the largest ultimate investor in France. Other European countries such as Germany, Belgium or the Netherlands are also top direct investors and their carbon footprint in France is significant.

Overall, the carbon footprint of inward FDI is lower than that of outward FDI, primarily due to:

- France energy production largely relies on low-GHG emitting nuclear power.
- FDI contributes €568 billion to France's International Investment Position (2024), with FDI assets (€1,499 billion) exceeding FDI liabilities (€931 billion).
- Outward FDI in high-GHG sectors, such as manufacturing, is larger than inward FDI which is more service-oriented.

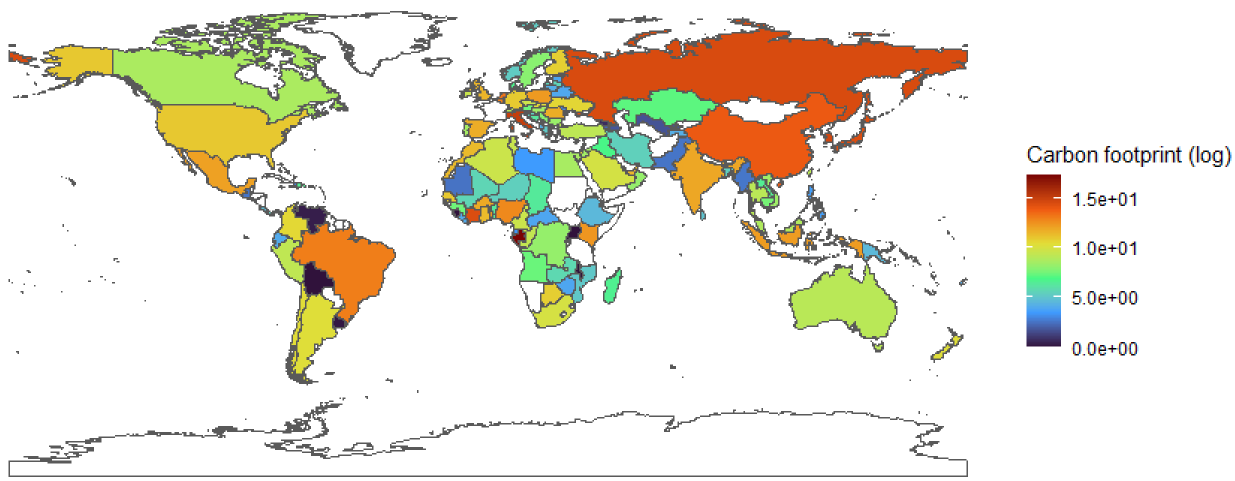
The logarithmic scale eases reading Figures 8 and 9. Over the period, French outward FDI GHG emissions are highest in Gabon (2022), Canada (2021) and Russia (2020 and 2019, i.e. before the war).

Figure 8 Scopes 1 and 2 GHG footprint of FDI in France (tons of CO_2e; in logarithmic scale; 2022)



Source: Authors' elaboration

Figure 9 Scopes 1 and 2 GHG footprint of French FDI abroad (tons of CO_2e; in logarithmic scale; 2022)



Source: Authors' elaboration

Quantifying CO_2 emissions in the Dutch economy according to the control criterion

This section describes the method of Van Rossum et al. (2014), who allocate emissions in Dutch industries to domestically owned and foreign-owned enterprises, respectively. Note that they considered CO_2 emissions, and not all greenhouse gas emissions. The method consists of the following steps:

- Identify enterprises which are foreign controlled
- Estimate stationary emissions by type of ownership based on micro information
- Estimate emissions of mobile sources by type of ownership
- Identify remaining emissions and allocate them to foreign-controlled and domestically controlled enterprises
- Aggregate the emissions by type of ownership

These steps are now described in more detail.

Identify enterprises which are foreign controlled

The identification of enterprises in the Dutch economy which are controlled by foreign enterprises was carried out using the information about the ultimate controlling institutional unit. This database is part of the regular process at Statistics Netherlands to compile the foreign affiliates statistics (FATS).

Estimate stationary emissions by type of ownership based on micro information

This starts by using existing data on emissions from stationary sources at the micro level. It is based on energy use data at micro level, which is collected for the regular energy statistics. This can be transformed into energy-related emissions, both from energy combustion and process-related emissions. The data is used for the compilation of several regular statistics. Subsequently, using the business register, the emissions at micro level are linked to the information about ownership. This allows for allocating the emissions to domestically owned and foreign-owned enterprises for about three quarters of emissions related to production. Enterprises that are not captured in this step will be taken care of later in the process.

Estimate emissions of mobile sources by ownership

Emissions from mobile sources mainly origin from transportation activities. At industry level, the ratio of emissions related to stationary and mobile sources is known. Using this ratio, and assuming that the ratio of foreign/domestic ownership is the same for emissions related to stationary and mobile sources, one can estimate emissions of mobile sources by ownership by industry.

Identify remaining emissions and allocate them by ownership

The previous steps have not yet captured all emissions. First, mostly smaller enterprises for which no information was available; second, activities that were not covered. For example, inland shipping, marine transportation (outside the territory), and air transportation.

At industry level, total emissions are known from the System of Environmental-Economic Accounting (SEEA). At industry level, subtract the emissions that were estimated in the previous steps. These remaining emissions still have to be allocated. For the enterprises that have not been taken into account in the previous steps, we collect the ownership information and the employment information. The remaining emissions are allocated proportionally to employment.

Aggregate emissions by type of ownership

The previous steps yielded different datasets about emissions. By merging them and aggregating them by industry and by ownership, we obtain estimates for the CO_2 emissions in an industry at foreign owned and domestically owned enterprises. The results should be considered experimental and not official statistics.

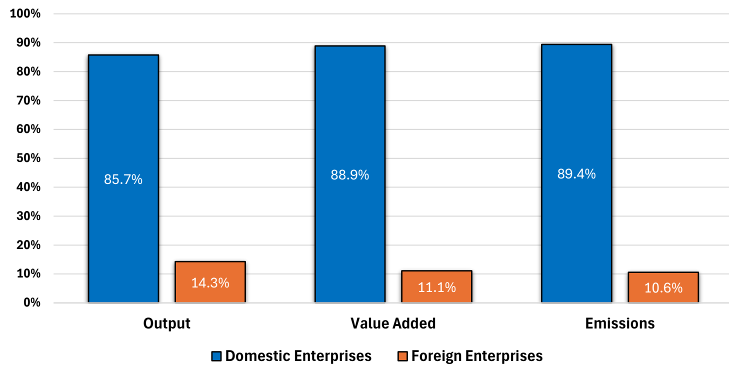
Carbon Footprint of Activities of Foreign MNEs in France

Based on the Scope 1 emissions estimated for France using the methodology described above, it was possible to calculate the emission intensity of foreign MNEs in France by industry. This information was then combined with data on total GHG emissions by industry in France, sourced from the OECD database on GHG emissions incorporated in trade and final demand, to estimate the emission intensities of domestic enterprises in France. Applying the methodology referenced as Case 6 in Figure 1, and utilizing global input-output tables from the OECD AAMNE database, enabled the estimation of the carbon footprint associated with the activities of both domestic and foreign enterprises in France. The summary results are presented in Figures 10 to 13.

Figure 10 provides a comparative overview of the contributions of domestic and foreign enterprises to France’s economic activity and associated production emissions in 2019. The results reveal that the share of production emissions attributed to foreign MNEs is slightly lower than their share of output and value added, indicating that foreign-owned enterprises tend to be less emission-intensive relative to their economic contribution.

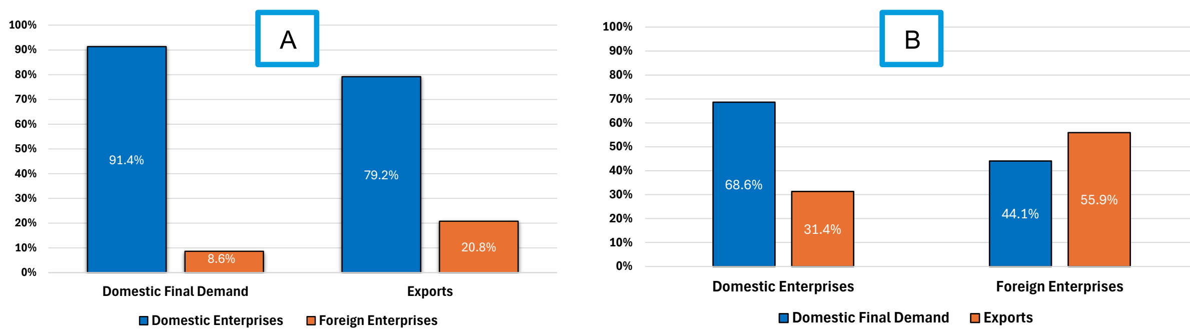
Figure 11 illustrates the proportion of emissions incorporated in France’s domestic final demand and exports that originate from both domestic and foreign enterprises. Panel A details the share of total embodied emissions attributed to each group, highlighting the contribution of foreign-owned firms to France’s export-related emissions. Panel B further breaks down how the emissions generated by domestic and foreign enterprises are distributed between domestic consumption and exports, confirming that 56% of the carbon footprint of MNEs are associated with their exports, while for the domestic enterprises the share in exports is only of 31%.

Figure 10 France 2019: Share of domestic and foreign enterprises in output, value added, and production emissions



Source: Authors' elaboration

Figure 11 France 2019:
A. How much of the emissions embodied in domestic final demand and exports come from domestic and foreign enterprises
B. How much of the emissions from domestic and foreign enterprises are allocated to domestic final demand and exports

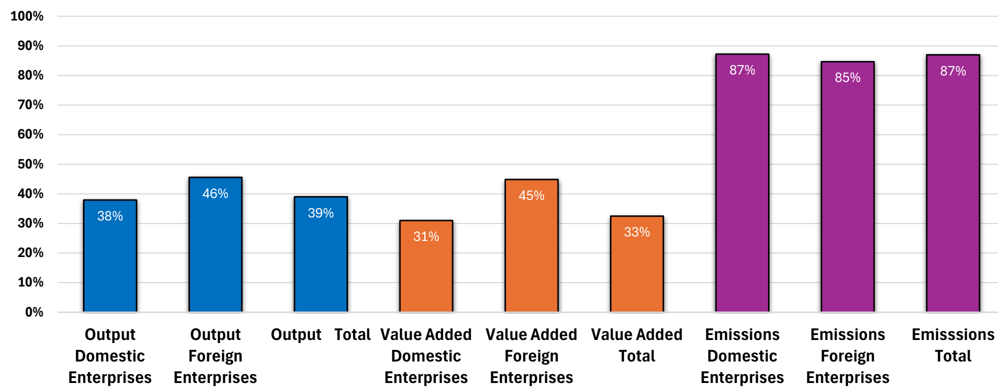


Source: Authors' elaboration

Figure 12 provides a detailed breakdown of the share of main emitting industries in France in terms of output, value added, and emissions for the year 2019. The figure highlights that these industries contribute around 87% of the country's total emissions but account for only 33% of the economy's value added, indicating that these industries are particularly emission-intensive relative to their economic contribution.

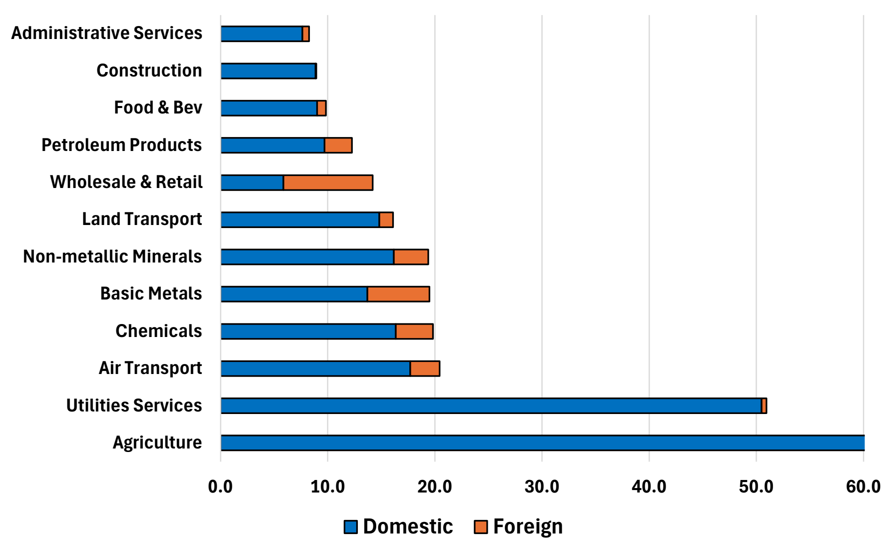
Figure 13 presents the GHG emissions by the main emitting industries in France for 2019, distinguishing between domestic and foreign enterprises. The figure reveals that certain sectors, such as Agriculture and Utilities, are responsible for the largest shares of emissions, with ownership primarily held by domestic enterprises. The contribution of foreign enterprises to emissions is mainly observed in the industries of Transportation (air and land), Wholesale and Retail, Basic Metals, Non-metallic Minerals, and Chemicals.

Figure 12 France 2019: Share of main emitting industries in output, value added, and emissions



Source: Authors' elaboration

Figure 13 France 2019: GHG emissions by main emitting industries, separated by domestic and foreign enterprises (million tonnes of CO_2e)



Source: Authors' elaboration

In 2019, France's foreign MNEs contributed fewer emissions relative to their economic output compared to domestic firms, with 56% of their carbon footprint linked to exports. Key emission-intensive industries produce most emissions despite contributing less to economic value. Agriculture and utilities, mainly domestically owned, are major emitters, while foreign firms impact sectors like transportation, metals, and chemicals.

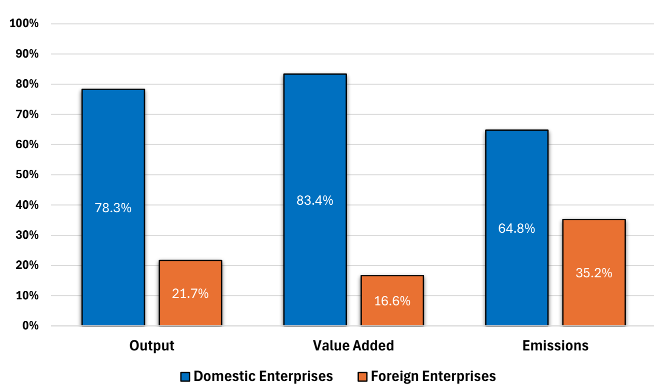
Carbon Footprint of Activities of Foreign MNEs in the Netherlands

Based on the experimental work of Van Rossum et al. (2014) and Statistics Netherlands (2024), who estimated CO_2 emissions from foreign MNEs in the Netherlands, it was possible to estimate the CO_2 emission intensity of foreign MNEs by industry. Similar to the case in France, the same procedure was applied to estimate the GHG emission intensities of domestic enterprises in the Netherlands. This enabled the estimation of the carbon footprint associated with the activities of both domestic and foreign enterprises in the Netherlands. The summary results are presented in Figures 14 to 17.

Figure 14 examines the contributions of domestic and foreign enterprises to the Netherlands' economic output, value added, and production-related emissions in 2008. The analysis reveals notable differences between these groups: while domestic firms tend to account for a larger share of total output and value added, foreign enterprises play a significant role in production emissions. This suggests that foreign-owned firms may operate in more emission-intensive sectors or employ production processes with higher carbon footprints compared to their domestic counterparts.

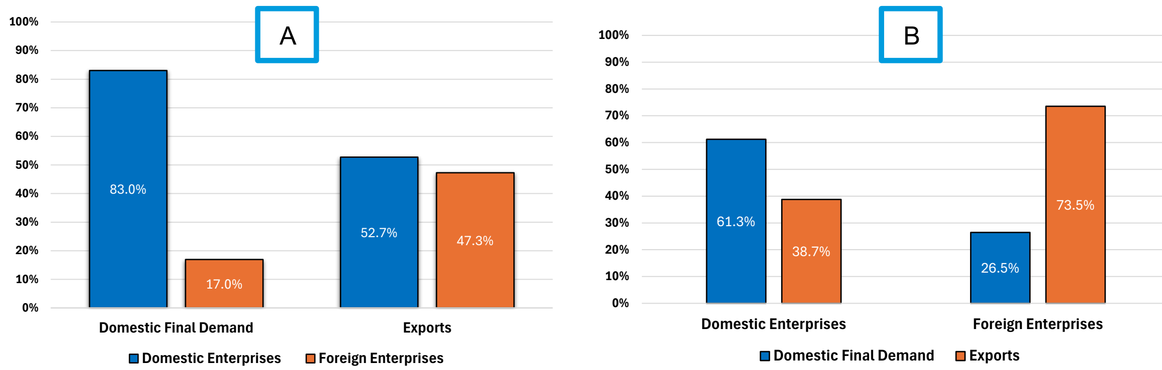
Figure 15 analyzes the distribution of emissions in the Netherlands in 2008, highlighting the contributions of domestic and foreign enterprises to both domestic consumption and exports. Foreign enterprises account for a significant share of emissions embodied in exports, reflecting their deep integration into global supply chains and focus on international markets. Meanwhile, emissions from domestic enterprises are primarily associated with domestic demand. This distinction underscores the need for environmental policies to consider both the source of emissions and their final use, employing targeted strategies by enterprise ownership and end-use to more effectively reduce overall carbon emissions.

Figure 14 Netherlands 2008: Share of domestic and foreign enterprises in output, value added, and production emissions



Source: Authors' calculations based on Van Rossum et al. (2014) and Statistics Netherlands (2024).

Figure 15 Netherlands 2008:
A. How much of the emissions embodied in domestic final demand and exports come from domestic and foreign enterprises
B. How much of the emissions from domestic and foreign enterprises are allocated to domestic final demand and exports



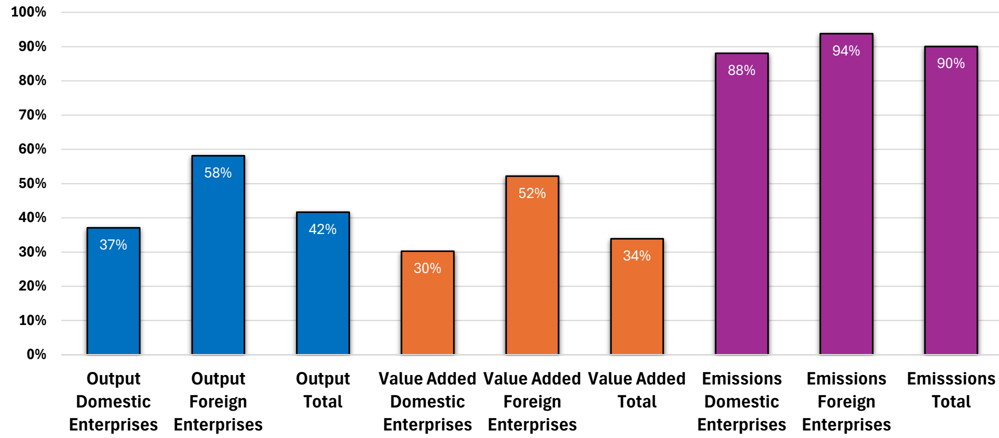
Source: Authors' calculations based on Van Rossum et al. (2014) and Statistics Netherlands (2024).

Figure 16 provides a comparative analysis of the principal emitting industries in the Netherlands in 2008, examining their respective shares of economic output, value added, and GHG emissions. The data indicate that these industries are responsible for a large proportion of national emissions relative to their economic significance: while they account for approximately 90% of the country's total GHG emissions, they contribute only 34% to the economy's value added, demonstrating that these industries are particularly emission-intensive compared to other sectors.

Figure 17 presents the GHG emissions of the main emitting industries in the Netherlands for 2008, distinguishing between domestic and foreign enterprises. The figure reveals that certain sectors, such as Agriculture (primarily domestic enterprises) and Utilities, are responsible for the largest shares of GHG emissions. The contribution of foreign enterprises to emissions is mainly observed in Utilities, Chemicals, Air Transport, Petroleum Products, and Basic Metals industries.

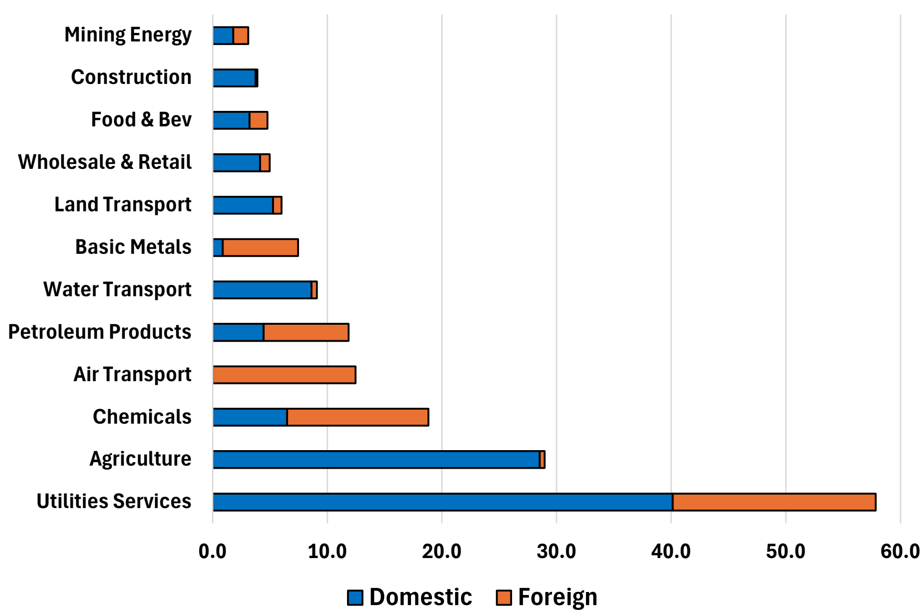
In 2008, the main emitting industries accounted for 90% of GHG emissions but only 34% of economic value added, with domestic firms in the Netherlands being less emission-intensive relative to their contribution to economic output and value added compared to foreign firms. The emissions from foreign enterprises were especially linked to exports and emission-intensive sectors such as Utilities, Chemicals, and Air Transport. highlighting their high emission intensity. Policies should target these areas with tailored approaches, encouraging cleaner technology and recognizing both domestic and global emission impacts.

Figure 16 Netherlands 2008: Share of main emitting industries in output, value added, and emissions



Source: Authors' calculations based on Van Rossum et al. (2014) and Statistics Netherlands (2024).

Figure 17 Netherlands 2008: GHG emissions by main emitting industries, separated by domestic and foreign enterprises (million tonnes of CO_2e)



Source: Authors' calculations based on Van Rossum et al. (2014) and Statistics Netherlands (2024).

Final comments & way forward

As policymakers increasingly demand more precise insights into the carbon footprint of FDI and the activities of MNEs, it becomes crucial to adopt methodologies that account for the complex realities of modern economies. This paper presents a flexible approach for estimating these footprints, tailored to different national data contexts. It emphasizes the importance of capturing the heterogeneity of production structures and emission intensities between domestic and foreign-owned enterprises.

The analysis of France and the Netherlands demonstrates how the proposed methodology estimates carbon emissions by distinguishing between domestic and foreign-owned enterprises, highlighting their shares in output, value added, and emissions. It reveals that MNEs generate a larger share of emissions tied to exports, reflecting their role in global value chains, while domestic firms' emissions are mainly linked to local consumption. This distinction, along with differences in sectoral composition and emission intensity, underscores the importance of detailed ownership and sectoral data. Robust data and methods like MRIO, FATS, and TEC are essential for accurately understanding FDI's carbon footprint and informing effective emission reduction policies at national and international levels.

To further enhance the estimation of FDI-related emissions, future efforts should prioritize the integration of ownership information, detailed sectoral data, and trade linkages into emission accounting frameworks, especially emissions by industry by ownership. Standardizing data collection practices and methodologies—through collaboration among national statistical offices, international organizations (such as the IMF, OECD, Eurostat, and UNCTAD), and academic researchers—will be essential for improving both the accuracy and comparability of estimates across countries.

Methodologies such as MRIO models, FATS, and TEC have proven effective in tracing emissions through global value chains and differentiating between domestic and foreign enterprise contributions. However, the paper also highlights the potential for further methodological advancements by incorporating enterprise-level microdata and expanding coverage to include emissions embedded in exports, as well as indirect emissions transmitted through supply chains.

Looking ahead, there is an urgent need for improved and more granular data, including disaggregation by industry, ownership, and geographical location. Policymakers should also consider how emissions embodied in both domestic final demand and exports are allocated between domestic and foreign enterprises, as this has implications for both national climate strategies and international climate negotiations. Encouraging cleaner technologies in emission-intensive sectors and recognizing the interconnected nature of global emissions will be critical steps toward achieving meaningful climate action.

Ultimately, refining the tools for measuring the carbon footprint of FDI and MNEs will help ensure that climate policies are both effective and equitable, supporting a transition to a low-carbon global economy while accounting for the realities of international production and trade.

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