



The Effects of International Trade on Structural Convergence and CO₂ Emissions

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Abstract

This article introduces a new econometric model that includes an innovative measure of intersectoral structural change. This model describes the structural convergence (or divergence) of sector share patterns across countries (from the North-South or global perspective) influenced by international trade. The econometric analysis applies panel data estimators with different types of fixed effects to the 2013 and 2016 releases of the World Input-Output Database, covering the periods 1995–2009 and 2000–2014. The results show that international trade mostly promotes structural convergence, which is enhanced by sectoral capital intensities. It seems, however, that in this millennium, structural divergence, also fostered by international trade, occurred in terms of the CO₂ intensity of production.

Keywords Structural change · International trade · CO₂ · Macro-econometrics · Panel data · WIOD

JEL Classification C51 · F14 · F18 · O11 · O44

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1 Introduction

Economic growth, particularly that of large emerging economies, such as China or India, increases not only output and income but also CO₂ emissions. Because of the resulting contribution to global warming, the increase in CO₂ shall be mitigated. Structural change, i.e., the shift in an economy's composition across all sectors,¹ can increase or decrease CO₂ emissions. Whereas the effects of international trade on productivity gains, economic growth and international technology spillovers (including energy- and CO₂-saving technologies) have been extensively researched,² the connection of intersectoral structural change among trading partners, i.e., structural convergence or divergence, and the resulting impact on CO₂ emissions remain unknown. Better knowledge of this mechanism and its effects would, however, be helpful for anticipating the international implications of national policies, such as border carbon adjustments: can policy-induced sectoral shifts be expected to spill over to trading partners within a sufficiently large time horizon?

Empirically, intersectoral structural change has significantly contributed to changes in energy use and CO₂ emissions.³ Econometric evidence of the effects of *international trade* on structural change, in general, seems to be scarce, and with respect to CO₂ emissions, in particular, seems to be missing. Some studies have examined the role of foreign direct investment (FDI) and European market integration in the convergence of European countries: in a working paper, Barrios et al. (2002) find convergence of per capita income and industry sector structure in the European Union supported by inward FDI; based on sectoral indices and descriptive statistics of exports, structural similarity and structural change, Crespo and Fontoura (2007) find similar results. Teignier (2018)'s model simulations indicate that trade in agricultural goods reduced agricultural employment of the 19th century Great Britain by 40% and the 20th century South Korea by 10%.

Against this background, our article tries to fill this research gap by exploring the *nexus between trade in intermediate goods and structural convergence* from an econometric point of view. It contributes to the extant literature by conceptually describing the economic mechanisms of structural change driven by trade, by introducing a new econometric model with a new measure of structural change with (North-South) con-/divergence, by studying sectoral CO₂ emissions (in addition to sectoral outputs) and by exploiting the newest version of the large bilateral, bisectoral dataset of the World Input-Output Database (WIOD).⁴

According to the Environmental Kuznets Curve (EKC) hypothesis, during the course of economic development, the sectoral structure of an economy shifts from agriculture toward (heavy) industries, leading to higher emissions. It then shifts further toward advanced knowledge-based industries and services, leading to lower emissions. Consequently, Organisation for Economic Co-operation and Development (OECD) countries are expected to exhibit sectoral structures that create *ceteris paribus* lower economy-wide CO₂ emissions than those of emerging countries at medium stages of development. To examine this

¹ By considering a large number of distinct sectors, our view goes beyond the classical transition from agriculture over industry to services.

² See, e.g., Coe et al. (1997), Saggi (2002), Keller (2004), Cole (2006), Perkins and Neumayer (2009), Havranek and Irsova (2011) and Hübler and Glas (2014).

³ See, e.g., Schäfer (2005), IEA (2007), Kahrl and Roland-Holst (2009), Li et al. (2014) and Voigt et al (2014).

⁴ <https://www.rug.nl/ggdc/valuechain/wiod/>.

economic transition process, we first deploy a North-South setup with OECD and emerging countries and then extend it to all countries covered by the WIOD.

Our article particularly addresses the open question of whether (intermediate goods) exports from an (advanced) economy to another (emerging) economy make these two economies more similar or more different with regard to their sectoral structures and related CO₂ emissions. We denote these two alternatives as *structural convergence* and *structural divergence*. Assuming that both economies continue their economic growth process and that emerging economies catch up with industrialized countries, convergence decreases average CO₂ emissions across sectors, whereas divergence increases them.

Theoretically, the role of international trade in structural change is ambiguous. On the one hand, according to classical trade theories by Ricardo and Heckscher–Ohlin, different economies concentrate their production and exports on different sectors, resulting in *structural divergence*. Additionally, Krugman's New Economic Geography predicts the agglomeration of economic activities, which supports the emergence of specialization and clustering (Midelfart et al. 2003). Induced and directed technological change (Acemoglu 2002, 2010) may reinforce sectoral heterogeneity across countries.

On the other hand, when knowledge or, more specifically, (energy- and CO₂-saving) technologies, spread across borders, supported by international trade, the use of similar technologies will result in similar productivities across sectors and similar sectoral structures within economies, resulting in *structural convergence*. Similarly, intensifying *inter-industry* trade supports the emergence of similar sectoral structures across trading partners (Midelfart et al. 2003). Eventually, in the theoretical long-term equilibrium of a fully integrated world economy, the sectoral structures will be equalized.

The overview by Herrendorf et al. (2014) (Section 6.6.1 International Trade) reconciles the views of these two camps by arguing that in a country with high productivity growth, the development of the manufacturing sector share exhibits a hump shape, while in a country with low productivity growth, it exhibits a downward-sloping shape (Yi and Zhang 2010). In accordance with the outcome of the Environmental Kuznets Curve theory, this theory implies that structural con- and divergence or hump-shaped developments (Stefanski 2014) are theoretically possible across economies depending on (sectoral) productivity growth and the phase of economic development.

Therefore, whether structural con- or divergence dominates, in general, across economies and sectors or, in particular, sectors at specific periods of time is an empirical question that we will answer. Compared with the existing literature, our analysis is, to the best of our knowledge, the first study showing econometrically that *trade in intermediate goods, in general, promotes structural convergence*. This means, intermediate goods, used as production inputs, may embody technologies and knowledge that enhance the specialization of trading partners into similar sectors, not into different sectors as predicted by the traditional trade theories.

In addition to measuring sector shares in terms of output values, we measure them in terms of CO₂ emissions as a new approach. Although both measures reflect relative sector sizes, they can, in general, differ. If, for example, the output share of the transportation sector increases, while its emissions intensity strongly decreases, its emissions share can *ceteris paribus* decrease. Therefore, structural convergence based on CO₂ emissions is an explicit measure for converging sectoral emissions patterns across countries. Based on that, we find indications for structural divergence in terms of the CO₂ intensity of production that began in this millennium. This insight is relevant for policy makers because it points to so-called carbon leakage (from industrialized to emerging economies) which undermines climate policy efforts. Several robustness checks, addressing cross-sectional dependence

(Pesaran 2006, 2015, 2021), different time lags, an interaction term and energy shares as the dependent variable confirm our findings.

The article proceeds as follows. Section 2 derives the conceptual framework, Sect. 3 describes the data, and Sect. 4 presents the econometric results. Section 5 discusses the results, and Sect. 6 concludes the article. The supplementary online appendix provides further statistics and robustness check results.

2 Concept

In this section, we develop the econometric model of structural change driven by international trade and further determinants, first for one economy and then for two economies connected via trade. The model follows the view of the classical trade theories by Ricardo and Heckscher–Ohlin by assuming that sectoral exports and imports affect the extent of sectoral domestic production and hence the sectoral structure of the economy. Different to models explaining trade volumes, such as gravity models, our model uses trade as an explanatory factor of sector shares. In the next step, we will discuss the theoretical effects of international trade on structural change and present two alternative testable hypotheses for the effect of international trade on structural change.

Sectoral one-economy model:

In economy e and sector c at time t , let the sectoral output value determining the sector size be denoted by Z_{ect} . Z_{ect} can be measured as the sectoral (gross) output value Y_{ect} , as physically measured CO₂ emissions C_{ect} or, alternatively, as physically measured (gross) energy use E_{ect} (or, in general, other suitable indicators; see the elaborations below). Z_{ect} is determined via a production function f_1 which is monotonously increasing in each of the input factors K_{ect} , L_{ect} and in intermediate goods imports M_{ect} . K_{ect} is the value of the sectoral capital stock, and L_{ect} is the physically measured⁵ sectoral labor input.

$$Z_{ect} = f_1(K_{ect}, L_{ect}, M_{ect}) \quad (1)$$

The magnitude of Z_{ect} depends on the size of the economy; for example, a sector c is larger in China than in Liechtenstein. To render Z_{ect} size- (scale-) independent and comparable across economies, let us divide the left-hand side of Equation (1) by the total size of economy e , i.e., the sum of the sizes of all sectors c in economy e at time t , denoted by $\sum_c Z_{ect}$. Similarly, to render the right-hand side sector size-independent, we divide the factor K_{ect} by the factor L_{ect} , and imports M_{ect} by the (output-based) sector size Y_{ect} ⁶:

$$\frac{Z_{ect}}{\sum_c Z_{ect}} = f_2\left(\frac{K_{ect}}{L_{ect}}, 1, \frac{M_{ect}}{Y_{ect}}\right) \quad (2)$$

⁵ For example, it is measured as the number of persons working in a sector.

⁶ Theoretically, one could divide all variables in the equation by the same other variable, particularly Y_{ect} . Econometrically, however, this would increase the likelihood of creating endogeneity problems. Furthermore, the factor ratio $\frac{K_{ect}}{L_{ect}}$ is meaningful in the Heckscher–Ohlin framework, while the import intensity $\frac{M_{ect}}{Y_{ect}}$ is a standard measure in trade econometrics. Importantly, defining all indicators in intensity form renders them likely to be stationary.

f_2 signifies a monotonous function. While M_{ect} denotes the total value of intermediate goods imports from the rest of the world, import intensity $\frac{M_{ect}}{Y_{ect}}$ indicates the strength of international (trade) connections.⁷ This relation is in the spotlight of this analysis. It is ex ante unclear whether a higher import intensity is associated with a smaller or larger sector share. Therefore, its theoretical underpinning will be detailed in the following part deriving testable hypotheses on trade and structural change after the two-economy extension. Notably, trade in intermediate goods is a possible driver of specialization in different sectors (goods), whereas trade in final goods is a result/aim of specialization. Trade in final goods, however, is not explicitly studied in this analysis.

The term $\frac{K_{ect}}{L_{ect}}$ reflects the capital-to-labor ratio, which is a key driver of specialization according to the Heckscher–Ohlin theory (see the explanations of the testable hypotheses below). The capital-to-labor ratio indicates capital intensity and, indirectly, the technology intensity of production (given that capital embodies technologies). Referring to the Heckscher–Ohlin theory, economies that are more capital- than labor-abundant will specialize in sectors with relatively high capital-to-labor ratios resulting in larger shares of these sectors in the economy.

Given that the CO₂ intensity of production, measured as CO₂ emissions per output value, differs across sectors, the output and CO₂ shares will differ too. When the sectoral CO₂ intensities change due to efficiency gains, the corresponding output- and CO₂-based sector shares will change to different extents. Whereas CO₂ emissions C_{ect} capture the emissions released within a sector, the energy input E_{ect} is associated with emissions in previous production stages that are attributed to the corresponding sector in which they occur, for instance, the electricity sector. Consequently, these two indicators differ in general. To understand the relation between Y_{ect} , E_{ect} and C_{ect} as well as the influence of the import intensity $\frac{M_{ect}}{Y_{ect}}$ and the capital-to-labor ratio $\frac{K_{ect}}{L_{ect}}$, let us formalize the following relationships, where the function κ governs the energy intensity of sectoral production and the function ζ the CO₂ intensity of sectoral energy use:

$$Y_{ect} = f_3 \left(\dots, \kappa \left(\dots, \frac{M_{ect}}{Y_{ect}}, \frac{K_{ect}}{L_{ect}} \right) \cdot E_{ect} \right), \quad E_{ect} = \zeta \left(\dots, \frac{M_{ect}}{Y_{ect}}, \frac{K_{ect}}{L_{ect}} \right) \cdot C_{ect} \quad (3)$$

f_3 denotes another monotonous function. The output value of production Y_{ect} increases in various input factors and in the energy input E_{ect} . Among other determinants, κ and ζ are both a function of the import intensity $\frac{M_{ect}}{Y_{ect}}$ and the capital-to-labor ratio $\frac{K_{ect}}{L_{ect}}$. Therefore, Y_{ect} , E_{ect} and C_{ect} and their corresponding sector shares do not necessarily develop proportionally or in the same direction. For example, (as we will empirically see) the sectoral structures of countries can become more similar in terms of output shares, but more different in terms of CO₂ emissions shares. This means, output and CO₂ shares develop in different ways or at different rates across countries. One possible reason is that the pace of technical progress differs between total (factor) productivity versus energy and/or CO₂ efficiency (cf. Hübler and Glas 2014). Thus, implicitly, production is becoming more emission-intensive in some countries relative to other countries. Accordingly, f_1 and f_2 in Eqs. (1) and (2) in general differ when Z_{ect} is replaced by Y_{ect} , E_{ect} or C_{ect} .

⁷ The argument “1” in f_2 represents a constant that will be canceled out when computing relative changes.

Sectoral two-economy model:

Now, let us focus on the dyadic trade connections between specific sectors in specific countries and compare the two trading partners in terms of their sectoral structures and the determinants of these connections. For this purpose, let us label source countries of trade as s , source sectors as i , recipient countries of trade as r and recipient sectors as j .

The resulting two-economy model describes long-term convergence processes. From this perspective, we expect a time lag between changes in the determinants on the right-hand side and their effect on the left-hand side, because the underlying techno-economic processes require time to materialize (for related empirical evidence, see Hübler and Glas (2014)). For the time being, let us assume a one-period time lag denoted by $(t - 1)$.⁸

Let σ_{srj} capture any remaining time-invariant economy- and/or sector-specific determinants within the cross-section, for example, education, infrastructure or (constant) productivity (growth). In the Heckscher–Ohlin framework, they include differences in factor endowments, particularly capital and labor endowments, between the economies s and r . Together with the sectoral factor inputs or intensities that enter Equations (1) and (2), the factor endowments determine specialization patterns such that capital-intensive (labor-intensive) economies specialize in capital-intensive (labor-intensive) sectors/goods. θ_t captures any time-variant determinants that jointly affect all economies and sectors in the same way in each time period t , for example, the development of input and output prices, an oil or gas price shock, a pandemic or conflict shock. ε_{srjt} captures any remaining unexplained random influences (noise).

From this viewpoint and with this notation, our previous model is generalized to the following model of convergence defined via a monotonous function f_4 :

$$dz_{srjt} = f_4(dk_{srj(t-1)}, m_{srj(t-1)}, \sigma_{srj}, \theta_t, \varepsilon_{srjt}) \quad (4)$$

$dz_{srjt} = \left| \left(\frac{Z_{rjt}}{\sum_j Z_{rjt}} - \frac{Z_{sjt}}{\sum_j Z_{sjt}} \right) / \frac{Z_{sjt}}{\sum_j Z_{sjt}} \right| = \left| \frac{Z_{rjt}}{\sum_j Z_{rjt}} / \frac{Z_{sjt}}{\sum_j Z_{sjt}} - 1 \right|$ represents the relative distance (the absolute normalized difference with a positive sign) between the (output, CO₂ or energy) shares of the same sector j in two countries s and r connected via trade, where $i = j$ is suppressed for simplicity. As introduced before, the division by $\frac{Z_{sjt}}{\sum_j Z_{sjt}}$ renders dz_{srjt} independent of sector size; i.e., small and large sectors in small and large economies are weighted equally. When the countries s and r become more similar (different) in terms of their sectoral structures, dz_{srjt} will decrease (increase). As argued with the help of Equation (3), function f_4 governing the relative distance differs in general when Z_{ect} is replaced by Y_{ect} , E_{ect} or C_{ect} , because Y_{ect} , E_{ect} or C_{ect} can develop differently in each economy s and r .

Similarly, $dk_{srj(t-1)} = \left| \left(\frac{K_{rj(t-1)}}{L_{rj(t-1)}} - \frac{K_{sj(t-1)}}{L_{sj(t-1)}} \right) / \frac{K_{sj(t-1)}}{L_{sj(t-1)}} \right| = \left| \frac{K_{rj(t-1)}}{L_{rj(t-1)}} / \frac{K_{sj(t-1)}}{L_{sj(t-1)}} - 1 \right|$ represents the relative distance between capital intensities in the sector j (with $i = j$) of the two trading partners. As a result, the expressions on the left and right sides match.

International trade is generalized as a bilateral, bisectoral $sirj$ relation. To keep the model tractable, we sum up the trade flows over source sectors i to obtain a bilateral trade relation with the intermediate goods imports of sector j in r from all sectors of s . Hence, $m_{srj(t-1)} = \frac{\sum_i M_{sirj(t-1)}}{Y_{rj(t-1)}}$ is the modified central trade measure under scrutiny.

⁸ In a robustness test, we will consider different time lags (number of years) and find that the results are robust to the use of different time lags, see Section 5 and Appendix B.3.

Testable hypotheses on trade and structural change:

There are basically two opposite possible approaches to the explanation of structural con-/divergence in the context of international trade.

The first approach refers to the classical trade theories of Ricardo and Heckscher–Ohlin. These theories describe trade in final goods as a result of specialization with the aim to improve welfare. Different to these theories, we consider trade in intermediate goods as a possible *driver* of specialization in different goods/sectors. Trade in final goods is not explicitly considered in our analysis. In these theories, countries specialize in the production of final goods and hence sectors for which they have a productivity-based comparative advantage or for which they have relatively abundant endowments with the required production factors. Following these theories, sector shares and trade intensities may reflect sector-specific productivities (Eaton and Kortum 2002). Induced factor- and sector-specific directed technological change (Acemoglu 2002, 2010) may reinforce the heterogeneity of economic production depending on country-specific factor endowments, policies affecting sectors in different ways and other economic conditions.⁹ New Economic Geography, popularized by Krugman, describes the agglomeration of economic activities. Local knowledge spillovers and linkages with customers and suppliers support the emergence of local specialization and clustering (Midelfart et al. 2003; Crespo and Fontoura 2007). It follows from this theory that over time, countries shift their production toward different sectors. This implies that countries' sectoral structures diverge, i.e., become more different over time. Intermediate goods imports (M) and capital (K) accumulation are expected to enhance this effect: Referring to the Heckscher–Ohlin theory, they extend the availability of production inputs. Referring to the Ricardian theory, they may change sectoral productivities (relative to each other). In this context, capital reflects technologies, knowledge and absorptive capacity (with respect to the adoption of technologies and knowledge). In terms of the previously defined model (Eq. 4), the resulting hypothesis reads as follows:

H1: International trade fosters structural divergence, i.e., $\frac{\partial(dz_{srjt})}{\partial(m_{srjt(i-1)})} > 0$.

H1 implies that sectoral distances become larger. A corresponding hypothesis can be formulated for the effect of capital on divergence. In a Ricardian world with full specialization, in each economy, the shares of some or all but one sector will become zero, i.e., $\frac{Z_{ect}}{\sum_c Z_{ect}} = 0$, and thus, sectoral differences will diverge to the share of the sector of specialization, i.e., $dz_{srjt} = \max \left\{ \frac{Z_{sijt}}{\sum_i Z_{sijt}}, \frac{Z_{srjt}}{\sum_j Z_{srjt}} \right\}$, where, in practice, both sector shares may become zero (no specialization in this sector among these two particular countries), and hence, $dz_{srjt} = 0$.

The second approach refers to international technology (knowledge) diffusion in the course of globalization with international trade and economic development. Accordingly, over time, countries' sectoral technologies and, hence, productivities converge, i.e., become more similar. Similarly, on the consumption side, the international spread of knowledge, culture, habits, tastes and preferences can be enhanced by international trade linkages, which will increase the similarity of consumers residing in different countries and, via changes in consumption patterns, increase the similarity of sectoral production structures. This is particularly important for trade in intermediate goods: traded machinery, for example, embodies technologies and may be accompanied by traded services inducing spread of knowledge and convergence of sectoral productivities across countries. Additionally,

⁹ Whereas technological change normally increases sectoral productivity and, hence, sectoral output, it can increase or decrease sectoral (factor) inputs (of labor, capital, energy or CO₂ caused by fossil fuel inputs) depending on whether technological change is factor-augmenting or factor-saving.

interindustry trade may support the emergence of similar sectoral structures across trading partners because it allows for bidirectional exchange of goods produced in different countries via trade in terms of varieties of the same good within the same sector (Midelfart et al. 2003). This implies that countries' sectoral structures have a tendency to converge, i.e., become more similar over time, and that intermediate goods imports (M) and capital (K) accumulation are expected to enhance this effect. Accordingly, the resulting hypothesis reads as follows:

H2: International trade fosters structural convergence, i.e., $\frac{\partial(dz_{srjt})}{\partial(m_{srj(t-1)})} < 0$.

H1 implies that sectoral distances become larger. A corresponding hypothesis can be formulated for the effect of capital on convergence. In the theoretical long-term equilibrium of a fully integrated world economy, $\frac{z_{sjt}}{\sum_j z_{sjt}} = \frac{z_{rjt}}{\sum_j z_{rjt}} \forall (s, r, j)$, and thus, $dz_{srjt} = 0$.

3 Data

In this section, we describe the data source and aggregation of the panel data in terms of countries and sectors.

Data source and setup:

In addition to using the newest 2016 release of the large dataset of the World Input-Output Database (WIOD),¹⁰ we deploy the 2013 release for comparison.¹¹ We combine the World Input-Output Tables (WIOT) containing bilateral, bisectoral¹² trade (in mill. 2010-US-\$, see below) data with socioeconomic accounts containing sectoral (gross) outputs (in mill. 2010-US-\$), labor (in 1,000 employment units) and capital (in mill. 2010-US-\$) data and with environmental accounts (the 2019 extension¹³ of the WIOD 2016) providing sectoral CO₂ emissions (in 1000 tonnes) and sectoral energy use (in terrajoules) data. Following the model setup of the previous section, we sum up all intermediate good imports entering each sector across their sectors of origin while maintaining source-destination country dyads.

In the WIOD 2016, monetary values are expressed as 2010-US-\$, i.e., measured in constant prices of the base year 2010; similarly, in the WIOD 2013, monetary values are expressed as 1995-US-\$. They are created by applying the corresponding deflator¹⁴ and, in the case of output and capital, by converting the national currency values to US-\$ using the corresponding exchange rates contained in the WIOD. CO₂ emissions refer to direct emissions caused by fossil-fuel-based energy use and process emissions released within the corresponding sector (excluding the indirect emissions embodied in intermediate inputs). This allows us to study the change in production technologies in each sector. An alternative

¹⁰ <https://www.rug.nl/ggdc/valuechain/wiod/>, Timmer et al. (2015, 2016).

¹¹ The WIOD 2013 and 2016 do not exactly match in terms of sectoral definitions; therefore, and to keep the number of observations computationally tractable, we deploy them separately.

¹² This means that international trade can flow from any sector in any country to any sector in another country.

¹³ Corsatea et al. (2019).

¹⁴ We apply the WIOD deflator containing the price levels of intermediate inputs to discount trade values, price levels of (gross) output to deflate (gross) output values and price levels of (gross) value added to deflate capital values.

measure, (gross) energy use, refers to the total direct energy input (consumption), including electricity consumption, in each sector.

We restrict the numerical setup to data sourced from the WIOD¹⁵ to keep it as consistent as possible in terms of sector definitions and accounting methods and to keep the numerical requirements tractable. In the time dimension, where t denotes years, the 2013 release covers 1995 to 2009; the 2016 release covers 2000 to 2014. In the cross-section, our *North-South* setup includes 31 industrialized countries (OECD, North) in the WIOD 2013 and 34 industrialized countries in the WIOD 2016 versus 9 emerging countries (South) in both samples.¹⁶ Depending on the available sectors in the original data source, we aggregate the original sectors into 26 sectors j (equivalently, i) in the WIOD 2013 and 36 sectors in the WIOD 2016.¹⁷ Appendix C provides detailed sector lists and mappings resulting in over 140 thousand observations in the North-South sample and 870 thousand observations in the full sample of the WIOD 2016 as well as over 95 thousand observations in the North-South sample and 520 thousand observations in the full sample of the WIOD 2013. The *full sample* combines emerging and industrialized countries into 40 economies (countries) in the WIOD 2013 and 43 economies in the WIOD 2016.

In the full sample, each country exports to each other country; i.e., all countries are source s and recipient r at some point. In the North-South setup, solely industrialized (OECD) countries s export to emerging countries r .

Descriptive statistics:

Figures 1 and 2 draw on the WIOD 2013 and 2016. They illustrate the developments of typical sectors, computed as averages across countries, with each country group (emerging and industrialized countries or, in short, South and North). Sectoral developments refer to direct CO₂ emissions or (gross) output shares of each sector in total CO₂ emissions or (gross) output of the corresponding country. Each single dot represents one observation, the solid (for the WIOD 2013) or dashed (for the WIOD 2016) lines depict estimates obtained via locally estimated scatterplot smoothing (Cleveland et al. 1992), and the shaded areas indicate 95% confidence intervals. The investigation of descriptive statistics

¹⁵ This includes deflators and exchange rates.

¹⁶ *Emerging countries (South) in the WIOD 2013 and 2016:* “BRA” Brazil, “BGR” Bulgaria, “CHN” Mainland China, “MEX” Mexico, “RUS” Russia, “TWN” Taiwan, “ROU” Romania, “IND” India, and “IDN” Indonesia. *Industrialized countries (North) in the WIOD 2013 and 2016:* “AUS” Australia, “AUT” Austria, “BEL” Belgium, “CAN” Canada, “CYP” Cyprus, “CZE” Czechia, “DEU” Germany, “DNK” Denmark, “ESP” Spain, “EST” Estonia, “FIN” Finland, “FRA” France, “GBR” Great Britain, “GRC” Greece, “HUN” Hungary, “IRL” Ireland, “ITA” Italy, “JPN” Japan, “KOR” Republic of Korea, “LTU” Lithuania, “LUX” Luxembourg, “LVA” Latvia, “MLT” Malta, “NLD” The Netherlands, “POL” Poland, “PRT” Portugal, “SVK” Slovakia, “SVN” Slovenia, “SWE” Sweden, “TUR” Turkey, and “USA” The United States of America. *Additional industrialized countries (North) in the WIOD 2016:* “CHE” Switzerland, “HRV” Croatia, and “NOR” Norway.

¹⁷ *Sectors in the WIOD 2013 and 2016:* A01 Agriculture, B Mining, C10-C12 Food, C13-C15 Textile, C16 Wood, C17 Paper, C19 Refined Petr., C20 Chemicals, C22 Rubber, C23 Minerals, C24 Metal, C26 Computers, C27 Electrical equip., C30 Transport equip., C33 Repair, D35 Energy, F Construction, G Trade, H49 Land transport, H50 Water transport, H51 Air transport, H52 Warehousing, H53 Post, I Accommodation, JKLMN Private Services, and OPQRS Public Services. *Additional sectors in the WIOD 2016:* A02 Forestry, A03 Fisheries, C18 Printing, C21 Pharma., C25 Non machinery, C28 Machinery, C29 Vehicles, C31-C32 Furniture, E36 Water, and E37-E39 Waste. Sectors T Household and U Household are discarded in both samples due to the absence of trade.

Average sector shares in industrialized and emerging countries over time

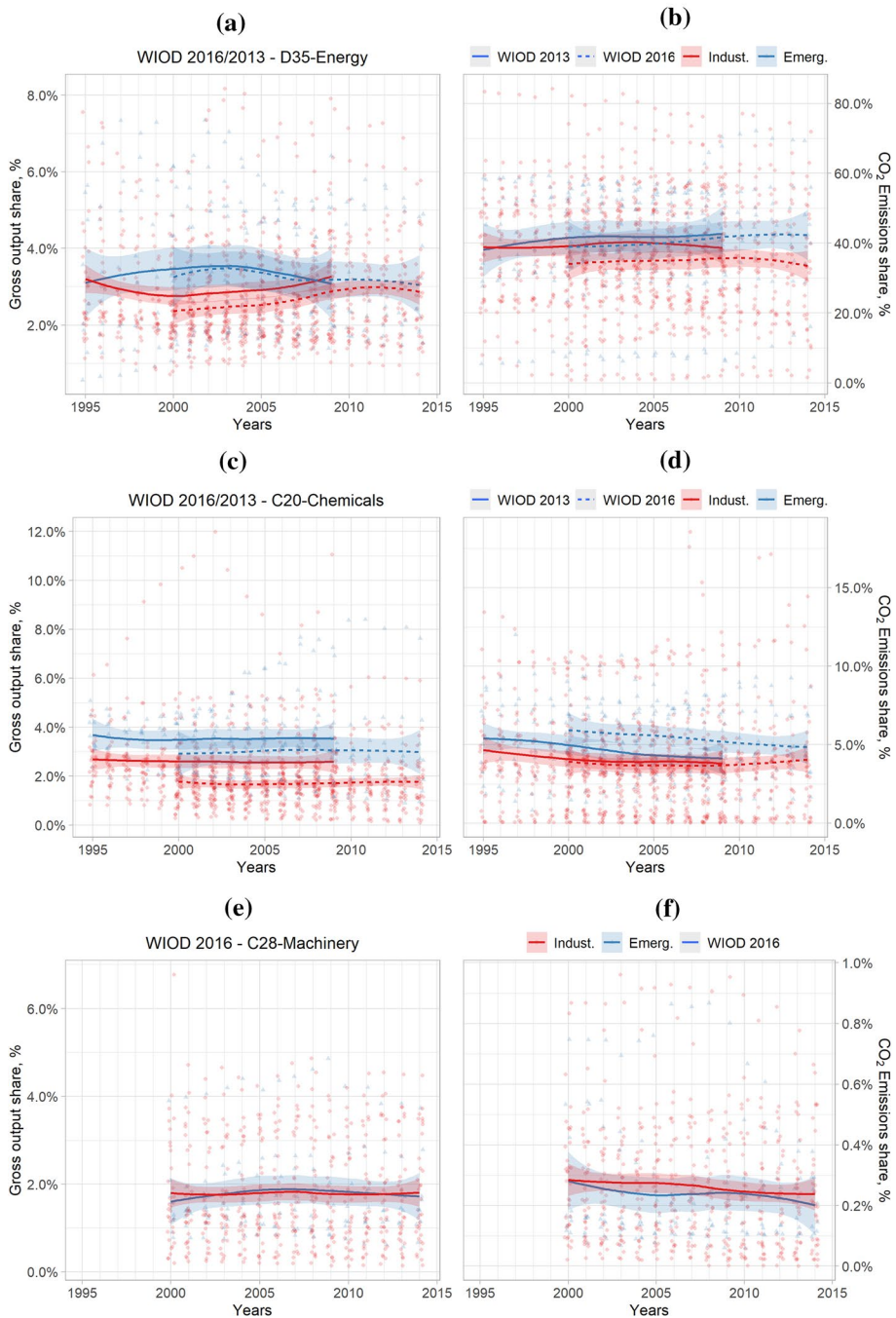


Fig. 1 Average sector shares in industrialized and emerging countries over time. Source: Own illustrations based on data taken from the WIOD 2013 and 2016 releases

reveals sectoral developments, including South-North con-/divergence, which suggest a detailed econometric exploration of their drivers.

In the energy sector (electricity, gas, water, steam and air conditioning supply; Fig. 1a, b), emerging countries (in blue) exhibit larger shares than do industrialized countries (in red) in terms of both average output and CO₂ shares. While at the end of the time frame, average output shares reveal a convergence tendency, average CO₂ shares show a divergence tendency. Whereas average output shares move around 3%, average CO₂ shares exceed 40% in emerging countries, which points to the high CO₂ intensity of the energy sector.

In the energy-intensive chemicals sector (Fig. 1c, d), sector shares have similar sizes in terms of output as in the energy sector and are again larger in the South. In contrast, CO₂ shares are an order of magnitude lower than in the energy sector. The CO₂ shares in the South converge to those of the North. Compared with the energy-intensive chemical sector, the CO₂ shares of the machinery sector (Fig. 1e, f) are another order of magnitude lower (about 0.2%). The output and CO₂ shares of the machinery sector in the South and North are nearly identical and change little over time.¹⁸

Regarding land transport (Fig. 2a, b), the South exhibits larger output shares than the North but smaller CO₂ shares (with a slightly increasing trend in both regions), which indicates an advantage for the South with regard to CO₂ emissions intensity.

In the construction sector (Fig. 2c, d), emerging countries overtake industrialized countries in terms of output shares, while the opposite occurs in terms of CO₂ shares. This indicates significant CO₂ emissions reductions in the South, although the Southern CO₂ share exhibits a slightly increasing trend.

In agriculture (Fig. 2e, f), clearly, the southern output shares exceed those of the North more than do CO₂ shares, which indicates less CO₂ emission-intensive agricultural production in the South than in the North. Mostly southern output shares, but also CO₂ shares, converge to those in the North over time.

The next section will explore possible drivers of these sectoral developments (in the South relative to the North) in an econometric analysis. Appendix A.1 provides summary statistics of the economic indicators in the different data samples as they appear in the econometric analysis. Appendix A.2 uses the full sample to present all available data, showing the correlations among indicators appearing in one regression. Accordingly, all correlations are low, i.e., within ± 0.2 . The figure also illustrates the relation of the correlation partners by scatterplotting each indicator as a function of its partner. Red lines sketch the nonlinear relation between correlation partners by using a nonparametric smoothing algorithm. They indicate moderate relations between the regressors and dependent variables of the econometric model presented below. Histograms depict the distributions (the density of observations covering an area with a value of one) of the indicators. Accordingly, most of the logarithmic observations are located around zero.

¹⁸ The machinery sector is one of the sectors that can be separated from the generic industry in the WIOD 2016 but not in the WIOD 2013.

Average sector shares in industrialized and emerging countries over time

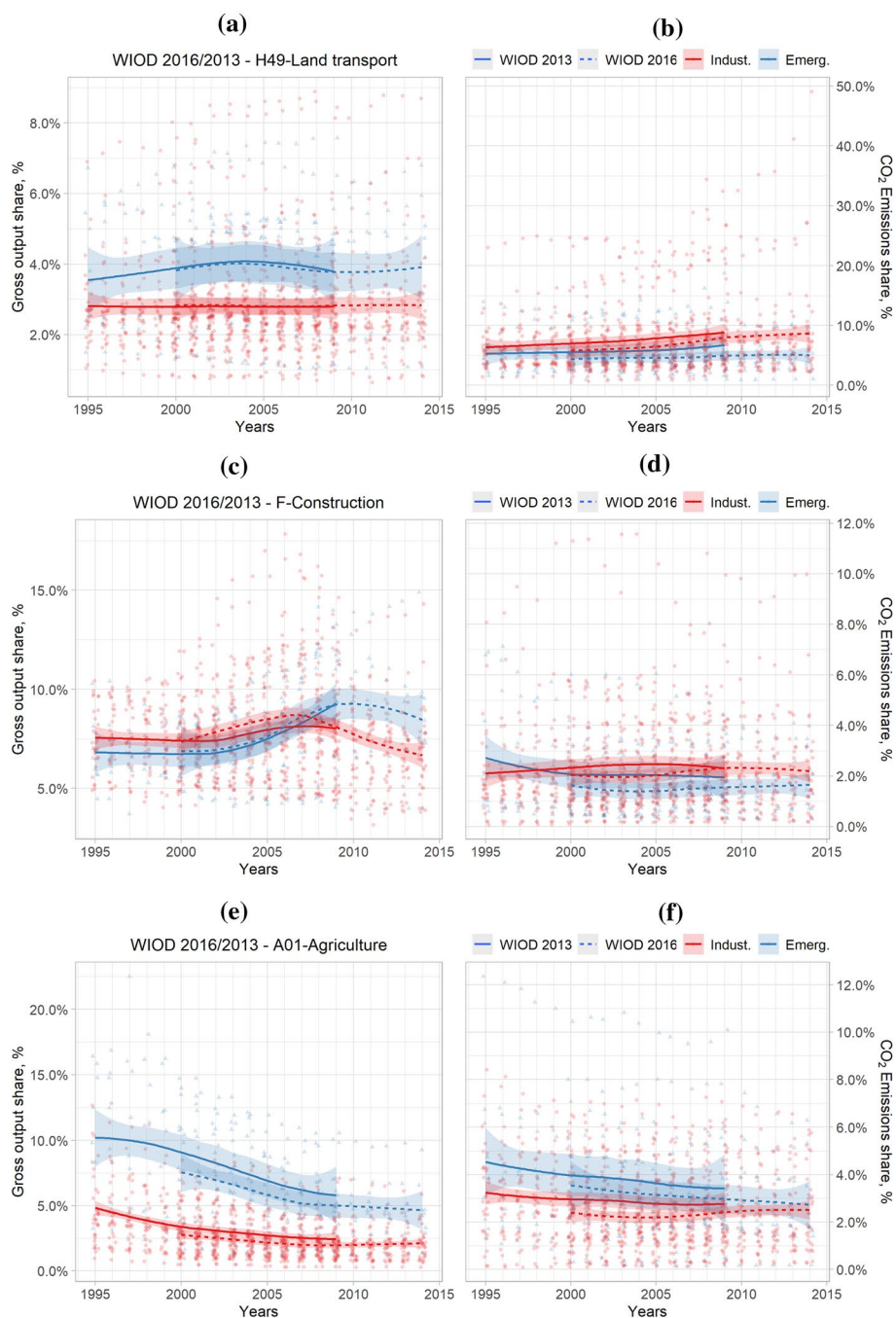


Fig. 2 Average sector shares in industrialized and emerging countries over time. Source: Own illustrations based on data taken from the WIOD 2013 and 2016 releases

4 Econometrics

This section first describes the econometric approach and test procedures for implementing it and then presents the regression results.

Econometric approach:

To explicitly write out Equation (4), we rearrange terms and assume a multiplicative model, particularly a Cobb–Douglas function following Hasanov et al. (2021):

$$dz_{srjt} = (m_{srj(t-1)})^\alpha (dk_{srj(t-1)})^\beta e^{\sigma_{srj}} e^{\theta_t} e^{\varepsilon_{srjt}} \quad (5)$$

We take natural logarithms on both sides to obtain:

$$\ln(dz_{srjt}) = \alpha \cdot \ln(m_{srj(t-1)}) + \beta \cdot \ln(dk_{srj(t-1)}) + \sigma_{srj} + \theta_t + \varepsilon_{srjt} \quad (6)$$

with the relative distance between sector shares of the source and the recipient, $dz_{srjt} = \left| \frac{Z_{rjt}}{\sum_j Z_{rjt}} / \frac{Z_{sjt}}{\sum_j Z_{sjt}} - 1 \right|$; the sectoral import intensity, $m_{srj(t-1)} = \frac{\sum_i M_{sirj(t-1)}}{Y_{rj(t-1)}}$, which is in the spotlight in the analysis; and the relative distance between the sectoral capital-to-labor ratios of the source and of the recipient, $dk_{srj(t-1)} = \left| \frac{K_{rj(t-1)}}{L_{rj(t-1)}} / \frac{K_{sj(t-1)}}{L_{sj(t-1)}} - 1 \right|$.

These indicators are all constructed by using the WIOD. While we restrict the explicit inclusion of economic indicators to those with direct economic relevance and that are covered by the WIOD with the required high bilateral and bisectoral resolution, we deploy a very large number of fixed effects, which exploit the technical (computational) limits of the estimation procedure.

To estimate triadic fixed effects σ_{srj} and θ_t , we use binary variables that take a value of one for each bilateral sectoral trade relation and each year. Index srj combines source country s , recipient country r and recipient sector j characteristics, while t indicates the individual time dimension. The joint use of σ_{srj} and θ_t leads to a two-way fixed effects model, which in short will be denoted by srj & t . Alternatively, either σ_{srj} or θ_t can be used to implement single fixed effects models with cross-sectional fixed effects (in short, srj) or time fixed effects (in short, t). α and β are the relevant parameters to be estimated, while ε_{srjt} is the error term. Because of the log-log-specification, α and β represent elasticities, reflecting the effect of relative changes in import intensity or the capital-to-labor ratio on relative changes in the dependent variable.

If H1 holds, then it follows for Equation (6) that $\alpha > 0$ (and $\beta > 0$), and if H2 holds, then $\alpha < 0$ (and $\beta < 0$).

To examine whether the effect of international trade on structural change is enhanced or dampened by a higher relative capital-to-labor ratio (and the technologies embodied in capital), we add their multiplicative joint effect as follows:

$$\begin{aligned} \ln(dz_{srjt}) = & \alpha \cdot \ln(m_{srj(t-1)}) + \beta \cdot \ln(dk_{srj(t-1)}) + \gamma \cdot \ln(m_{srj(t-1)}) \cdot \ln(dk_{srj(t-1)}) \\ & + \sigma_{srj} + \theta_t + \varepsilon_{srjt} \end{aligned} \quad (7)$$

Table 1 Panel regression results with output shares using the WIOD 2016

Fixed effects	Dep. var.: relative distance between sectoral output shares $\ln(dz_{s,rj})$					
	North-South			Full sample		
	<i>srj</i>	<i>t</i>	<i>srj</i> & <i>t</i>	<i>srj</i>	<i>t</i>	<i>srj</i> & <i>t</i>
Import intensity $\ln(m_{srj(t-1)})$	-0.00919** (0.00462)	-0.08615***** (0.00521)	-0.02947***** (0.00484)	-0.00368* (0.00216)	-0.05888***** (0.00222)	-0.01815***** (0.00229)
Capital-to-labor rat. $\ln(dk_{srj(t-1)})$	-0.02336 (0.01739)	-0.03883 (0.04457)	-0.01067 (0.01733)	-0.02236***** (0.00572)	0.01650 (0.01103)	-0.02127***** (0.00572)
Interaction term $\ln(m_{srj(t-1)}) \cdot \ln(dk_{srj(t-1)})$	-0.00183 (0.00172)	-0.01759***** (0.00478)	-0.00095 (0.00172)	-0.00370***** (0.00071)	-0.00800***** (0.00140)	-0.00378***** (0.00071)
Num. of observat.	143,435	143,435	143,435	871,733	871,733	871,733
Degr. of freedom	133,174	143,418	133,161	809,344	871,716	809,331
R^2	0.00013	0.02835	0.00089	0.00020	0.01853	0.00052
F -stat.	1.901	117.103*****	12.436*****	13.333*****	487.013*****	35.522*****

Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.005$; ***** $p < 0.001$. Robust standard errors clustered at the *srj*-level are reported in parentheses. *srj* indicates the combined dimensions of fixed effects for source country *s*, recipient country *r* and recipient sector *j* characteristics; *t* denotes the dimension of the individual time fixed effects; *srj* & *t* indicates the two-way fixed effects model

Table 2 Panel regression results with output shares using the WIOD 2013

Fixed effects	Dep. var.: relative distance between sectoral output shares $\ln(d_{z_{ijt}})$					
	North-South			Full sample		
	<i>srj</i>	<i>t</i>	<i>srj & t</i>	<i>srj</i>	<i>t</i>	<i>srj & t</i>
Import intensity $\ln(m_{srj(t-1)})$	0.00679 (0.00575)	-0.03892 ^{*****} (0.00567)	-0.01090 [*] (0.00588)	0.01331 ^{*****} (0.00272)	-0.03945 ^{*****} (0.00252)	-0.01309 ^{*****} (0.00279)
Capital-to-labor ratio $\ln(dk_{srj(t-1)})$	0.00426 (0.03079)	0.02679 (0.05910)	-0.00667 (0.03051)	-0.00785 (0.00926)	0.03185 ^{**} (0.01301)	-0.01428 (0.00919)
Interaction term $\ln(m_{srj(t-1)}) \cdot \ln(dk_{srj(t-1)})$	-0.00162 (0.00296)	-0.01294 ^{**} (0.00622)	-0.00245 (0.00294)	-0.00086 (0.00113)	-0.00455 ^{****} (0.00165)	-0.00228 ^{**} (0.00113)
Num. of observat.	97,774	97,774	97,774	541,855	541,855	541,855
Degrees of freedom	90,526	97,757	90,513	501,375	541,838	501,362
R^2	0.00026	0.01256	0.00029	0.00016	0.01274	0.00019
F -stat.	2.042	34.316 ^{*****}	2.164 [*]	8.201 ^{*****}	239.673 ^{*****}	9.102 ^{*****}

Significance levels: ^{*} $p < 0.1$; ^{**} $p < 0.05$; ^{***} $p < 0.01$; ^{****} $p < 0.005$; ^{*****} $p < 0.001$. See Table 1 for notes

The interaction term $\gamma \cdot \ln(m_{srj(t-1)}) \cdot \ln(dk_{srj(t-1)})$, with parameter γ to be estimated, will be included in the main regressions but excluded from a robustness check.¹⁹

Test procedures:

We carry out the following standard test procedures. We check that the correlations among regressors are sufficiently low (i.e., within ± 0.2 ; see Appendix A.1 and the end of the previous Sect. 3) to avoid multicollinearity. The standard F -tests for the null hypothesis of all estimated coefficients jointly being zero are reported for each regression (see the last rows in Tables 1 to 4). In the estimations yielding significant results, the F -statistics are, in most cases, (very) high. The regression results in the first column of Tables 1 and 2 exhibit insignificant F -statistics and, in most cases, insignificant t -statistics, indicated by missing asterisks, for single regressors as well. The R^2 values are low in all regressions, which hinges on the model specification with economic indicators being specified as shares, ratios or intensities, measured in relative (and absolute) terms.

To address heteroscedasticity and serial-correlation problems, throughout our regression analysis, we report heteroscedasticity- and serial-correlation-robust standard errors based on Arellano (1987) clustered at the *srj*-level. Besides, we identify cross-sectional dependence in terms of common correlated effects (CCE) introduced by Pesaran (2006, 2015). We will address it in our first robustness check instead of using heteroscedasticity- and serial-correlation-robust standard errors. Following Pesaran (2021), we run Breusch-Pagan and (bias-corrected) scaled LM^{20} tests as well as Pesaran CD^{21} and average (absolute) correlation tests that all indicate cross-sectional dependence. Following, De Hoyos and Sarafidis (2006) and Hoechle (2007), we find that the cross-sectional dependence is driven by unobserved common determinants that are uncorrelated with the regressors. So, the standard fixed effects and random effects estimators are consistent. By using a modified variance-covariance matrix proposed by Driscoll and Kraay (1998), however, the efficiency of the estimations will be improved in the first robustness check (see Appendix B.1, North-South sample).

Additionally, we carry out tests designed for panel data. We apply Fisher-type Augmented Dickey-Fuller unit root tests (Dickey and Fuller 1979; Im et al. 2003) to ensure that the data are stationary. Consequentially, we test all dependent and independent variables in all datasets (the WIOD 2016 and 2013) and all subsamples (North-South and full sample) separately. We find that the unit root null hypothesis is always clearly rejected in favor of stationarity (excluding a time trend at the 0.00001 confidence level), also when considering cross-sectional dependence (Pesaran 2007). The standard Hausman test for fixed versus random effects clearly rejects the null hypothesis of consistent random effects in all specifications; therefore, we restrict our analysis to the use of fixed effects (dummy variables).

To test for cross-sectional and time-dependent heterogeneity, we apply F - and LM -tests evaluating different types of fixed effects against the null hypothesis of a pooled regression or reduced dimensionality (i.e., a reduced number) of fixed effects. Appendix A.3 shows the results. For all specifications, the F - and LM -tests clearly reject the null hypothesis of all fixed effects jointly being zero, i.e., the pooled regression. The F - and LM -tests also

¹⁹ To identify the overall effect of trade on structural change, we need to consider both the single effect and the joint effect (the marginal effect at a given capital-to-labor ratio) or refer to Equation (6) without the interaction term.

²⁰ This means Lagrange Multiplier.

²¹ This means cross-sectional dependence.

clearly reject the null hypothesis of fixed effects with reduced dimensionality; i.e., cross-sectional fixed effects plus time fixed effects (two-way fixed effects, srj & t) are preferable over cross-sectional fixed effects (srj) only or time fixed effects (t) only.

For the choice between cross-sectional or time fixed effects versus two-way fixed effects, however, Kropko and Kubinec (2020) recommend the choice of a single type of fixed effects to enable a clear-cut interpretation of the estimation results with respect to variant and invariant effects in the time and cross-sectional dimension, instead of generating a mixture of both, which is difficult to interpret. Therefore, we use and compare the three fixed effects specifications (srj , t and srj & t). When using cross-sectional fixed effects, the variation remaining in the data is generated within the time dimension across years. When using time fixed effects, in contrast, the variation remaining in the data is generated in the cross-sectional dimension via differences between countries and sectors, which may be interpreted as a snapshot of the current situation or as long-term (equilibrium) effects. When using two-way fixed effects, both types of variation overlap, similar to a pooled regression (cf. Kropko and Kubinec 2020).

Regression results:

Tables 1 to 4 present the main panel regression results based on Equation (7).

Based on the WIOD 2016, Table 1 uses output shares as the dependent variable. The statistically significant and negative coefficients of import intensity in all columns of Table 1 unequivocally confirm H2, stating structural convergence induced by international trade. The effect of the relative distance of the capital-to-labor ratio (in short, capital-to-labor ratio) on structural change is significant in the full sample estimations with fixed effects in the cross-section (srj) and in the cross-section plus time dimension (srj & t) only. In these significant cases, the coefficients also confirm H2, stating structural convergence induced by more capital-intensive production.

In Table 1, the interaction term's coefficients are significant and negative, supporting H2 in all full sample estimations and those North-South sample estimations with time (t) fixed effects, but insignificant in the remaining two North-South sample results. Accordingly, simultaneously higher import and relative capital intensities jointly enhance convergence.

Table 2 shows the same estimations with output shares as the dependent variable based on the WIOD 2013, which provides a smaller number of observations than does the WIOD 2016, potentially reducing the statistical significance of the results. Therefore, the coefficient of import intensity becomes insignificant in the North-South sample with cross-sectional fixed effects (srj) and weakly significant and negative with two-way fixed effects (srj & t). The effect of import intensity becomes significant and positive in the full sample with cross-sectional fixed effects srj , supporting H1, stating structural divergence. Nonetheless, the majority of the estimates (t in the North-South sample and t and srj & t in the full sample) supports H2, stating structural convergence as before. The effect of the capital-to-labor ratio is significantly positive, in favor of H1, in the full sample with time (t) fixed effects only. The effect of the interaction term stays always negative and significant in half of the estimates.

Table 3 replaces the output shares used as the dependent variable by CO₂ shares (including direct emissions from fossil fuel use and process emissions), drawing on the WIOD 2016. In this table, the sign of the estimates depends on the choice of fixed effects. Cross-sectional fixed effects (srj) allow for variation in time and exhibit a positive effect of import intensity on structural change, i.e., divergence, as expressed by H1. This positive effect is, however, dampened by the negative effect of the interaction of import intensity and

Table 3 Panel regression results with CO₂ shares using the WIOD 2016

Fixed effects	Dep. var.: relative distance between sectoral CO ₂ shares $\ln(dz_{srjt})$					
	North-South			Full sample		
	<i>srj</i>	<i>t</i>	<i>srj</i> & <i>t</i>	<i>srj</i>	<i>t</i>	<i>srj</i> & <i>t</i>
Import intensity $\ln(m_{srjt(-1)})$	0.04035 ^{*****} (0.00674)	-0.11613 ^{*****} (0.00590)	0.00751 (0.00695)	0.03647 ^{*****} (0.00301)	-0.08952 ^{*****} (0.00249)	0.00093 (0.00320)
Capital-to-labor rat. $\ln(dk_{srjt(-1)})$	-0.05548 ^{**} (0.02329)	-0.07578 (0.04877)	-0.03318 (0.02309)	0.00721 (0.00760)	0.04137 ^{*****} (0.01231)	0.01120 (0.00758)
Interaction term $\ln(m_{srjt(-1)}) \cdot \ln(dk_{srjt(-1)})$	-0.00600 ^{**} (0.00242)	-0.01562 ^{***} (0.00557)	-0.00446 [*] (0.00239)	0.00107 (0.00096)	-0.00080 (0.00157)	0.00100 (0.00095)
Num. of observat.	143,241	143,241	143,241	869,736	869,736	869,736
Degrees of freedom	132,980	143,224	132,967	807,351	869,719	807,338
<i>R</i> ²	0.00139	0.03885	0.00016	0.00080	0.02058	0.00001
<i>F</i> -stat.	15.331 ^{*****}	154.797 ^{*****}	2.008	49.367 ^{*****}	577.997 ^{*****}	1.079

Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.005$; ***** $p < 0.001$. Robust standard errors clustered at the *srj*-level are reported in parentheses. *srj* indicates the combined dimensions of fixed effects for source country *s*, recipient country *r* and recipient sector *j* characteristics; *t* denotes the dimension of the individual time fixed effects; *srj* & *t* indicates the two-way fixed effects model

Table 4 Panel regression results with CO₂ shares using the WIOD 2013

Fixed effects	Dep. var.: relative distance between sectoral CO ₂ shares $\ln(dz_{srjt})$					
	North-South			Full sample		
	<i>srj</i>	<i>t</i>	<i>srj & t</i>	<i>srj</i>	<i>t</i>	<i>srj & t</i>
Import intensity $\ln(m_{srjt(-1)})$	-0.01337** (0.00547)	-0.11022***** (0.00722)	-0.01433*** (0.00554)	-0.00884***** (0.00260)	-0.11411***** (0.00336)	-0.01183***** (0.00267)
Capital-to-labor ratio $\ln(dk_{srjt(-1)})$	0.00233 (0.02695)	-0.08977 (0.07339)	0.00321 (0.02698)	-0.00388 (0.00817)	-0.02225 (0.01835)	-0.00480 (0.00817)
Interaction term $\ln(m_{srjt(-1)}) \cdot \ln(dk_{srjt(-1)})$	-0.00108 (0.00251)	-0.01630** (0.00810)	-0.00104 (0.00251)	-0.00103 (0.00098)	-0.00871***** (0.00245)	-0.00117 (0.00098)
Num. of observat.	95,069	95,069	95,069	519,131	519,131	519,131
Degrees of freedom	87,920	95,052	87,907	479,498	519,114	479,485
<i>R</i> ²	0.00031	0.03874	0.00034	0.00010	0.03558	0.00016
<i>F</i> -stat.	2.597*	88.327*****	2.872**	4.900*****	465.869*****	7.691*****

Significance levels: **p* < 0.1; ***p* < 0.05; ****p* < 0.01; *****p* < 0.005; ******p* < 0.001. See Table 3 for notes

the capital-to-labor ratio throughout the North-South sample.²² Time fixed effects (t), in contrast, allow for variation in the cross-section and result in a negative effect, supporting structural convergence, as expressed by H2. The combination of both types of fixed effects (srj & t) and hence both opposing effects, not surprisingly, results in insignificant estimates. This finding refers to the North-South and full samples. In contrast to these estimates for trade, the capital-to-labor ratio exhibits a significant and negative effect, supporting structural convergence with cross-sectional fixed effects (srj) in the North-South sample, but a significant and positive effect, supporting divergence with time fixed effects (t) in the full sample. It exhibits insignificant effects in the remaining cases. Nonetheless, the joint effect of import intensity and the capital-to-labor ratio is always (weakly) significant and negative, supporting convergence, in the North-South sample.

Table 4 deploys CO₂ shares as the dependent variable using the WIOD 2013. The results are similar to those deploying output shares drawing on the WIOD 2016 presented in Table 1. The estimated coefficients of import intensity are significant and negative in all estimations, supporting H2, stating structural convergence. The effect of the capital-to-labor ratio is, however, always insignificant. The joint effect of import intensity and the capital-to-labor ratio expressed by the interaction term is always negative but statistically significant in specifications with time (t) fixed effects only.

All estimated coefficients represent elasticities, describing the impact of relative changes in a driver of structural change on relative changes in the (absolute) difference between the sector shares of the recipient and source country for international trade. The estimated (absolute) magnitudes of these elasticities vary between 0.02 and 0.05 among the statistically significant coefficients of the capital-to-labor ratio. The (absolute) magnitudes of the interaction terms are about an order of magnitude smaller. The variation in the (absolute) magnitudes of the coefficients of import intensity is substantial; the magnitudes vary between about 0.004 and 0.116.

5 Discussion

This section interprets and compares the regression results, particularly those of the main panel regressions presented in the previous section, those of alternative robustness checks and those of supplementary sectoral estimates.

Main regression results:

Basically, the results promote the view that international trade supports the international convergence of sectoral structures via the spread of knowledge, technologies, preferences and so forth, such that countries' sectoral structures become more similar. Similarly, more intensive utilization of capital and embodied technologies supports the international convergence of sectoral structures. Using the WIOD 2016 sample and output value shares as the dependent variable, this result holds unequivocally and significantly.

For the WIOD 2013 sample period from 1995 to 2009, however, the results provide an indication that over time, international trade has enhanced the international divergence of sectoral output structures. This means that in accordance with classical Ricardian trade

²² The sole effect of the import intensity excluding the interaction is positive; see Appendix Table B6.

theory, in the world economy, countries specialize in the production of different goods. Similarly, in the global (long-term) cross-section, relatively more intensive capital use seems to foster the sectoral divergence of output structures.

When considering CO₂ shares taken from the WIOD 2013 as the dependent variable, in contrast, the results clearly confirm the previous finding that trade fosters structural convergence.

For the later WIOD 2016 sample period from 2000 to 2014, however, the results point to a possible regime change. From global and North-South perspectives, the results indicate the international divergence of sectoral structures occurring via Ricardian specialization in more or less CO₂-intensive production. This result points to international outsourcing of CO₂-intensive production to emerging economies or so-called carbon leakage.

To obtain an impression of the time horizon required for the convergence dynamics to materialize and to become visible, we carry out crude estimates (Hübler and Glas 2014). In the specifications with cross-sectional (*srj*) or two-way fixed effects (*srj* & *t*), the elasticities estimated for the effect of import intensity have an order of magnitude of about -0.01. This means that *ceteris paribus*, by solely focusing on the impact of trade (putting aside other confounders of sectoral changes), doubling the import intensity (increasing it by 100%) leads to an annual 1% decline in the relative distance between the sector shares in recipient and source countries. The resulting half time, i.e., the time to reduce the relative distance by 50%, is almost 70 years. The elasticities suggested by the specifications with time fixed effects (*t*) reach an order of magnitude of -0.1. The corresponding resulting half time amounts to seven years. In any case, despite the assumption of this substantial increase in import intensity, the dynamics require decades or even centuries to approach the theoretical long-term equilibrium of internationally equalized sector shares. Consequently, we talk about long-term effects. This insight should be taken into account when considering the possible international impacts of national policies.

Robustness check results:

The following robustness checks address cross-sectional dependence, exclude the interaction terms used so far, explore different time lags of the regressors and replace CO₂ emissions with energy use to construct the dependent variable. The robustness checks overall confirm the main panel regression results.

1. Cross-sectional dependence: The countries in the world economy are connected via socioeconomic, institutional, geographic, and political relationships with each other. Besides international trade, for example, global capital and labor mobility render countries interdependent. Indeed, our corresponding test results (Pesaran 2021) underpin the existence of such cross-sectional dependence across countries. Therefore, instead of heteroscedasticity- and serial-correlation-robust standard errors proposed by Arellano (1987), in this robustness check, we utilize cross-sectional dependence-robust standard errors following Driscoll and Kraay (1998), De Hoyos and Sarafidis (2006) and Hoechle (2007). The results are reported in Appendix B.1 referring to the North-South sample.²³ Accordingly, statistical efficiency has increased, resulting in more significant estimates and higher *F*-statistics compared with Tables 1 to 4. Particularly, the negative effect of the capital-to-labor ratio causing structural convergence (H2) and the interaction term with the import intensity have become significant in Table B1 (North-South sample with output shares and

²³ Because the huge number of observations in the full sample exceeds the technical limits of our hard- and software, we need to restrict this robustness check to the North-South sample.

WIOD 2016) within the first column incorporating cross-sectional (srj) fixed effects. In this regression, the significance of the negative effect of the import intensity has increased as well. Similarly, in Table B2 (North-South sample with output shares and WIOD 2013) within the second column with time (t) fixed effects, the negative effect of the interaction term has become highly significant. In the first column incorporating cross-sectional (srj) fixed effects, the previously insignificant positive effect of the import intensity causing structural divergence (H1) has become significant. Likewise, in Table B3 (North-South sample with CO₂ shares and WIOD 2016), the effects of the capital-to-labor ratio and the interaction term have become significant or highly significant in columns one to three. In column three with two-way fixed effects (srj & t), additionally the positive effect of the import intensity has switched from insignificant to weakly significant. In Table B4 (North-South sample with CO₂ shares and WIOD 2013), on the contrary, the negative estimate of the import intensity coefficient has become insignificant in columns one and three with cross-sectional (srj) and two-way fixed effects (srj & t). In column two with time (t) fixed effects, the coefficients of the capital-to-labor ratio and the interaction term have become (weakly) significant and negative. In summary, the results of the first robustness check confirm the relevance of capital and its interaction with imports for structural convergence. They also confirm the contribution of international trade to structural divergence with regard to CO₂ emissions in this millennium and indicate divergence with regard to output shares in the last millennium.

2. Exclusion of the interaction term: In this robustness check, we leave out the interaction term for the purpose of comparison. The results for the WIOD 2016 are presented in Appendix B.2. The estimated coefficients of import intensity are very robust to the exclusion of the interaction term between import intensity and the capital-to-labor ratio. The coefficients of the capital-to-labor ratio, in contrast, experience changes in significance levels and signs; particularly, most coefficients are statistically significant and positive, supporting structural divergence (H1). This result nevertheless aligns with economic theory and intuition: more intensive capital use itself tends to result in increasing specialization in the activities that can be performed best with this capital and its embodied technologies; once, however, new goods, knowledge, technologies, etc., arrive from abroad, capital will incorporate technological improvements such that production will become more similar to that at the source of the goods, knowledge or technologies. Thus, international trade appears to be a prerequisite for international structural convergence (H2), while capital accumulation supports this trade-driven mechanism. This is reflected by the (if statistically significant) negative interaction terms.

3. Different time lags of the regressors: Convergence processes occur gradually over time. To check the influence of considered time lags between the determinants and effects of convergence, we vary the time lag between them. The results for the WIOD 2016 with the time (year) lags $t - 2$ and $t - 3$, instead of $t - 1$, for all regressors are presented in Appendix B.3. While some significance levels change, the results are barely qualitatively and quantitatively affected. As a notable exception, in the full sample with cross-sectional fixed effects (srj), $t - 3$ lags and output shares as the dependent variable, presented in Table B8, the effect of imports becomes significant and positive. Similarly, in the North-South and full samples with two-way fixed effects (srj & t), $t - 2$ or $t - 3$ lags and CO₂ shares as the dependent variable, as presented in Tables B9 and B10, the positive effect of imports becomes significant.

4. *Energy shares as the dependent variable:* In the robustness check presented in Appendix B.4, we replace the CO₂ emission shares by (gross) energy input shares. Compared with CO₂ emissions, (gross) energy use includes electricity and other non-CO₂-emitting energy inputs. In both samples, the WIOD 2013 and 2016, all statistically significant coefficients of import intensity and its interaction with the capital-to-labor ratio have a negative sign, supporting structural convergence (H2). The coefficients of the capital-to-labor ratio are always insignificant. Particularly, in the WIOD 2016, import intensity has a significant and negative effect on structural change with cross-sectional (srj) or time (t) fixed effects but not with two-way fixed effects (srj & t); in the WIOD 2013, import intensity has a significant and negative effect with time (t) fixed effects, and in the full sample, it has a weakly significant and negative effect with two-way fixed effects (srj & t). This means in summary that regarding the impact of imports estimated with the WIOD 2013, the energy share results are in line with the previous CO₂ share and output share results (except the single significantly positive effect of import intensity when using output shares). With the WIOD 2016, however, the energy share results confirm the previous finding of convergence (H2) being driven by imports with output shares but do not confirm the previous finding of divergence (H1) being driven by imports obtained with CO₂ shares and cross-section fixed effects (srj).

Sectoral regression results:

To understand how structural change actually occurs, we look at the sectoral level. To this end, we carry out the panel regressions separately for each sector j . As before, we use cross-sectional (sr), time (t) or two-way (sr & t) fixed effects based on the WIOD 2013 or 2016. Appendix B.5 presents the selected results of the sector-specific estimations. In each table, all available sectors are included and ordered by their CO₂ intensities, i.e., CO₂ emissions per output value, of trade recipient countries r . The left columns of the tables show the sector shares in trade recipient countries r at the beginning and end of the sample period in terms of emissions or output. This reveals whether the sectors were shrinking or expanding during the sample period.

Table B13, for example, indicates that the energy sector is the most CO₂-intensive sector, which slightly expanded between 2000 and 2014, and exhibits a significantly negative effect of import intensity (structural convergence) but a significantly positive effect (structural divergence) of the relative distance of the capital-to-labor ratio and its interaction with import intensity on the relative distance of output shares. The number of observations in this sector is 25,284, and the number of fixed effects is 1,806. Whereas R^2 is low, the F -statistic for the null hypothesis of all estimated coefficients jointly being zero is high, clearly rejecting the null hypothesis.

The sectoral panel regression results overall confirm the cross-sectoral panel regression results. The estimates with the WIOD 2016 and output value shares as the dependent variable overall confirm the hypothesis of structural convergence (H2) being driven by trade. While in the estimations with cross-sectional fixed effects, about half of the coefficients of import intensity are statistically significant, most of which have a negative sign, in the specification with time fixed effects, most of them are significant, all with a negative sign.

In accordance with the previous cross-sectoral results, in the WIOD 2016 sample, the use of CO₂ shares as the dependent variable leads to mostly positive coefficients of import intensity among the relatively small number of statistically significant results when cross-sectional fixed effects (sr) are included. Based on the WIOD 2013 sample, in contrast, the significant estimates of the effect of imports are mostly negative, in favor of the convergence hypothesis (H2). This result supports the previous finding of structural divergence

(H1), i.e., the specialization in more or less CO₂-intensive activities starting around the year 2000. When using time fixed effects (t), in contrast, more coefficients of imports become statistically significant, and all of them are negative, in favor of the convergence hypothesis (H2) as before.

There are less significant estimates of the effect of the capital-to-labor ratio than of import intensity. Although negative signs prevail for the capital-to-labor ratio, these estimated signs are mixed. The estimates of the interaction effect between import intensity and the capital-to-labor ratio show a similar picture as do the estimates of pure capital-to-labor ratio effects.

6 Conclusion

Classical Ricardian trade theory predicts differences between economic structures of countries engaged in international trade in final goods because each country specializes in specific sectors (goods) according to comparative advantages. Most of our results, however, show that international trade in intermediate goods leads to increasing similarity in terms of sectoral structure. This mechanism may be driven by the spread of knowledge, technologies, preferences, habits and so forth during the course of globalization. This finding holds when sector shares are measured using output value shares or energy input shares and, for the data sample covering the time period before the turn of the millennium, it also holds when using CO₂ emissions shares. Running panel regressions for the available sectors separately confirms these cross-sectoral panel regression results.

Because advanced technologies need to be embodied in capital, this mechanism is enhanced when intermediate goods imports are accompanied by more intensive capital use, which is visible in the results. This means that the joint effect of import- and capital-intensive production enhances sectoral convergence, whereas the sole effect of a higher capital-to-labor ratio on structural convergence appears to be ambiguous because capital use without sufficient imports may embody old-fashioned technologies. Capital can thus be referred to as an enhancer of structural convergence.

The finding of structural convergence being driven by international trade basically means good news for climate and energy policy: over a sufficiently long time horizon, energy- and CO₂-emissions-saving intersectoral structural change in industrialized countries will automatically spill over to emerging countries via international trade. The results indicate, however, that starting at the turn of the millennium, structural divergence, also fostered by international trade, occurred in terms of the CO₂ intensity of production. This outcome is confirmed when running panel regressions for the available sectors separately. Among other explanations, this outcome might point to carbon leakage, which might be fostered by stronger climate policy measures in industrialized countries than in developing countries. However, this outcome does not hold when replacing CO₂ emissions shares with energy input shares. Energy input shares refer to gross energy use including electricity and non-emission-relevant energy sources. They are affected by (total factor) productivity gains and energy-specific productivity gains. CO₂ emissions shares, in contrast, capture the emissions intensity and decarbonization of energy supply and industrial production.

Nonetheless, this insight is somewhat alarming for climate policy makers because it implies that more stringent climate policy in industrialized countries may decrease direct CO₂ emissions in particular sectors of industrialized countries but increase them in the same sectors of emerging (or developing) countries, resulting in structural divergence. As

long as no global climate policy solution is in place, this mechanism will weaken the effectiveness of unilateral climate policy in the globalized world economy. Therefore, in addition to the potentially productivity-enhancing and energy-saving effects of international trade (Cole 2006; Perkins and Neumayer 2009; Hübler and Glas 2014), policies should directly strengthen the international transfer of environmentally friendly and, particularly, CO₂ emissions-saving technologies. The ultimate goal is a global climate policy solution that avoids carbon leakage effects.

These empirical results should, however, be treated with caution, especially because some outcomes depend on the time frame (data sample) and choice of the exploited variation in the data (cross-section, time fixed effects or both). Furthermore, in addition to OECD countries, the dataset of the WIOD is limited to a number of heterogeneous emerging countries, where China and India are the dominant actors, and does not cover any developing countries. Although our results indicate structural convergence, such processes require a long time horizon, probably decades, to materialize. Therefore, the question remains as to whether international specialization in more or less CO₂-intensive production, as indicated by our analysis for this millennium, is a temporal statistical, negligible phenomenon or the beginning of a considerable long-term process.

Future research may address further drivers of structural change that may independently or in connection with international trade foster structural divergence or convergence. It may also include an extended set of countries once required data are available or selected countries or sectors with specific data as case studies.

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