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Working Paper Does a value-added smile curve imply an environmental frown curve?

Research Paper, No. 29

Provided in Cooperation with: EcoAustria – Institute for Economic Research, Vienna (Austria)

Suggested Citation: Schwarzbauer, Wolfgang; Bittó, Virág; Koch, Philipp; Steininger, Jonathan (2024) : Does a value-added smile curve imply an environmental frown curve?, Research Paper, No. 29, EcoAustria - Institute for Economic Research, Vienna

This Version is available at: https://hdl.handle.net/10419/306347

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Vienna, October 2024

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This publication was supported by the Austrian National Bank (Anniversary Fund project no. 18883).

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October 2024

Imprint: EcoAustria – Institute for Economic Research, Am Heumarkt 10, 1030 Wien, Austria, Tel: +43-(0)1-388 55 11

www.ecoaustria.ac.at

Does a value-added smile curve imply an environmental frown curve?*

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October 2024

Abstract

Global value chains (GVCs) play a crucial role in today's international trade. High value-added activities tend to cluster at the start and the end of GVCs, resulting in a U-shaped relationship across production steps known as the "smile curve". The distribution of CO_2 emissions along the value chain, however, is relatively unexplored. Here, we map embodied CO_2 emissions in GVCs to test whether emissions are distributed differently across production stages than value–added. We find that activities with high high emissions per unit of labour compensation cluster at early stages (e.g. energy production, mining), while late stages (e.g. retail trade) exhibit lower emission intensities. This results in a downward-sloping emissions curve with tentative evidence of a frown-curve pattern. We explore several examples at different levels of aggregation and provide an interactive platform to explore the mapping of value-added and emissions across GVCs.

JEL Classification Codes: C67, F18, F62, F63, F64, Q56

Keywords: Greenhouse gas emissions, Sustainable Development, Transition towards green economy, Global Value Chains, Multi-Regional Input-Output Model, International Trade, Climate change

^{*}This project was supported by the Austrian National Bank (Anniversary Fund project no. 18883)

1 Introduction

Global production networks have become integral to goods and services production, driven by the surge in globalization over recent decades. Research demonstrates that crossborder inter-industry production networks have not only become more prevalent but also increasingly complex. By 2014, trade in global value chains (GVCs) constituted approximately two-thirds of global trade in value-added terms (World Bank Group, IDE-JETRO, OECD, UIBE, & World Trade Organization, 2017). Despite a recent deceleration in globalization's pace, GVC participation has continued to expand. According to the Global Value Chain Report 2023 (World Bank Group, IDE-JETRO, UIBE, & World Trade Organization, 2023), backward participation rates in GVCs rose from 20 percent in 1995 to 28 percent in 2022, indicating a substantial worldwide increase in the use of foreign intermediates for export production.

Baldwin (2013) attributes this evolution to two distinct waves of unbundling, driven by advances in transport and ICT. The first unbundling occurred in the latter half of the 20th century, prompted by declining transport costs. This reduction made it increasingly profitable to separate production from consumption locations, leading to widespread outsourcing to low-cost countries. The second wave of unbundling emerged from ICT advancements, enabling further segmentation of production stages globally. Consequently, production not only dispersed geographically but also became increasingly fragmented within each production location, as documented by numerous scholars (Borin & Mancini, 2017; Johnson & Noguera, 2012; Miroudot & Ye, 2018, 2021; Nagengast & Stehrer, 2016; Timmer, Erumban, Los, Stehrer, & de Vries, 2014; World Bank Group et al., 2023).

The "smile curve" hypothesis, originally proposed by ACER founder and CEO Stan Shih, asserts that value-added shares tend to be higher in pre-production (e.g., R&D, design) and post-production (e.g., marketing, distribution) stages, relative to standardized manufacturing processes, resulting in a U-shaped relationship.

While the distribution of value-added along value chains is well-documented, the allocation of embodied emissions remains less explored, despite the fragmentation of production leading to emissions being scattered globally. Since China's accession to the WTO in the early 2000s and the subsequent shifts in production, not only have production and incomes soared, but emissions have also risen dramatically. However, this emission increase is not limited to China alone. Research by the OECD has shown that non-OECD countries, which tend to be net-exporters of emissions, have overtaken OECD countries in terms of both production-based and consumption-based emissions in recent years (see OECD, 2021).

This article focuses on the linkages between production and emission shifts driven by the emergence of GVCs in the past quarter-century. We employ the smile-curve approach, originally developed to map the distribution of output and value-added in GVCs (Meng, Ye, & Wei, 2020), and extend it to the measurement of emissions. Our particular emphasis is on the co-location of low value-added and emission-intensive activities as production shifts from advanced to less developed economies. In doing so, we analyze the stages at which CO_2 is emitted within specific value chains and how this relates to value-added creation. We further investigate how patterns of value-added and emissions along value chains vary across countries, sectors, and over time. A special focus is also devoted to comparing value-added and CO_2 emissions in the context of the pollution haven hypothesis and carbon leakage.

Our central hypothesis is that the majority of industrial global value chains exhibit a U-shaped value-added curve and an inverted U-shaped emissions curve. Our aim is to develop a unified framework and provide an interactive tool¹ to explore the interactions between these two curves.

This article is structured as follows: The second section provides a brief overview of the existing literature on production, value-added, and emissions in global value chains, with a focus on the smile curve approach. Section three outlines the data and methodology used to assess the co-location of production, value-added, and emissions within GVCs. Section four presents the results of our analysis, and the final section concludes by discussing the key findings.

2 Related literature

2.1 Value–added in global value chains

The seminal contribution of Johnson and Noguera (2012) defined the core of the literature concerned with the positioning of countries within Global Value Chains (GVCs). They introduced the VAX measure, the ratio of value-added to gross exports, as an indicator of the intensity of production sharing in a given sector.

To construct a visual representation of a value chain, one requires indicators that capture the length of linkages between industries and help position the industries along the chains. The concept of "Average Propagation Length" (APL) was introduced by Dietzenbacher, Luna, and Bosma (2005) and Dietzenbacher and Romero (2007), referring to the distance between production stages and final demand in terms of the number of production steps. Building on this, various contributions (Antràs & Chor, 2013, 2018; Antràs, Chor, Fally, & Hillberry, 2012) extended and refined the approach, defining an "upstreamness" measure to describe the number of production stages a product undergoes before reaching final demand. Moreover, Miller and Temurshoev (2017) proposed their own "input downstreamness" measure, while Wang, Wei, Yu, and Zhu (2017) argued for distinguishing four types of production activities (domestic, final product trade, simple GVCs, and complex GVCs) based on the complexity of value chains.

Antràs and Chor (2018) provided an overview of the upstreamness measures developed in previous studies (Antràs & Chor, 2013; Antràs et al., 2012; Fally, 2011, 2012). The upstreamness measure denotes the distance of a production sector from final demand,

¹see our interactive website.

based on the share of products sold to final consumers or industries that directly serve final demand. Conversely, the downstreamness measure, originally introduced by Fally (2012), captures the distance of an industry from the primary factors of production, reflecting its value-added contribution relative to the intermediate inputs used. The study computes these measures using the World Input-Output Database for 1995-2011 and incorporates a theoretical model to interpret the WIOD data and conduct counterfactual exercises.

An additional strand of literature employs a slightly different approach in decomposing the value chain and tracing value-added based on its sources and absorption (in the case of intermediate inputs) or final consumption. Meng et al. (2020) presents a generalized accounting system for analyzing the distance between producer and consumer industries within an international Input-Output framework. A key feature of this study is its detailed focus on the creation of value-added along the value chain. In this framework, satisfying final demand for a good is associated with inducing value-added in a range of participating industries. Two directions are considered: The forward industrial linkage-based valueadded propagation length (U) refers to the average number of production stages to final demand, with a higher U indicating greater upstreamness. Conversely, the backward industrial linkage-based value-added propagation length (D) represents the average stages for a final product to induce value-added of all supplier industries.

2.2 Global value chains and emissions

Regarding the relationship between global value chains and emissions, the literature has explored several key aspects. Gross Domestic Product (GDP), particularly GDP per capita, is widely recognized as a significant determinant of CO_2 emissions. While earlier research, such as Shafik (1994), described this relationship as linear, the notion of decoupling emissions from economic growth has emerged. This suggests emissions may decrease due to mitigation efforts (as proposed by Holtz-Eakin & Selden, 1995) or adjustments in institutions and environmental regulations in response to rising per capita income. The Environmental Kuznets Curve (EKC) hypothesis posits an inverted U-shaped relationship between emissions and GDP (per capita), as explored by de Bruyn, van den Bergh, and Opschoor (1998) and Holtz-Eakin and Selden (1995). Shahbaz and Sinha (2019) specifically examined the EKC hypothesis in the context of CO_2 emissions.

Additionally, the literature views international trade as another influential factor linked to CO_2 emissions, with varied effects. On one hand, the expansion of trade volume is associated with increased pollution from heightened production or transportation. On the other hand, trade can contribute to environmental improvements through technological advancements (e.g., tightened regulations enabled by increased trade income) and compositional shifts in production.

Furthermore, the level of environmental stringency is associated with trade-related emissions. The pollution haven hypothesis suggests that differing environmental regulations between developed and developing countries lead to a transfer of production from the former to the latter, which specialize in environmentally intensive sectors. Carbon leakage is the widely used notion for when emission-intensive production activities are relocated as environmental regulations tighten. Mitigating the adverse effects of carbon leakage can be achieved through free trade agreements incorporating environmental provisions (as noted by Brandi, Schwab, Berger, & Morin, 2020). Additionally, subsequent studies have indicated that the impact of trade on emissions varies depending on the type of exports. Zugravu-Soilita (2018) identified a reduction in emissions associated with trade in environmentally friendly goods, while Mealy and Teytelboym (2022) utilized the economic complexity framework for green products and showed that countries with comparative advantages in exporting complex and green products tend to have higher environmental patenting rates, lower CO_2 emissions, and more stringent environmental policies.

Alternative macro determinants of CO_2 emissions, such as urbanization and population density, RD intensity, or the quality of institutions, are mentioned in the overviews provided by Briglauer, Köppl-Turyna, Schwarzbauer, and Bittó (2023b) and Briglauer, Köppl-Turyna, Schwarzbauer, and Bittó (2023a), who offer a comprehensive literature review and empirical study on the effects associated with applications of the information and communication technology (ICT) sector on CO_2 emissions.

Zhu, Shi, Wu, Wu, and Xiong (2018) make use of the GTAP database and consider emissions embodied in global trade utilizing the differences in the production- and consumption-based emissions accounting frameworks. They aggregate global trade to 30 geographical units (countries/regions) and 18 sectors, showing that with the reference year of 2011, already nearly 20% of global emissions had been stemming from embodied emissions in international trade (based on the production-based accounting principle). Countries with the largest net exports in terms of emissions embedded in trade were China, Russia, and India, while the EU, the US, and Japan had been the largest importers of embodied carbon during that period.

Research on the carbon content of international trade often employs multi-regional environmental input-output frameworks, with a specific focus on global value chains and, in some cases, considering value-added and emissions in GVCs together. An early contribution to this literature by Weber and Matthews (2007) analyzed bilateral trade between the USA and its seven most important trade partners from 1997 to 2004. Their results show that due to volume and compositional effects (larger import volumes and shifts in trade patterns), the subsequent increase in embodied emissions in US trade can be estimated to have been between 4 and 16 percentage points.

At the center of the analysis by Zhang et al. (2019) is the economic and environmental importance of the BRICS group (Brazil, Russia, India, China, and South Africa). Based on the WIOD database and emissions data up to 2009, the study utilizes an inputoutput framework to derive the value-added and embodied emission contributions of these economies in global trade. The most dominant economy in terms of both emissions exports and imports was China, also presented as a major transit country forwarding emissions within the BRICS (mostly China-Russia, Russia-China, and China-Brazil) as well as outside the group, primarily in the form of intermediate goods with relatively low emissions inflows. The most prominent absorbents of emissions outflows from the BRICS group were the USA, Japan, Germany, the UK, and Italy.

Zhong, Goh, and Su (2022) focus on both emissions and value-added embodied in trade from 2000 to 2014 for 43 countries. By utilizing input-output tables, they derive the domestic contents in bilateral exports, which shows a reduction in emissions intensity over time across the sample countries. In the second part of the study, they estimate a gravity model, examining the effects of institutional arrangements (trade and environmental policies) on the emissions intensity of bilateral exports. The results indicate that an open trade policy tends to come with lower emissions intensity in exports, as the composition of exported goods shifts towards higher value-added and lower emissions activities. Simultaneously, the presence of carbon leakage is found through higher emissions intensities in imports.

2.3 The Smile Curve hypothesis

With the fall of transport costs, the need to produce close to the location of consumption (globalization's first unbundling) was followed by what Baldwin (2013) termed globalization's second unbundling: the need to organize production stages in proximity due to advances in ICT. This geographical splitting of production stages led to the emergence of global value chains, which have become important characteristics of global trade and production sharing. The combination of trade liberalization, free capital movement, and low transport costs boosted the worldwide sourcing of production and relocations, especially from the 1990s onwards. This resulted in the relocation of low value-added, labor-intensive production stages to sites with low labor costs, while high value-added tasks were retained in developed economies.

Originally coined by ACER founder and CEO Stan Shih, the "smile curve" hypothesis asserts that value-added shares in pre-production (e.g., R&D, design) and post-production (e.g., marketing, distribution) stages tend to be higher than in standardized manufacturing processes, resulting in a U-shaped relationship. The smile curve approach integrates the value chain model originally developed by Porter (1985), the literature on firm choices in supply chains (e.g., Acemoglu, Johnson, & Mitton, 2009; Antràs & Chor, 2013; Antràs & Helpman, 2006), and the literature on international trade and the fragmentation of production (e.g., Timmer, Miroudot, & de Vries, 2019; World Bank Group et al., 2017).

Studies identifying smile curves empirically have used input-output data at the industrial level (Baldwin, Ito, & Sato, 2014; Meng & Ye, 2022; Meng et al., 2020) or at the firm level (Rungi & Del Prete, 2018; Saliola & Zanfei, 2009). Timmer et al. (2019) and Stöllinger (2021) further enriched this framework by incorporating functional specializations of locations along the value chain. Meng and Ye (2022) added another dimension by differentiating between domestically owned and foreign-owned firms and their roles in global production networks. While most research has focused on smile curves at the firm and sectoral levels, new evidence (compare Baldwin & Ito, 2021) suggests that, at the aggregate economy level, value-added has shifted to services sectors for developed countries, while for less developed economies in Asia, the value-added from domestic services (typically at the beginning and end of the smile curve) has been reduced and increasingly supplied by advanced economies and China. Apart from sourcing labor-intensive tasks and jobs from developing countries, there is a debate on whether high-emission-intensive (and low value-added) stages of value chains have also been outsourced to developing countries, potentially resulting in an inverted U-shaped emissions curve along global value chains, as outlined by the World Bank Group et al. (2023).

3 Estimation of the smile/frown curve in global value chains

3.1 Methodology

Our approach is based on input-output tables and thus on the modelling approach developed by Leontief (1936). Put simply, input-output tables are the representation of all monetary flows between all producers (intermediaries) and final demand within a defined geographical area over a given period.

We define $c = c_1, c_2, \ldots, c_I$ as the set of countries in our input-output system; $s = s_1, s_2, \ldots, s_J$ are the sectors within each country, hence $c_i s_j$ is the index for countries i sector j and $n = dim(c) * dim(s)^2$ as the number of all sectors across all countries. Therefore, our notation for a common interregional input-output system is:

- $Z_{n \times n}$: intermediate transaction matrix capturing the flows between all sectors.
- $X_{n \times 1}$: vector of gross output of each sector
- $A_{n \times n}$: technical coefficient matrix where $a_{c_i s_j} = \frac{z_{c_i s_j, c_i s_j}}{x_{c_i s_j}}$
- $Y_{n \times dim(c)}$: capturing demand of each country for each sector; and hence also capturing final product exports and final product imports of each country.³

Hence, in an Input-Output setup it must hold that

$$X = A * X + Y \Leftrightarrow X = (I - A)^{-1}Y \Leftrightarrow X = BY,$$
(1)

with $B_{n \times n} = (I - A)^{-1}$ as Leontief inverse.

Figure 1 displays a multi-region input–output model (MRIO). The first row, second cell $z_{c_1s_1;c_1s_j}$ represents the intermediate flows from sector 1 in country 1 to sector j in

 $^{^{2}}dim(vector)$ refers to the dimension of the vector

³If we are interested in the final product demand imports of country c_1 , we only need to look at column c_1 of $Y_{n \times dim(c)}$ and the rows $c_i s_j$ with $i \neq 1$. If we are interested in the final product exports of the sector $c_1 s_1$ we need to look at the matrix $Y_{n \times dim(c)}$ at the row $c_1 s_1$ along the columns c_i with $i \neq 1$.

MRIO-Table		Intermediate use (Z)					Final Demand Y				
		Country c ₁		Country c ₂ Country		Country c _i	Country c ₁	Country c ₂		Country c _i	Gross Output
		Industry s ₁	Industry s _j	$\text{Industry} s_1 \dots s_j$	Industry c s ₁ s _j	Industry c $s_1 \ldots s_j$					
Industry s ₁		Z c1s1;c1s1	Z c1s2; c1sj	Intermediate exports of sector c1s1			Exports of final products sector c ₁ s ₁				
Country c1 Industry sj		Z _{c1sj;c1s1}		(Z)						(X)	
Country c2	Industry s ₁										
oountry 02	Industry s _j					Imports of					
			te Imports of ntry c ₁				final products; of c1	(Y)			
Country c _i	Industry s ₁	1					0.01				
oountry of	Industry s _j										
Value added		(VA)									
Gross Output			(X)]					

Figure 1: MRIO illustration

country 1. The sum along the rows and along the columns (X) should be equal and give the gross output of each sector in each country.

Referring to the methodology originally developed by Antràs et al. (2012) and extended by Ye, Meng, and Wei (2015) and Meng et al. (2020); we can derive the three key elements to construct the smile-curve from an input-output setup: the **value–added intensity** (y-axis) of each sector, the **sector's share of value–added** (weights) and the **position of each sector in the corresponding value chain** (x-axis).

3.1.1 Intensities and Share

For value-added we can derive the value-added intensity by

$$\hat{V} = (I_{n \times n} - diag(A * u)) \tag{2}$$

with u as $s \times 1$ unit vector. Equation 2 is similar to the one used in Aslam, Novta, and Rodrigues-Bastos (2017) and the idea is straightforward: subtract all intermediate input shares of a specific sector (row-sum across A) from 1 we can derive the value-added per labour compensation⁴.

Equivalently, for plotting the value-added intensity (y-axis), we can divide the value-added from the IO table by labor compensation:

$$v_{c,s} = \frac{va_{c,s}}{labcomp_{c,s}} \tag{3}$$

Using the value–added intensity as defined in Equation 2, we can derive the value–added induced by a given demand vector Y^* as follows

$$VA_{1\times 1}^* = VBY_{n\times 1}^* = VX^*$$
(4)

As we are interested in the value-added created in each sector at the total value chain, we can decompose the value-added $VA_{n\times 1} = [va_{c_1s_1}, va_{c_1s_2}, \dots, va_{c_Is_J}]$ by taking

⁴Note that this is similar to national accounting: Intermediate Inputs + Value-Added = Gross Output by dividing that equation by gross output and rearranging we end up at equation (2).

the diagonal matrix of the value-added intensity vector:

$$VA_{n\times 1}^* = \hat{V}BY^* \tag{5}$$

The value–added share, induced by demand Y^* is therefore the quotient of 5 and 4. We will refer to this as the *value–added gain* (VAG):

$$VAG_{n\times 1} = \frac{\hat{V}BY_{n\times 1}^*}{VBY_{1\times 1}^*} \tag{6}$$

For the case of emissions, our principal interest, we replace value–added with CO₂.⁵ We calculate the CO₂-intensity to plot the environmental loss curves similar to equation (3), i.e. $co_{2c,s} = \frac{co_{2c,s}}{labcomp_{c,s}}$.

Following the subsequent steps above and calculating CO_2 -intensities similar to Equation (2) for value-added, we arrive at the equation for the *environmental loss (ELO)*:

$$ELO_{n\times 1} = \frac{\hat{C}BY_{n\times 1}^*}{CBY_{1\times 1}^*} \tag{7}$$

3.1.2 Position in global value chains

The distance measure we will use refers to Ye et al. (2015) and Meng et al. (2020) building on Antràs et al. (2012) and the idea of Dietzenbacher et al. (2005), who first applied the concept of the average propagation length (APL) on an input-output production network. In detail, the measure U_k we use focuses on the propagation length of value-added (see Meng et al., 2020). In simple terms the measure U_k is the ratio of a weighted value-added contribution to the unweighted value-added contribution of an industry,

$$U_k = \frac{\hat{V}B^2 Y^*}{VBY^*} \tag{8}$$

with $U_k > 1$ indicating that the sector is further away from final demand and $U_k = 1$ indicating that the sector is directly at final demand. In the graphs shown in the following sections, we will reverse the scale of the forward distance for a more intuitive interpretation: the distance at the origin of the value chain is 0, while the distance is greater the closer the sector is to the consumer.

⁵Just for clarification, and to give a full picture of how CO₂ intensity can be calculated in an inputoutput framework: We are referring to a CO₂ intensity that considers only sector-related CO₂ emissions (production-based accounting). That is, only the emissions generated in that specific sector, without considering the emissions of the intermediate inputs of the sector. The intensity can therefore be interpreted as the marginal *sector* emissions. Another CO₂ intensity often used in the literature is the consumptionbased CO₂ intensity, which also considers the emissions of intermediate inputs. The consumption-based CO₂ intensity could be easily derived by multiplying the production-based intensities by the Leontief inverse $C_{cons} = C_{pro} * B$. The interpretation of these is a bit more useful as they are the marginal total emissions. Thus, they reflect all the additional emissions that would be added by producing an additional good across the whole value chain (Perman, 2003). However, as we want to allocate CO₂ emissions along the value chain, we use production-based intensities.

We will consider the final demand of each country for each product separately, regardless of where it is produced. Therefore, our demand matrix Y^* will be an $n \times n$ matrix, with the columns representing the different demands (one column for each country's demand for each sector). The rows represent all sectors. Thus, each column contains a large number of zeros, except in the rows which are the similar product than the demanded product. For example, if we look at the US demand for machinery and equipment n.e.c. (C28), regardless of whether the machinery and equipment is imported from China or Germany, the column representing the US demand for machinery and equipment n.e.c. (USA_{C28}) has zeros in all rows except those for product C28 (e.g. has numbers in row DEU_{C28} and also in CHN_{C28}). By using this matrix where each column represents a different final demand, we can calculate the forward distance for all sectors for each final demand at once.

Unfortunately, the input-output system is more aggregated as it seems. It is not possible to differentiate between services used after fabrication ("post-fabrication" or "postsale") and the services used before the sale ("pre-sale"). For example it's not possible to differentiate between the water transport of the final product to the final use after the sale and the water transport of the intermediate input in the pre-sale stage. The distance in equation (8) just gives a weighted average distance across pre- and post-sale. However, a smile curve exists of both parts, of a pre-fabrication part and a post-fabrication part. Similar to Ye et al. (2015), we assume that the post-sale sectors are domestic, and further assumed the following sectors as relevant post-sale sectors in the goods value chain: transport sectors (Land transport and transport via pipelines (H49), Water transport (H50), Air transport (H51), Warehousing and support activities for transportation (H52), Postal and courier activities (H53)) and the sector Wholesale and retail trade (G). These sectors must be closer to final demand than the closest pre-sale sector. To ensure this, we have simply added these to the right of the pre-sale sectors. Thus, the distance of the post-sale sectors can't be interpreted as an average distance, but only as being closer to final consumption than the pre-sale sector. As we cannot disentangle the pre-sale and post-sale environmental loss/ value-added gain of these sectors with input-output data, we currently use the maximum value they could have using the total environmental damage/added value of the industry for both pre- and post-sale.

3.2 Data

We use three datasets on a country-industry basis. For input-output-relationships we rely on the 2021 edition of the Inter-Country Input-Output database published by the OECD, which contains information on input-output linkages between 45 industries⁶ (ISIC rev. 4) in 66 countries for the period of 1995 to 2018. Among the countries covered there are 38 OECD as well as 28 non-OECD member countries ranging from high-income through lower middle-income countries.

⁶For the industry classification compare 4.

The OECD TECO₂ dataset contains indicators on CO₂ emissions stemming from production as well as embodied in global final demand, therefore highlighting the differences between production- and consumption-based CO₂ emissions across sectors and countries (Yamano & Guilhoto, 2020). In this paper we follow the production-based approach, using CO₂ emissions from fuel combustion as the main emissions-related indicator. This indicator is provided by the International Energy Agency (IEA), and it relies on emissions stemming from 46 unique fuel products including coal, peat, oil shale, oil, natural gas and waste. This data contains fuel combustion emissions for 34 unique flows, covering e.g. the aviation industry as well as maritime transport too, across 138 economies. These flows are then assigned when assembling the dataset to sectors of TECO₂ covering both resident industries and households in both domestic and foreign territories. TECO₂ is a meaningful source for our analysis as it is partially using the ICIO dataset to decompose the emissions data from the IEA to sectors and households, which ensures that the sectoral classification and data structure of the two sources match.

An additional data source we rely on is the Trade in Employment (TiM) dataset by the OECD (Horvát, Webb, & Yamano, 2020), which is needed to calculate the value–added as well as the emissions relative to labor compensation. This dataset contains information on how GVCs affect employment in different sectors and countries by showing how changing compositions of final demand are associated with changes in employment in certain sectors in certain countries. It is based on the ICIO tables and complementary to the TiVA indicators by OECD, and the three are therefore harmonized in terms of sectoral classification and time coverage, meaning that they cover 45 industries for the period of 1995-2020. The current (2023) edition of TiM covers 84 economies.

4 Does a value–added smile curve imply an environmental frown curve?

4.1 Example: Swedish final demand for motor vehicles

4.1.1 Value-added

Once the elements of the smile curve are calculated, it is possible to construct a visual representation of the smile curve. Figure 2 depicts the value chain induced by Swedish final demand for motor vehicles ($C29^7$).

With respect to value–added, we observe a U-shaped curve, starting with higher intensities, then reaching a local minimum at intermediate production stages and eventually recovering to higher value–added intensities in the pre-sale stage. The figure also reveals high complexity of the value chain as it is composed of a wide variety of industries in different countries. The value–added intensities, i.e. the share of value–added per labor compensation, of the participating industries are distributed between slightly above 0 and

⁷See table 4 in the appendix.

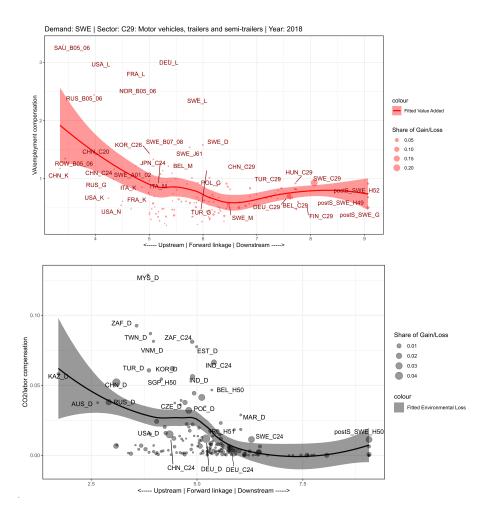


Figure 2: Value-added and environmental loss curves of the Swedish final demand for motor vehicles (C29), 2018

3. In most industries, value-added is below total labor compensation, while some highly capital-intensive industries such as mining and quarrying (B_{0506}) or real estate activities industries (L) exhibit a value-added intensity above unity. Value-added contributions (i.e. the size of the points) are highly unevenly distributed, with few sectors showing a high value-added contribution. Specifically, a large share of value-added embodied in the consumption of cars in Sweden can be traced to the car manufacturing sectors in Sweden (SWE_{C29}) and Germany (DEU_{C29}) as well as professional, scientific and technical services in Sweden (SWE_M).

The post-sale section of the graph features by construction domestic industries. As discussed in section 3.2, this results from the construction of the post-manufacturing section of the curves only a certain number of domestic post-sales industries were included as those industries are the ones directly involved in the marketing, sales, distribution and other supporting activities related to the final goods of the car manufacturing sector.

4.1.2 CO_2 emissions

The bottom panel of Figure 2 presents the environmental loss curve regarding the final demand of cars in Sweden in 2018. The figure illustrates how fragmented the value chain is in terms of origins of intermediate products and services, with several sectors embodying CO_2 emissions that are eventually consumed by final demand for motor vehicles in Sweden.

Most industries in the value chain have relatively low CO_2 intensities. Still, there are a number of emission-intensive sectors, in particular energy sectors (D) and metal manufacturing (C24). Along the pre-manufacturing section of the environmental loss curve, the energy industries occur to have high emission intensities along with significant shares of the overall emissions induced along the entire value chain. Energy industries of multiple countries are involved, such as Taiwan, Vietnam, South Africa or Turkey. The German and Chinese energy industry represent a high extent of environmental loss, accounting for around 4.6 and 4.3% of all CO_2 emissions created along the value chain, respectively. Several metal manufacturing industries, such as the ones in Sweden, Germany and China represent relatively large shares of environmental loss.

4.2 Example: Changes over time

There have been considerable changes in value chains over time in terms of both composition and relative value–added and emissions intensities. This is clearly reflected in the data, particularly when exploring changes in the contribution of China. Figure 3 presents the value–added and emission curves regarding the final demand of electronic products in the USA for the years 1995 and 2018. In order to keep the visualization compact, single data points have been condensed onto their respective country level, adding up their contributions.

One important aspect of the figure is the role of China (marked with distinct colours). Even though the average value–added intensity of Chinese industries along the value chain decreased, their overall share across other industries of other economies has grown. This points to a conclusion that China, on average, has contributed to the value chain with activities that overall have lower value–added on average. Concerning the environmental loss curves (lower panel) the same is true, Chinese industries became slightly less emissions intensive over time, but their overall contribution to the emissions associated with activities along the value chain has increased. In fact, it increased to a much higher extent than for value–added.

Another relevant example is Mexico, as it is a major trade partner for the USA for electronic products and consumer appliances: Mexican industries tended to have a much higher value–added intensity on average in 1995, and it has decreased quite significantly by 2018, while the size of the bubbles (the overall contributions) remained largely unchanged. In case of emissions, the same pattern can be observed, but to a lesser extent.

Also, it is apparent how the single large contribution of China shapes the environmental loss curve in the year of 2018. Part of the U-shape for this curve can be directly

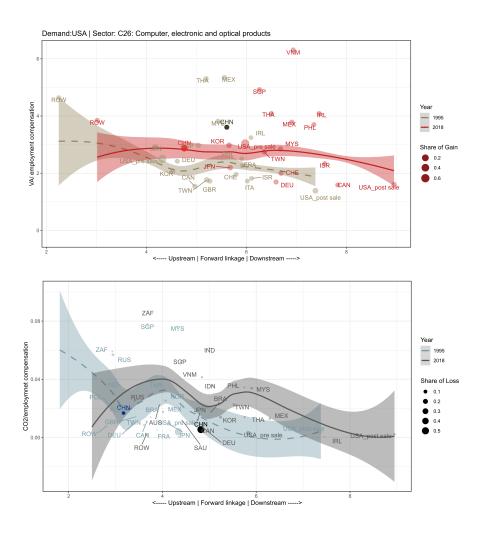


Figure 3: Changes in smile curves and environmental loss curves of the US electronics industry (C26), 1995-2018

associated with the influence of Chinese industries.

4.3 Generalisation

4.3.1 Individual value-added and emissions curves

Instead of discussing individual examples, we will now focus on the overall picture emerging from the mapping of value–added and emissions across production stages. To this end, we will fit a second order polynomial to all the demands for industrial goods in the 66 economies (and the rest of the world) of our system. Thus, we will run two equations separately for 17 industrial demands for each country⁸ using the value–added gain (equation 6) and environmental loss contributions (equation 7) as weights for the sector observations:

$$v_{j,k} = f(U) = \alpha_{1,0} + \beta_{1,1} U_{j,i,k} + \beta_{1,2} \left(U_{j,i,k} \right)^2 + \epsilon_{1,i,j,k}$$
(9)

⁸Overall we run 1.139 regressions per year.

$$c_{j,k} = f(U) = \alpha_{2,0} + \beta_{2,1} U_{j,i,k} + \beta_{2,2} \left(U_{j,i,k} \right)^2 + \epsilon_{2,i,j,k}$$
(10)

where $v_{j,k}$ and $c_{j,k}$ are the value-added and CO₂ intensities described above, $U_{j,i,k}$ is the forward distance and $\epsilon_{1,i,j,k}$ and $\epsilon_{2,i,j,k}$ are unrelated *i.i.d.* errors.

We then compute the first and second derivative (i.e. $\frac{\partial f}{\partial U}$ and $\frac{\partial^2 f}{\partial U^2}$) with respect to the forward distance. This allows us to test for the shape of the polynomial for a given interval $[U_{j,i,k}^{lb}, U_{j,i,k}^{ub}]$. We can distinguish between three cases:

- 1. Inverted U-shape: in the interval there is one point for which $\frac{\partial f}{\partial U} = 0$ and $\frac{\partial^2 f}{\partial U^2} < 0$
- 2. U-shape: in the interval there is one point for which $\frac{\partial f}{\partial U} = 0$ and $\frac{\partial^2 f}{\partial U^2} > 0$
- 3. neither: the curve is either upward or downward sloping in the interval $[U_{i,i,k}^{lb}, U_{i,i,k}^{ub}]$

We perform the analysis for emissions and value–added curves for the years 1995 and 2018. The results are displayed in table 1.

		2018			1995	
	U-shape	inverted U	neither	U-shape	inverted U	neither
VA	30%	31%	39%	54%	21%	24%
$\rm CO_2$	24%	38%	38%	42%	31%	27%

Table 1: Shapes of VA and emissions curves (1995 & 2018)

In 1995, the majority of value-added curves (54%) exhibited a U-shape relationship, 21% were inverted U-shaped and 24% neither U- nor inverted U-shaped. For the emissions case we observe the majority of cases to be U-shaped, but less than a third exhibited an inverted U-shape.

In 2018, roughly 40% of all value–added curves exhibited neither a u- nor an inverted U-shape, a similar share can be observed in case of the emissions curves. Overall this points at considerable changes in the last three decades. First, the U-shape pattern in GVCs seems to be less dominant in 2018 than 1995. Second, also the inverted U-shape pattern in emissions was less frequent than initially thought and has become even less important over time. Overall, this means that there was some support for the underlying hypothesis in the mid 1990s but there is no support for it in recent years⁹.

Looking at the transitions between 1995 and 2018 (compare table 2), we can see that the majority of value-added curves preserved their shapes, whereas in the case of CO_2 , the conversion from either U-shape to "neither" or "neither" to inverted U shape was more prevalent. This points at major shifts in production stages in terms of CO_2 within global value chains.

⁹A similar observation can be made for subsets in our sample, i.e. the the OECD, the G7 or the EU27. Results are displayed in table 3 in the appendix

	2018						
1995		value-adde	d			$\rm CO_2$	
	U	inverted U	neither		U	inverted U	neither
U	45%	14%	42%		37%	17%	46%
inverted U	10%	64%	26%		13%	62%	26%
neither	15%	40%	45%		17%	43%	41%

Table 2: Transitions between shapes (2018 vs. 1995)

4.3.2 Country-level and industry level value–added and emissions curves

To further generalise our results, we will aggregate the individual curves of the previous subsection on the country level and/or final demand products. So, instead of looking at 1,139 individual final demands for industrial goods per year, we summarize the value-added and emissions curves by modifying equations 9 and 10 focusing at the demand for industrial products in a given country:

$$c_{j,k} = \alpha_0 + \sum_{j=1}^{17} \beta_{1,j} * U_{j,i,k} + \sum_{j=1}^{17} \beta_{2,j} * (U_{j,i,k})^2 + \epsilon_{i,j,k}$$
(11)

$$v_{j,k} = \alpha_0 + \sum_{j=1}^{17} \beta_{1,j} * U_{j,i,k} + \sum_{j=1}^{17} \beta_{2,j} * (U_{j,i,k})^2 + \epsilon_{i,j,k}$$
(12)

where $c_{j,k}$ $(v_{j,k})$ is the relevant CO_2 -intensity (value-added-intensity) of industry kin final demand of country j and $U_{j,i,k}$ is a measure of distance of industry k in final demand of industry i in country j. $\beta_{1,j}$ and $\beta_{2,j}$ are the slope parameters of the demand induced emissions and value-added curves, that are allowed to vary across demands in a particular country. To aggregate to the country demand the individual industrial demands are averaged. To capture the uncertainty we perform bootstrapping (50 iterations per demand) and point estimates and 95% confidence bounds are averaged across iterations.

The results on the country level are displayed in figure 4 for the G7 economies.

In most cases we observe a slight U-shape curvature for the average emissions curve, except for Japan, for which we find an inverted U-relationship. For most G7-economies we find major emissions contributions by sectors in China, while at more downstream stages emissions tend to be mainly produced at home.

Comparing the curves for the G7 economies for 2018 and 1995 (see figure 10 in the appendix), both, the beginning and the end of the emissions curve have flattened, especially close to end-use. On the other hand, the middle part has increased in average CO_2 -intensity.

Interestingly, these curves did not to change over time significantly in most cases, as can be observed in figure 10 in the appendix. The exception being Japan, which displayed no inverted U-shape pattern in 1995.

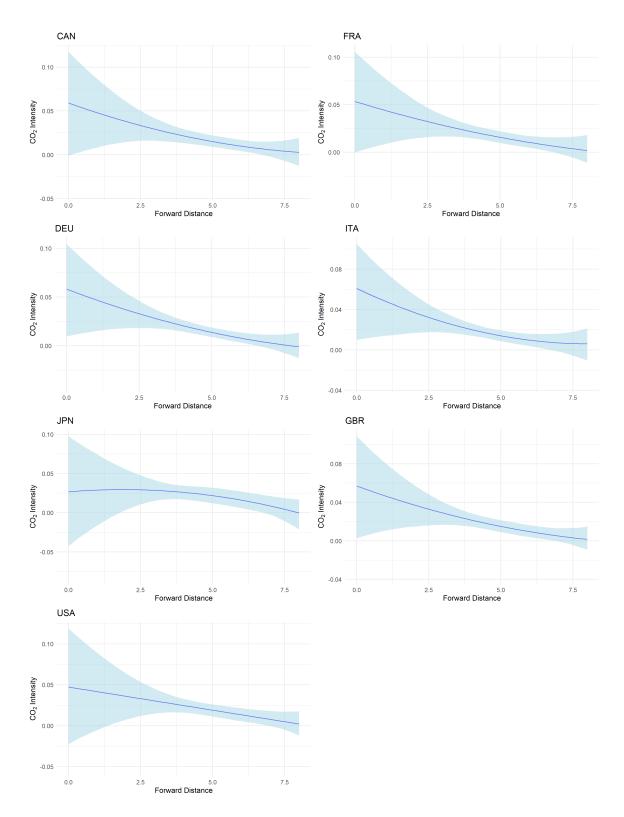


Figure 4: Environmental loss curves (G7), 2018

Likewise, we can focus on a particular demand category:

$$c_{i,k} = \alpha_0 + \sum_{i=1}^{67} \beta_{1,i} * U_{j,i,k} + \sum_{i=1}^{67} \beta_{2,i} * (U_{j,i,k})^2 + \epsilon_{i,j,k}$$
(13)

$$v_{i,k} = \alpha_0 + \sum_{i=1}^{67} \beta_{1,i} * U_{j,i,k} + \sum_{i=1}^{67} \beta_{2,i} * (U_{j,i,k})^2 + \epsilon_{i,j,k}$$
(14)

where $c_{i,k}$ $(v_{i,k})$ is the relevant CO_2 - (value-added-) intensity of industry k in final demand of industry i and $U_{i,j,k}$ is a measure of the distance of a particular industry k in country j to final demand of product i. $\beta_{1,i}$ and $\beta_{s,i}$ are allowed to vary across country for a given demand category for industrial products. We aggregate across countries by using the weights of a country's final demand in global demand (based on the MRIO table) share for the given demand category. To account for uncertainty in aggregation we also perform bootstrapping methods (50 iterations) within the demand category.

The results are displayed in figures 5 and 6 for value–added and in 7 and 8 for environmental loss curves, respectively.

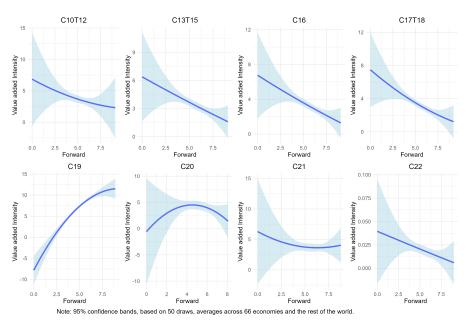


Figure 5: Value-added curves (Global sectors 1), 2018

It is visible that only a couple of industries exhibit second order curves with a maximum or minimum when summarized across countries, in our case industry C20, C21 and C25 (Chemical and chemical products, Pharmaceuticals, medicinal chemical and botanical products, Fabricated metal products). The rest of them can not be clearly categorized based on our parameters.

For emissions, the curvatures are slightly more pronounced for some industries, however, the overall picture is similar as for value–added. Industries C13T15, C19, C24, C25

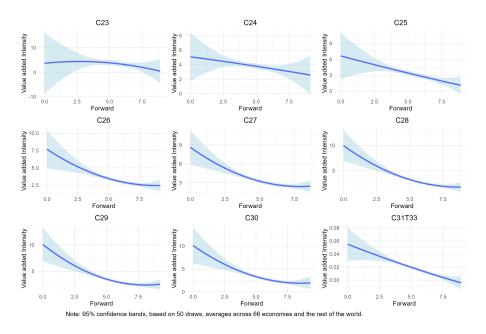


Figure 6: Value-added curves (Global sectors 2), 2018

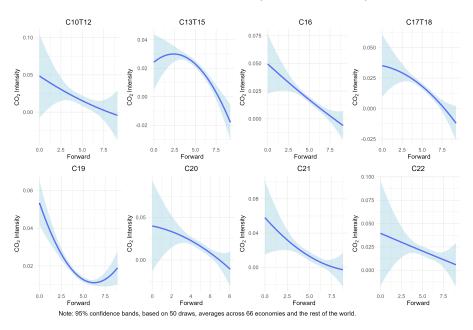


Figure 7: Emissions-curves (Global sectors 1), 2018

and C26 exhibit all inverted U-shapes. These industries are, respectively, textile manufacturing, coke and refinery, metal and fabricated metal products manufacturing, as well as the computer, electronic and optical equipment manufacturing industry.

Aggregating the results across all industrial final demand (using weights from the MRIO table) yields a global mapping of emissions and value-added contributions across production stages. Figure 5 depicts the condensed value-added and emissions curves for global final demand.

Interestingly, the value-added curve has a slightly U-shaped pattern, while the emis-

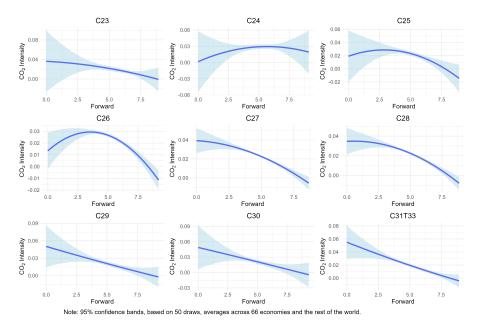


Figure 8: Emissions-curves (Global sectors 2), 2018

sions curve is slightly inverted. It is, however, difficult to discern definitive curvatures, as the confidence intervals widen when zooming out to the global perspective.

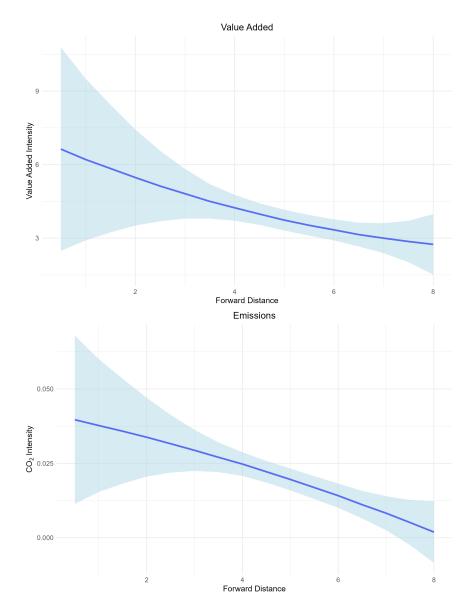


Figure 9: Global value–added and emissions-curves (all countries and demands for industrial products), 2018

5 Conclusion

The smile curve concept has emerged as a powerful tool for analyzing value-added distribution across global value chains (GVCs). This paper extends this framework by introducing environmental loss curves, which map embedded CO_2 emissions along GVCs. Using granular Input-Output data from the OECD, we analyze emissions and value-added contributions across 45 industries in 66 countries, with the flexibility to aggregate results for economic groups (EU27, OECD, G7) and specific industrial sectors over time.

Our methodological framework for estimating value-added and emission curves reveals distinct patterns in environmental profiles compared to traditional value-added distributions. While value-added typically follows a smile curve pattern, we find tentative evidence of a frown curve (inverted U-shape) in emissions across GVCs, although this pattern is less pronounced. Moreover, the classic smile curve in value-added has evolved over time, primarily due to the successful integration of emerging economies like China into GVCs.

The increasing fragmentation of GVCs and the incorporation of emerging economies over the past three decades has produced two notable effects: a flattening of the valueadded profile and an intensification of emissions in early production stages. This emission pattern can be attributed to the outsourcing of intermediate production to emerging economies with higher emission intensities, particularly in energy production.

Our study has three primary limitations that warrant attention. First, due to data constraints, we were unable to incorporate functional specializations into our framework, as done in previous studies (Stöllinger, 2021; Timmer et al., 2019). Second, the OECD TECO₂ database excludes emissions from chemical processes in manufacturing stages, which could significantly impact the emission patterns across value chains. Third, the Input-Output database by the OECD provides a large coverage of countries, but still lacks data on low-income countries, which might impact our results. However, databases with a larger coverage of countries, such as EORA, suffer from a lack of granularity with respect to industries and have been criticized for their accuracy (?). These limitations present promising opportunities for future research to enhance our understanding of both economic and environmental dimensions of global value chains.

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Appendix

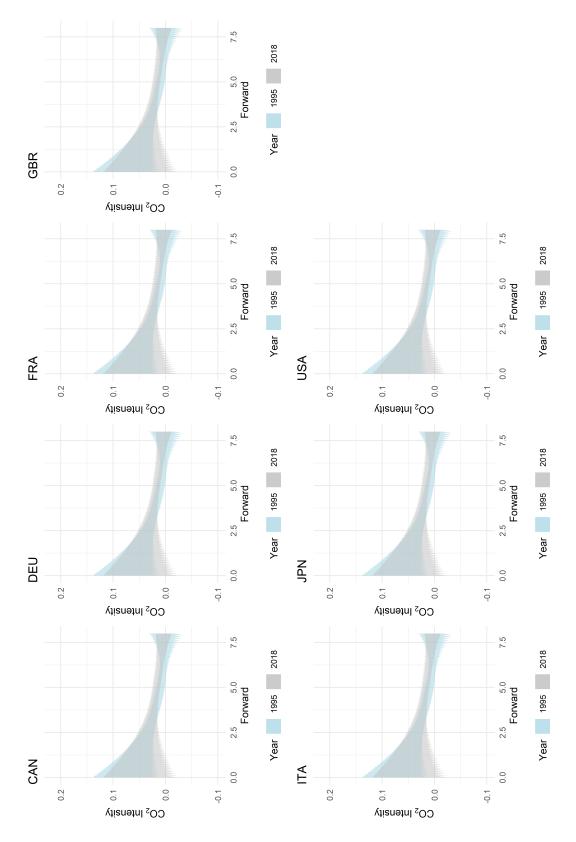


Figure 10: Environmental loss curves (G7), 1995 and 2018

		VA			CO_2	
		2018			2018	
	U-shape	inverted U	neither	U-shape	inverted U	neither
All	30%	31%	39%	24%	38%	38%
EU27	25%	29%	46%	25%	26%	48%
$\mathbf{G7}$	13%	33%	54%	24%	17%	59%
OECD	25%	29%	46%	25%	26%	48%
		1995			1995	
	U-shape	inverted U	neither	U-shape	inverted U	neither
All	54%	21%	24%	42%	31%	27%
EU27	48%	22%	30%	40%	31%	30%
G7	52%	16%	32%	63%	10%	27%
OECD	52%	19%	28%	48%	20%	32%

Table 3: Shapes of emissions and value–added curves (1995 & 2018)

Label	Industry	ISIC Rev.4
$A01_02$	Agriculture, hunting, forestry	01, 02
A03	Fishing and aquaculture	3
$B05_06$	Mining and quarrying, energy producing products	05,06
$B07_08$	Mining and quarrying, non-energy producing products	07, 08
B09	Mining support service activities	9
C10T12	Food products, beverages and tobacco	10,11,12
C13T15	Textiles, textile products, leather and footwear	13, 14, 15
C16	Wood and products of wood and cork	16
$C17_18$	Paper products and printing	17, 18
C19	Coke and refined petroleum products	19
C20	Chemical and chemical products	20
C21	Pharmaceuticals, medicinal chemical and botanical products	21
C22	Rubber and plastics products	22
C23	Other non-metallic mineral products	23
C24	Basic metals	24
C25	Fabricated metal products	25
C26	Computer, electronic and optical equipment	26
C27	Electrical equipment	27
C28	Machinery and equipment, nec	28
C29	Motor vehicles, trailers and semi-trailers	29
C30	Other transport equipment	30
C31T33	Manufacturing nec; repair and installation of machinery and	31, 32, 33
	equipment	
D	Electricity, gas, steam and air conditioning supply	35
	Table continues on the next page	

Label	Industry	ISIC Rev.4
Е	Water supply; sewerage, waste management and remedia-	36, 37, 38, 39
	tion activities	
F	Construction	41, 42, 43
G	Wholesale and retail trade; repair of motor vehicles	45, 46, 47
H49	Land transport and transport via pipelines	49
H50	Water transport	50
H51	Air transport	51
H52	Warehousing and support activities for transportation	52
H53	Postal and courier activities	53
Ι	Accommodation and food service activities	55, 56
J58T60	Publishing, audiovisual and broadcasting activities	58, 59, 60
J61	Telecommunications	61
J62_63	IT and other information services	62, 63
Κ	Financial and insurance activities	64,65,66
L	Real estate activities	68
М	Professional, scientific and technical activities	69 to 75
Ν	Administrative and support services	77 to 82
0	Public administration and defence; compulsory social secu-	84
	rity	
Р	Education	85
Q	Human health and social work activities	86, 87, 88
R	Arts, entertainment and recreation	90, 91, 92, 93
S	Other service activities	94, 95, 96
Т	Activities of households as employers; undifferentiated	97, 98
	goods- and services-producing activities of households for	
	own use	

Source: OECD ICIO.

Table 4: Industry classification