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A New Measure of Climate Transition Risk Based on Distance to a Global Emission Factor Frontier *

Benjamin N. Dennis[†] Talan B. İşcan[‡]

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Abstract

Targeted financing of transition to a “net zero” global economy entails climate transition risk. We propose a measure of transition risk at the country-sector dyad level composed of five tiers of transition risk based on two factors: i) the gap between a dyad’s existing emission factor (EF) – a measure of the greenhouse gas intensity of output – and the global ‘frontier’ sectoral EF, and ii) a dyad’s recent convergence towards the frontier EF. Dyads that are either close to the frontier or converging towards the frontier carry lower transition risk. Our measure, using 45 sectors across 66 countries, accounts for both direct greenhouse gas emissions as well as those that enter into production through complex supply chains as captured by intercountry, input-output tables, and can be applied at different levels of stringency to high, middle, and low income economies. Our measure thus accounts for, and sheds light on, EF reductions through investment in lower emissions production techniques in own facilities as well as sourcing intermediate inputs with lower embodied emissions.

Keywords: transition risk; greenhouse gas emissions; direct emissions, production emissions, convergence

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1 Introduction

Most nations have set greenhouse gas (GHG) emission reduction targets with the understanding that transition to a “net-zero” global economy will not occur without coordinated actions (IPCC, 2021). These actions encompass targeted government policies to accelerate the adoption of low or zero emissions technologies, as well as targeted financing of this transition. The potential for asset price devaluation and higher financing costs as a result of these policies, as well as the attendant changes in technology and behavior entails climate-change driven financial transition risk. At present, the measures of transition risk employed by financial institutions and regulatory authorities are varied (Monasterolo, 2020), not always easy to interpret (Bingler et al., 2021), assume either a pool of short-term shocks or a few long-term scenarios (Cartellier, 2022), and are based on a dichotomy of either “green” and “brown” sectors or high- or low climate sensitive sectors based on financial market data (Battiston et al., 2019). These approaches typically do not incorporate climate transition risk arising from the web of complex supply chains central to the contemporary global economy beyond designating some sectors as subject to high risk of “leakage” (implying that high abatement costs will erode the sector’s competitiveness).

Here we propose a novel climate transition risk measure based on how close a country’s sector is to the frontier emissions performance for that sector. The emissions frontier establishes a standardized and transparent benchmark relative to which performance can be measured. The distance to the frontier as a measure of risk recognizes what is technically and economically feasible (the frontier). The frontier and thus our measure of transition risk are dynamic due to changes in production techniques. Sustained convergence to the frontier can be rewarded with a reduction in transition risk and divergence or a lack of convergence can be penalized. Our measure of climate transition risk is data-driven based on the emission factor (EF) – emissions divided by output – and we apply it to GHG emissions data on country-sector dyads (e.g., the transition risk for the basic metals sector of Belgium). Our methods are related to environmentally extended input-output analysis (Yang et al. (2017); Ingwersen et al. (2022); Wiebe and Yamano (2016) and Yamano and Guilhoto (2020)) extending the analyses both internationally and to non-CO₂ GHGs to comprehensively address the global warming potential of industrial emissions. We calculate a sector-based transition risk measure across 66 countries and 45 ISIC industrial sectors using data consistently available since 1995 from the OECD, EPA, and FAO. Our measure allows for the incorporation of the full production supply chain using intercountry input-output tables and is comprised of two related sector-specific metrics:

- A *distance-to-the-frontier* transition risk measuring how far a country’s sectoral EF is from the contemporaneous 25th percentile EF in the global EF distribution for that sector. This measure adjusts for whether there is scope for reducing emissions based on the emission factors of advanced and commercially viable production techniques. There are no “brown” or “green” sectors in this approach, only sectors that are close to or farther away from their potentially lowest emission factors. Based on equity considerations, one could hold those sectors in historically high-emitting *countries* (per person) to higher standards (say, zero distance-to-the-frontier) (Baer

et al., 2000; Fanning and Hickel, 2023; Raupach et al., 2014).

- A *convergence to the frontier* transition risk measuring the pace of movement of a country’s sectoral EF to the frontier. A sector may be relatively far from the frontier, with a significant distance-to-the-frontier transition risk. However, if the EF in that sector is approaching the frontier, its convergence-to-the-frontier transition risk is reduced. Observed changes in EFs should matter by identifying those dyads that are converging, diverging, or remaining at a fixed distance to the frontier.

We combine these two transition risk metrics to divide country-sector dyads into five risk rating tiers from lowest to highest transition risk:

Tier 1: No EF gap

Tier 2: Low EF gap, converging

Tier 3: Low EF gap, non-converging

Tier 4: Low EF gap, diverging

Tier 5: High EF gap

These rating tiers are deliberately coarse for practical reasons. They are easier to implement in real world settings. They are also intended to accommodate uncertainty underlying the data.¹

Given the presence of supply chains in our analysis, we develop two EF measures. The first is a ‘direct emissions’ measure that focuses solely on production occurring within national borders within that sector. The second is a ‘production emissions’ measure that accounts for all upstream emissions embodied in intermediate inputs used in production. Both of these measures have their uses. Direct emissions are the ‘on-site’ facility emissions, whereas production emissions are ‘on-site’ plus ‘upstream’ emissions.² In addition, in the nomenclature of the Greenhouse Gas Protocol Standard ([Greenhouse Gas Protocol Initiative, 2004](#)), direct emissions correspond to Scope 1 emissions, while production emissions add Scope 2 and part of Scope 3 emissions. A focus on direct emissions may incentivize firms to upgrade their in-house technology to less GHG emissions intensive production techniques, while a focus on production emissions will incentive firms to more carefully select their suppliers on the basis of emissions criteria ([Kaplan and Ramanna, 2021, 2022](#)). It is critical to account for input-output relationships as transition towards zero emissions by each sector will ultimately lead

¹The EF gaps that we observe are in part determined by private abatement costs and elasticities of demand. In sectors where the abatement costs are low, we might expect smaller EF gaps, and where the price elasticity of demand is high, we might expect larger EF gaps (because even small increases in costs to reduce emissions may sharply erode competitiveness, referred to as ‘leakages’). An additional challenge is that abatement costs used in leading studies differ, perhaps due to conflation of private and social costs of abatement ([Kotchen et al., 2023](#)). Given data limitations, we are presently unable to explore these issues using our methodology.

²Direct plus indirect emissions constitute the full life-cycle assessment of emissions by product. While a life-cycle assessment provides a comprehensive interpretation of emission intensities, it is more suitable for products that make up final demand. Our approach therefore stops short of household demand, focusing rather on production as the level at which transition risk resides (tantamount to Step 2 of [Yang et al. \(2017\)](#), Fig.2). However, Waste and Recycling is one of the sectors and it is possible to apportion emissions by this sector to originating sectors (partial Scope 3 emissions).

to cascading changes in consumption behavior in the rest of the economy. For example, municipal waste from both firms and consumers must be dramatically reduced on a transition path to low emissions with implications for the large number of upstream sectors (Hoy et al., 2023). Each of these adaptations could plausibly be targeted by transition policies, creating transition risk. For example, restrictions could be placed on GHG emissions from domestic facilities, border taxes could be imposed on imported inputs with high associated GHG emissions, or consumption taxes could be levied on sectors that generate high downstream waste. Given that direct and production emissions collectively allow us to capture different stages of production, and that the emissions of these different stages will respond to different policies, we analyze the distance to the direct and production ER frontiers separately.

2 Related Literature

There are several approaches to climate transition risk. One approach assesses transition risk using price sensitivity to climate (news) shocks either at the firm level (Bauer et al., 2023; Bolton and Kacperczyk, 2021; Engle et al., 2020) or at the sector level for climate stress tests (Battiston et al., 2017; Vermeulen et al., 2018). Each firm’s exposure to transition risk can be based on factors such as the “E” component of ESG ratings or facility-level emissions. Using econometric techniques, one can then estimate a “climate” value-at-risk (VaR) measure for a portfolio composed of these firms. Sector-based analyses use high-level sectoral classifications such as “green” or “brown”, or use a measure of climate sensitivity, identified from high covariances of returns (either positive or negative) with climate policy shocks. Beyond the small number of jurisdictions that meet these data requirements, there are a variety of other challenges with this approach. ESG-ratings and other assessments of climate risk can be of questionable quality and are highly subjective, and firm-level emissions are often self-reported and sparse. Self-reporting tends to significantly undercount actual emissions (Brown et al., 2023; MacKay et al., 2021; Park et al., 2023). In addition, this approach assumes accurate pricing of climate risk. There is reason to doubt that market prices adequately incorporate climate risks.³

Approaches based on ESG or asset price data are in principle determined through a complex supplier network. However, it is typically not possible outside of a few specific products to track emissions embodied in intermediate inputs obtained through the global value-chain with the price sensitivity method. While there are firm-level approaches to complex supply chains (Pichler et al., 2023), significantly more data and greater standardization are needed to translate firm-level networks to intercountry input-output tables (Bacilieri et al., 2023). Moreover, aggregating facilities up to the firm-level is difficult and typically limited only to publicly traded firms although privately-held firms can make up a substantial share of certain sectors. As such, the data infrastructure for firm-level approaches is not yet sufficiently developed to produce an EF-based measure of climate transition risk. Sectoral financial data coverage also tends to be limited to a specific region and does not capture

³Many experts do not believe that market prices adequately capture climate risks, and market prices are not universally available globally for all relevant firms (Commodity Futures Trading Commission (CFTC), 2020; Stroebel and Wurgler, 2021).

complete global input-output relationships.

Within the sectoral approaches to climate transition risk, there are also scenario-based analyses (Monasterolo and Raberto, 2018; Carattini et al., 2023) using high-level classifications such as “green” or “brown” sectors, with heterogeneity across sectors in terms of their sensitivity to policy changes. In these scenarios, sectors deemed brown are automatically assigned a high transition risk. While a useful conceptual model, there are several reasons that a simple green–brown dichotomy of sectors is too crude for empirical climate transition risk analysis. Most sectors outside of the fossil-fuel energy sector fall on a spectrum of GHG intensity and have important input-output relationships with sectors with low emissions intensity that make it difficult to apply this dichotomy meaningfully.⁴

There are emissions intensive and hard-to-abate “brown” sectors that are nevertheless perceived to be necessities for transitioning to a low emissions economy (e.g., rare earth mining, concrete manufacturing). Importantly, a simple green–brown dichotomy makes no allowance for the technologically-feasible scope for reducing emissions, whereby applying a transition-risk premium to sectoral financing costs may become overly burdensome and ultimately counterproductive. It is possible for the distance between the technically feasible and economically viable frontier and the “brown” dyad’s EF to be so small that the transition risk is low. Similarly, the distance might be so large for a “green” dyad that the transition risk is high.

Furthermore, a green-brown dichotomy models a uniform economic structure for national economies. It treats lower and higher income economies, with varied integrations into the global economy the same. A climate transition risk measure which does not account for intercountry input-output relationships can disincentivize investment flows to certain countries, even when outsourcing of emission intensive sectors are responsible for observed economic structures. An alternative dichotomy considers “sunrise” and “sunset” sectors in the context of the transition to a low emission economy (Semieniuk et al., 2021). While there may be entire sectors that can be classified as sunrise or sunset, this transition will also happen within each of the sectors as procurement practices change and low emitting production techniques replace high emitting ones.

3 Methodology

Our key environmental impact indicator is the emission factor, which is calculated as follows:

$$EF = \frac{Emissions}{Gross\ output}. \quad (1)$$

This measure provides unit emissions in physical units (Mt) and output in US dollars (constant prices) that can be compared across countries and sectors. Using direct emissions for illustration (the same approach applies to production emissions), we rewrite equation (1) to focus specifically on direct

⁴The canonical brown sector is fossil fuel energy, which in theory is fully substitutable with less polluting forms of electricity generation. There are estimates of losses in fossil fuel assets during a net zero transition (Semieniuk et al., 2022). Other “brown” sectors are less easily handled, however, given their importance in providing inputs to burgeoning green sectors.

process emissions by sector h and region i attributable over a period (annualized) to this entity, E_i^h , divided by its gross output (in constant 2015 dollars), Q_i^h :

$$EF_i^h = \frac{E_i^h}{Q_i^h}.$$

where EF_i^h is the emission factor (EF) of sector h output in country i (dyad “ ih ”).

The EF of the dyad at time t will be:

$$EF_i^h(t) = EF_i^h(0)e^{g_i^h \times t}.$$

where g_i^h the rate of change in EF by the sector h in country i , and time 0 corresponds to earliest available emission levels. Likewise, the EF of the frontier will be:

$$\widetilde{EF}^h(t) = \widetilde{EF}^h(0)e^{\widetilde{g}^h \times t}$$

where \widetilde{EF}^h is the EF of the technological frontier for sector h globally, and \widetilde{g}^h the rate of change in EF by the technological frontier in sector h (25th percentile adjusted by historical emissions).

3.1 The EF Gap

The EF gap refers to the distance between the EF of a country-sector dyad and the contemporaneous 25th percentile EF for that sector across all countries. In our notation the EF gap is:

$$EF_i^h > \widetilde{EF}^h.$$

This measure:

1. rates each dyad by its performance relative to the EF frontier for that sector, allowing for progress in technology to move the frontier forward in each successive period,
2. rates each dyad by its peers, and
3. allows for the peers used to calculate the 25th threshold to vary, permitting high, middle and low income economies – for example – to use different thresholds

EF gaps are sensitive to annual variations in weather, fluctuations in relative prices and potentially unrelated shifts in technology and demand. We thus use averages over five-year periods for our EF gap measures. These periods are 1995-1999, 2000-2004, 2005-2009, 2010-2014, and 2015-2018 (where 2018 is the last year for which data are available). We estimate both direct GHG emissions (the so-called Scope 1 emissions) and production GHG emissions which also account for all emissions associated with intermediate inputs used in production (Scope 1 plus upstream Scope 2 emissions). To account for these inputs, which are typically globally sourced, we rely on OECD’s publicly-available intercountry input-output tables.

3.2 Convergence

We measure convergence as a reduction in a dyad’s average five-year EF gap from one five-year period to the next by greater than or equal to one standard deviation of the distribution of average EFs across countries for that sector. This measure has the virtue of being sensitive to changes in the distribution of EFs over time. With improvements in technology, during transition to a net-zero global economy, we would expect both g_i^h and \tilde{g}^h to be negative (although g_i^h can be positive as well if a dyad’s EF factor increases over time), and if there is convergence, then

$$g_i^h < \tilde{g}^h \leq 0.$$

If there is non-convergence

$$\tilde{g}^h < g_i^h.$$

As far as we are aware, there is no scientific consensus on optimal time profiles for sectoral emission reductions needed to achieve global net zero outcomes.

4 Results

4.1 Accounting for All Greenhouse Gasses

We construct our measure of transition risk using “flows” of GHGs under the understanding that they translate into environmental, economic, and human health impacts through their global warming potential (GWP). Much of the focus on global warming has been on carbon dioxide (CO₂) emissions. However, GHGs include many other potent molecules including methane (CH₄), nitrous oxide (N₂O), and fluorinated gasses, among others. These non-CO₂ GHGs are materially important factors that are sometimes overlooked in economic analyses. [Lamboll et al. \(2023\)](#) identify the evolving division of GHGs between CO₂ and non-CO₂ gasses as one of the key uncertainties in calculating the remaining carbon budget, i.e., the remaining net amount of CO₂ that can be emitted without exceeding a global warming limit (e.g., a target of 1.5°C warming over the baseline).

Carbon dioxide, which makes up around three quarters of the currently estimated stock of GHGs, is used as a numeraire to compare other GHGs, assigning it a GWP of 1 over different analytical timeframes (i.e., 20 years, 100 years, and 500 years).⁵ Methane has a global warming potential GWP of around 56 over 20 years, 21 over 100 years, and 6.5 over 500 years.⁶ Nitrous oxide has a GWP of 280 over 20 years, 21 over 100 years, and 170 over 500 years. Its lifetime is 120 years. There are 13 HFCs with differing GWPs and lifespans. GWPs range from 460 over 20 years, 140 over 100 years, and 42 over 500 years (for difluoroethane, C₂H₄F₂), to 9,100 over 20 years, 11,700 over 100 years, and 9,800 over 500 years (for hydrofluorocarbon, CHF₃). By simple average, HFCs have a GWP of 3,327 over 20 years, 2,531 over 100 years, 1,469 over 500 years, and an average lifespan of 50.3 years. Accounting

⁵<https://unfccc.int/process/transparency-and-reporting/greenhouse-gas-data/greenhouse-gas-data-unfccc/global-warming-potentials>

⁶On average, methane has a lifespan of around 12 years (± 3 years).

for non-CO₂ GHGs is important because they account for about 30% for the total contribution of anthropogenic GHG emissions to global radiative forcing (W/m²) using 100-year Global Warming Potentials (IPCC, 2021) —although they are highly concentrated in several sectors (Fig. 1).

Figure 1 illustrates the distribution across countries of the ratio of GHG to CO₂ emissions. If GHG emissions consisted solely of CO₂ emissions, then all distributions would collapse to one. The figure clarifies that for many industries CO₂ emissions do account for almost all GHG emissions. However, there are seven sectors that constitute important exceptions, specifically: Agriculture, hunting, forestry (D01T02), Mining and quarrying, energy producing products (D05T06), Coke and refined petroleum products (D19), Chemical and chemical products (D20), Computer, electronic and optical equipment (D26), Electrical equipment (D27), and Water supply; sewerage, waste management and remediation activities (D36T39). Consequently, we contribute to the literature by using a comprehensive GHG measure as part of our inter-country intersectoral exercise.

In addition to direct CO₂ emissions by sector, we also measure non-CO₂ GHG emissions

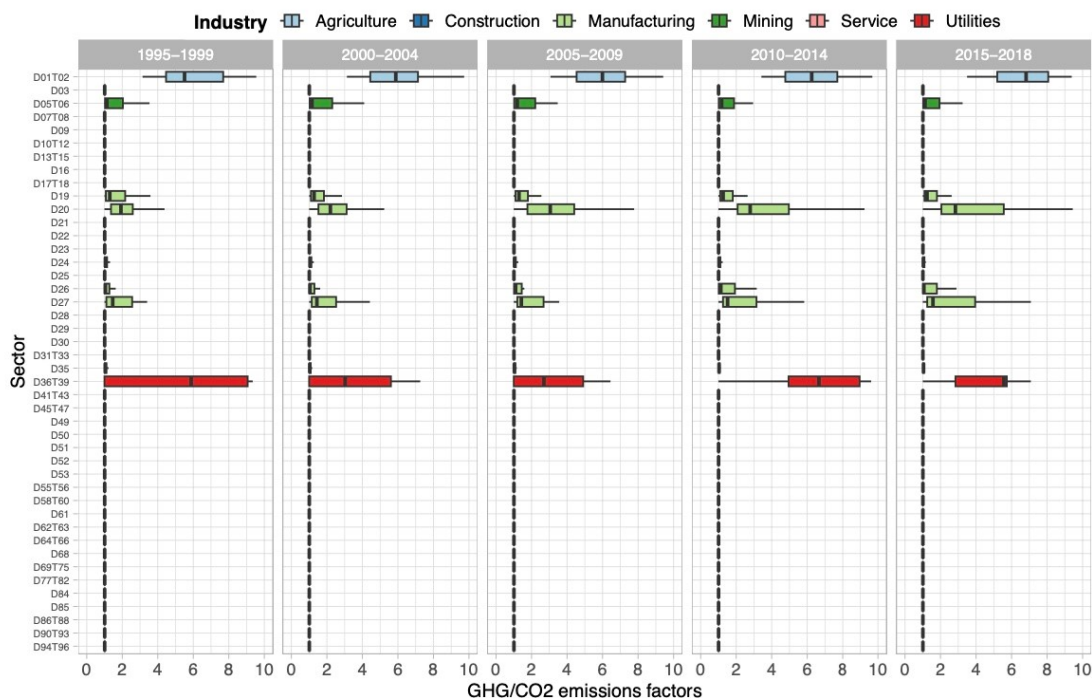


Figure 1: Cross-country sectoral total GHG emission factors relative to CO₂ emission factors

Note: We use horizontal whisker plots where the tips of the “whiskers” indicate the maximum and minimum values, whereas the ends of the “box” indicate the 25th and 75th percentile values and the mid-box “dash” indicates the median value. The sectors are ordered along the vertical axis, and we have color coded sectoral boxes by broader sector classifications as indicated along the top. There are five successive graphs arranged horizontally that correspond to successive periods.

4.2 Direct and Production Emission Factors

We compute emissions intensities using CO₂ emissions from fuel combustion based on OECD.*StatTeCO2* database, and non-CO₂ emissions based on data in (Environmental Protection Agency (EPA), 2019) (see Supplementary Material for details). We also carry out the analysis using all emissions attributable to direct process emissions and purchased inputs. We thus calculate the emissions embodied in one dollar value of production within a 2-digit ISCI (version 4) sector by accounting for all inputs into the production process using input-output tables (Wiebe and Yamano (2016); Yamano and Guilhoto (2020)):

$$\mathbf{PEF} = \text{colSums}(\mathbf{EF}(\mathbf{I} - \mathbf{A})^{-1}),$$

where the first term on the right-hand side is the emissions intensity matrix (for R regions and S industries, this is an $RS \times RS$ matrix) and the last term is the global Leontief inverse matrix containing each region’s input coefficients into another region’s production by sector, \mathbf{A} ($RS \times RS$ matrix). These data are from the OECD intercountry input-output database. The `colSums` operator gives the total emissions per one US dollar of production value embodied in a dollar’s value of production in a sector within a region. These emissions potentially originate from all the industries and regions of the world. Here the excluded “sector” is the households whose residential heating, cooling, and private road transport using motor vehicles separately contribute to emissions. Figure 2 Panel A (top) shows direct emission factors by sector and across time periods. Given that practically all region-sector pairs are net emitters, going up on the supply chain and accounting for all inputs increases the total emissions of an entity per unit value of output. Thus, in all cases, the production emission factor cannot be less than the direct emission factor. Production emissions are given in Panel B (bottom) of Figure 2. Comparing production emission factors to direct emission factors, we find that many more manufacturing sectors become substantial contributors to climate emissions once production emissions are taken into account. However, it is visibly striking how much manufacturing production emission factors have declined from the 1995-1999 period to the 2015-2018 period.

We measure both direct (process) emissions factors and production (including inputs) emissions factors

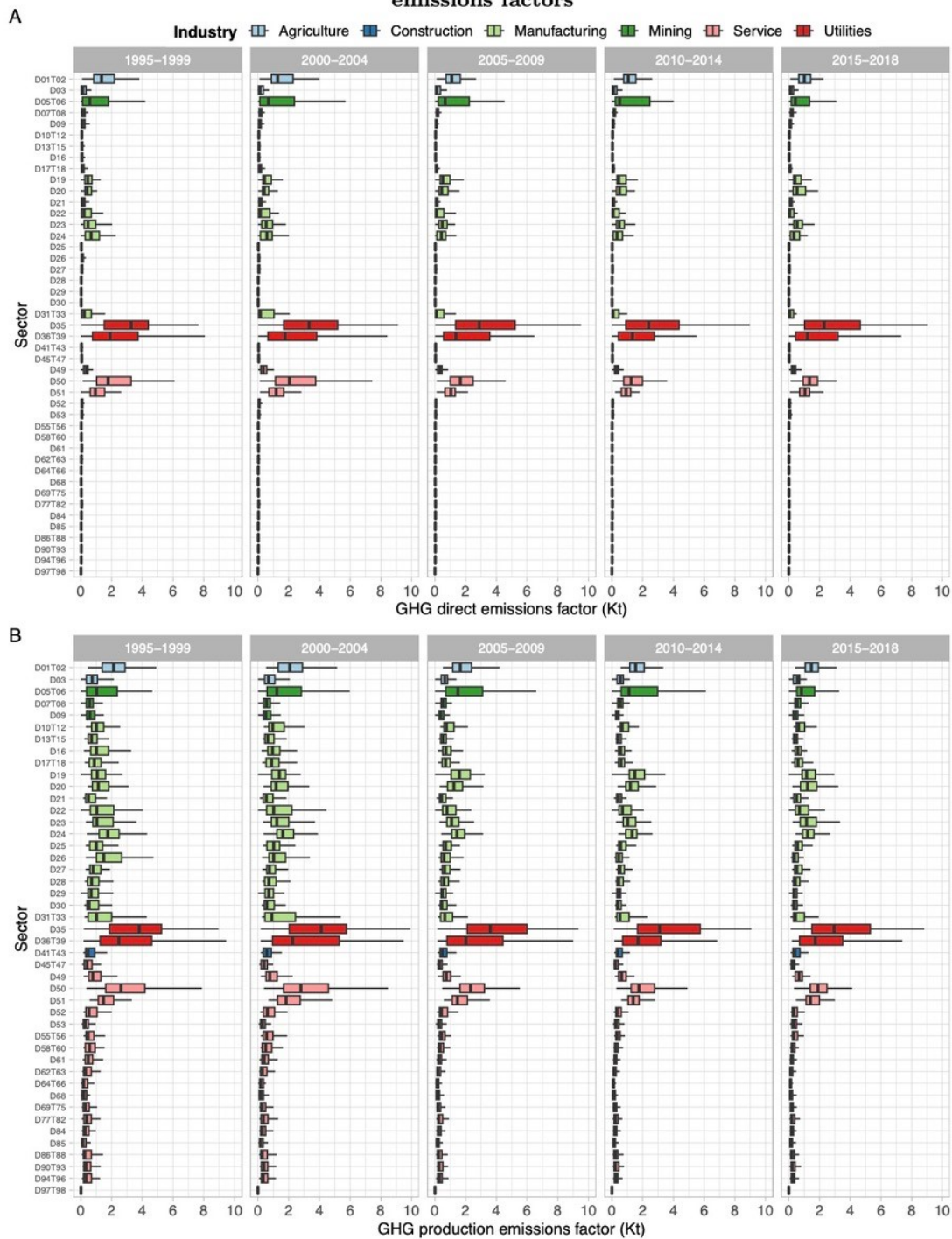


Figure 2: Cross-country distributions of sectoral GHG emission factors

Note: The horizontal axis measures kilotons of GHG emissions per one USD value of gross output in constant 2015 prices annualized over each time period.

4.3 Emission Factors and Per Capita Income

Concerns over the role different economies have played in generating the existing stock of GHGs in the atmosphere have challenged negotiations about emissions targets. Low income economies point to the carbon intensity of the growth history of high income economies as an argument for stricter targets for wealthier economies. There is a high likelihood that different standards will apply to countries with different emissions histories and income levels.

Our data supports a correlation between per capita income and GHG emissions per head as seen in Figure 3.

Historical emissions per head (person/capita) increase by income and should be accounted for in a just transition Income categories are quartiles based on the OECD sample, not to be confused with the World Bank’s income classification based on absolute thresholds.

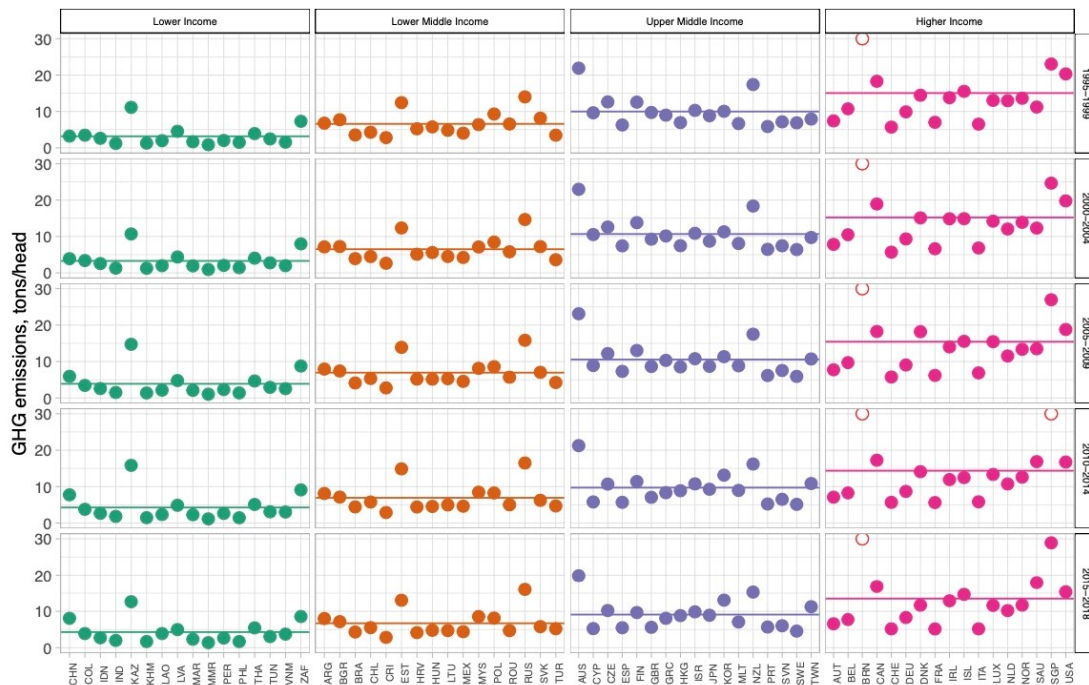


Figure 3: GHG emissions by income category (empty circles are off-scale)

Note: We plot GHG emissions in tons per head for four different quartiles of national per capita income. The income quartiles are denoted by separate panels organized horizontally from lower to higher income, and by color. Specific countries are listed by three digit code across the bottom of the graph. In addition, our five different five-year periods are organized in panels from top to bottom. Horizontal bars indicate average values. Note that we are not plotting emission factors and that the income categories are based on our quartile calculations using our OECD sample, not the more commonly used World Bank income classification. Thus, many European countries appear in the “upper middle income” quartile.

Several features jump out from Figure 3. First, in all time periods, higher income quartiles have higher emissions per head than lower income quartiles. Second, the variance of emissions per head increases as income levels rise. Rich countries like France, Italy, and Switzerland tend to have per

capita emissions on par with the lowest income quintile. Third, average emissions per head have been declining in the top two income quartiles while rising the lower two, although the changes are small within our vertical scale. Fourth, fossil fuel exporters tend to have higher per capita emissions (e.g., Australia, Brunei, Kazakhstan, and Russia).

Within each of our five-year windows, the level of emission factors are weakly, negatively associated with each window’s average income per head.

Table 1: Correlations of EF Levels with GDP Per Head Based on 5-year Windows

Sector	Direct EF	Production EF
Agriculture	-0.251	-0.288
Construction	-0.299	-0.413
Manufacturing	-0.023	-0.061
Mining	-0.100	-0.207
Service	-0.071	-0.176
Utilities	-0.200	-0.209

At this level of aggregation and without an economic model of comparative advantage, it is not possible to distinguish whether lower income countries on average specialize in high emissions intensive industries or lower income countries on average employ production techniques that are emissions intensive or a combination of both. The correlation between

$$\text{corr}(\text{GDP}_{\text{pc}_{t-1}}, \Delta\text{EFGHG}_t)$$

and

$$\text{corr}(\text{GDP}_{\text{pc}_{t-1}}, \Delta\text{PEFGHG}_t),$$

that is initial level of income and the change in the emissions intensity over the subsequent five years is also weak but positive, where we see the most significant correlation in agriculture. Low and lower middle income countries have been as effective as upper middle and high income countries in reducing their direct and production emission factors.

Table 2: Correlations of EF Growth with GDP Per Head Based on 5-year Windows

Sector	Direct EF	Production EF
Agriculture	0.026	0.137
Construction	-0.059	-0.081
Manufacturing	0.019	-0.017
Mining	0.001	-0.001
Service	-0.011	-0.003
Utilities	-0.027	-0.038

This can be seen in Figure 4 where we explore convergence by per capita income quartile, EF measure, and sector over time.

Emissions factors have generally been declining, however there is significant differences within each income category

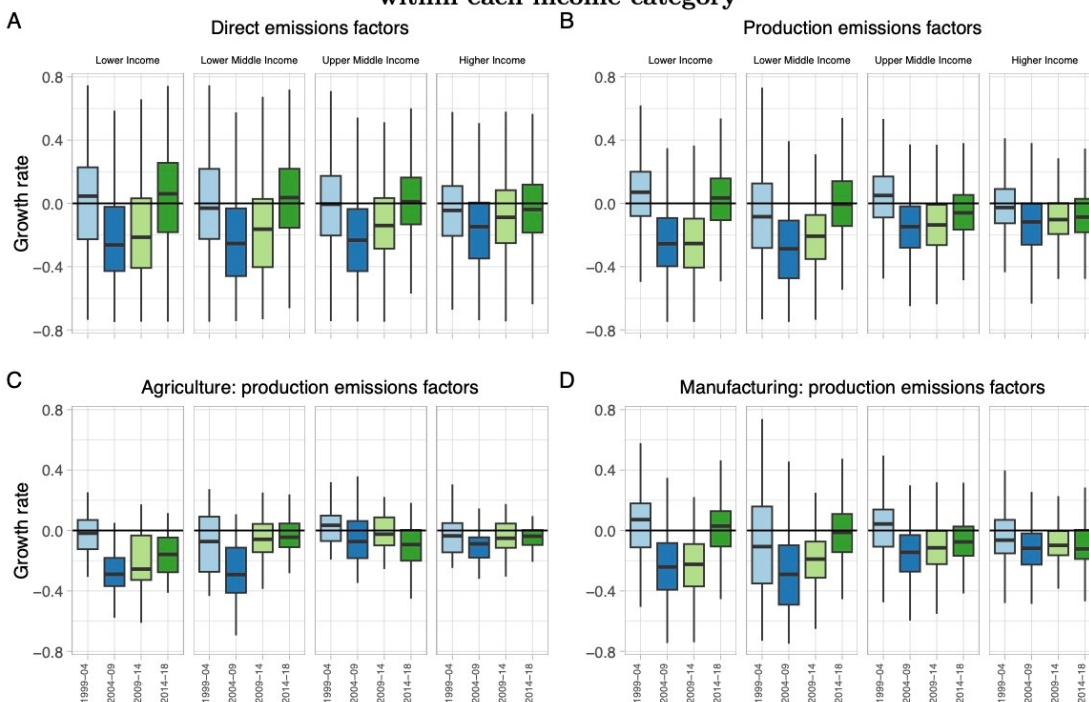


Figure 4: Growth of GHG emission factors by income category and major sectors

Note: This figure presents whisker plots (organized vertically) to illustrate the distribution of countries falling within each quartile. The growth rate of the emission factors within each five-year period are labeled on the left axis (we only cover four five-year periods here, as labeled at the bottom of the graph and denoted by color). The four panels correspond to the two emission factor measures along the top (i.e., direct and production), and two large aggregated sectors along the bottom (i.e., agriculture and manufacturing).

Focusing on median growth rates, we find a U-shape in reductions of EFs over time in most cases, with the greatest EF reduction occurring in the period 2004-2009. The ensuing periods, 2009-2014 and 2014-2018, tended to experience rising EFs sequentially. For the direct EF measure in the two lowest income quartiles, the final period of 2014-2018 saw increases in the EF, while the second highest income quartile saw no progress during that same period.

There are two main possibilities for why convergence in lower income quartiles was worse. One is that these countries experienced relatively slower adoption of less GHG intensive production techniques. Another is that the results are driven by composition of production both within and across countries. For example, in higher income quartiles, the composition of production might shift towards lower emission sectors as a result of a change in the preferences or behavior of domestic households that alters demand. If the same demand-inducing shifts are not occurring in low income countries, they may achieve a greater comparative advantage in high emission products, limiting their progress

in reducing emissions. Alternatively, compositional changes might result from the outsourcing of GHG intensive products within each sector from higher to lower income countries. Here we do not attempt to discriminate between these hypotheses. The fact that agriculture has the strongest correlation, and the expansion of pastures and cultivated land through land conversion from mature forests in low and medium low income countries suggest that the former driver might be important. At the same time, low and lower middle income countries on average had the fastest reductions in both direct and production emissions between the windows of years 2000–2004 and 2005–2009, and again between the windows 2005–2009 and 2010–2014. The production emission factors for the agricultural and manufacturing sectors have on average also declined and the reductions have been often more prominent among the low and lower middle income countries—although there is considerable variation between the windows of years.

4.4 Contributors to Changes in Emission Factors

We decompose the change over time in emissions as

$$\Delta \ln E_i^h = \Delta \ln Q_i^h + \Delta \ln EF_i^h$$

where Δ represents the change between two consecutive windows and again we use period averages of the variables within each window. This measure captures the contributions of changes in sectoral production and sectoral emission factors, respectively, to historical emissions. We normalize emissions within a region by its population and report the results in terms of emissions per head and gross output by head. Incomes have been changing globally through a combination of structural transformation and changes in production techniques with many countries in our dataset exhibiting steady increases in their income per capita over time (an income effect). In the absence of any improvements in emission factors, this income effect alone will lead to an increase in global emissions as output responds to the demands of a wealthier global population. This is reflected in the first term of the decomposition above. Emission factors have also been changing due to a combination of changes in production techniques and land use. With the adoption of new production techniques driven by cost minimization, emission factors could also change (an emission factor effect) but may not necessarily improve, say when coal replaces natural gas. In the absence of a change in income, this emission factor effect can mitigate rising emissions by decoupling emissions from income growth. This is the second term of the decomposition above.

Figure 5 shows a breakdown of the contribution of economic growth and the contribution of changes in emission factors to changes in overall emissions by period, sector, and per capita income quartile for both direct emissions (panel A) and production emissions (panel B).

Economic growth has been a major contributor to emissions across all sectors, despite improvements in emissions factors

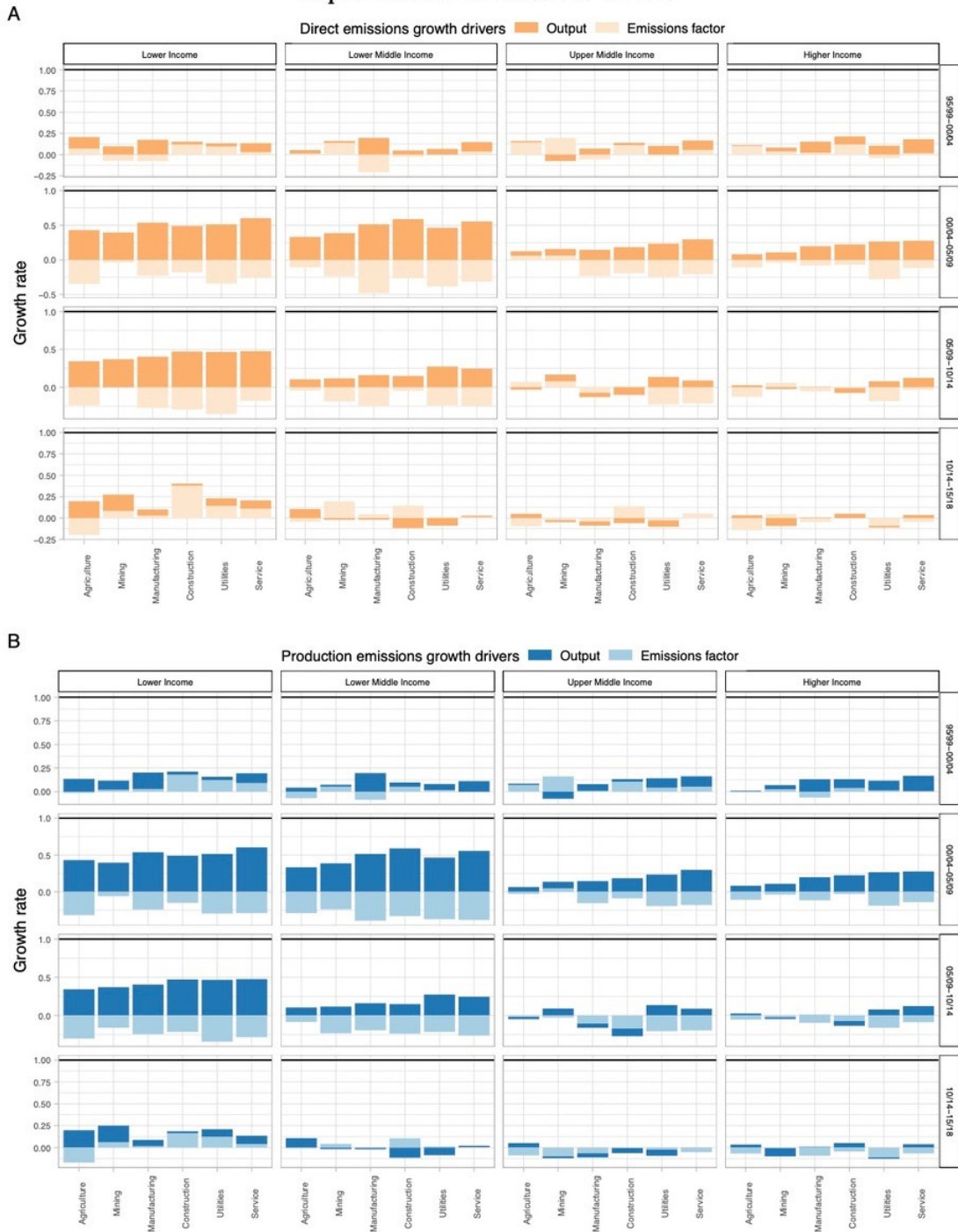


Figure 5: Drivers of GHG emissions growth by major sector and income category

Note: In each panel, quartiles are arranged from lowest to highest income from left to right. Changes in the average of two sequential five-year periods are arranged in order from top to bottom. For example, the top row of the panel illustrates the percentage change from the average of the period 1995–1999 to the average of the period 2000–2004. Within each quartile, sectoral aggregates are arranged according the labels at the bottom of each panel (i.e., agriculture, mining, manufacturing, construction, utilities, and services).

Our emissions growth drivers – output growth and emission factor growth – can contribute positively or negatively to overall emissions growth. Consider the case of emissions resulting from manufacturing output growth (either direct or production). For upper middle income countries, manufacturing activity declined across periods 2005–2009 to 2010–2014 and periods 2010–2014 to 2015–2018, leading to a negative impact of output growth on emissions. This observation (and the lack of manufacturing output growth in the highest income quartile), when combined with the robust growth in manufacturing output growth in the lowest income quartile, highlights the potential significance of compositional changes in gross output within regional economies in accounting for global changes in emissions. It is notable that other sectors also experienced decreases in output, especially construction and utilities. By contrast, output growth was a strong contributor to higher emissions across all sectors for the two lowest income quartiles in the middle two periods of our sample.

There is ambiguity in the impact of changes in emission factors on total emissions as well. Although emission factors have fallen in most cases, emission factors increased in every sector for the lowest income quartile across the periods 2010–2014 and 2015–2018. Indeed, deterioration of emission factors was the primary reason behind higher emissions in the construction and utilities sectors in this period.

The overall picture, taking both effects into account, is one in which emissions have tended to rise due to increased output that has only partially been attenuated by falling emission factors. There is very little difference between the direct emissions measure and the production emissions measure in our analysis suggesting that supply chain effects do not change the overall results. In our sample periods, we observe a reduction in the growth rate of total emissions across all sectors between the 2010–2014 and 2015–2018 periods for all income quartiles, and also between the 2005–2009 and 2010–2014 periods for the top three income quartiles. Indeed, total emissions declined modestly across all sectors for the top two income quartiles in the last period.

4.5 Evolution of the Emission Factor Frontier

We use the five-year average emission factor of the 25th percentile of the EF distribution across countries for a given sector as the frontier. This allows us to compensate for outliers in the economic sub-structure of our sectoral categories and to introduce a threshold that is likely to be technologically and economically feasible. The EF frontier can be established at the global level, or a separate EF frontier can be calculated for any given grouping of countries, such as our quartiles by per capita income. In Figure 6, we show the average 25th percentile EF for all countries for each sector for each of our five periods. Panel A (to the left) shows direct EF thresholds, and Panel B (to the right) shows production EF thresholds.

The frontier of emissions factor has been shrinking over time toward net zero, but progress is uneven across sectors

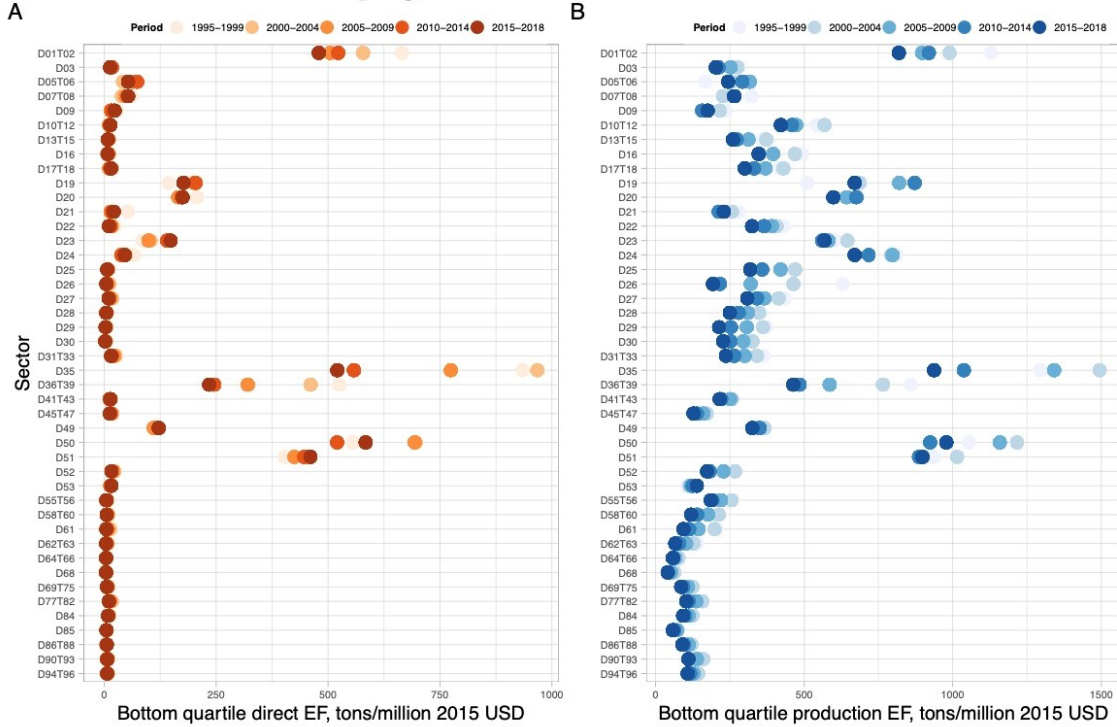


Figure 6: Bottom quartile of emission factors by sector

Note: The color coding is such that the color's shade darkens as five-year periods progress over time. Thus, if darker dots are to the left, this represents a reduction in emission factors.

Focusing first on direct EFs, we find that threshold EFs are, and have been, low for most sectors. This is not surprising for the service sectors represented by D52–D94T96. However, it is also noteworthy that many of the manufacturing sectors also have low direct EF thresholds (manufacturing sectors span the range D07T08–D33). Sectors with relatively high direct EFs include agriculture (D01T02), mining and quarrying (D05T06, D07T08), coke and refined petroleum products (D19), chemical and chemical products (D20), other non-metallic mineral products (e.g., cement) (D23), basic metals (D24), electricity, gas, steam and air conditioning supply (D35), water supply; sewerage, waste management and remediation activities (D36T39), land transport and transport via pipelines (D49), water transport (D50), and air transport (D51). With the exception of the transport sectors and non-metallic mineral products, direct EFs have most been trending downwards, especially for electricity (D35) and water supply and sewage/waste (D36T39). The electricity sector direct EF threshold, by far the largest among all sectors originally, has been cut almost in half from the 1995-1999 period average to the 2015-2018 period average.

Turning to the production EF threshold panel, it is apparent that all sectors have considerably higher EF thresholds once their supply chains are taken into account. While this is true even for service sectors, it is manufacturing sectors that experience the greatest increases relative to direct EF

thresholds. There are some interesting standouts when moving to production EFs among our sectors. For example, the food products, beverages and tobacco manufacturing sector (D10T12) vaults to high among the mid-tier manufacturing EFs, surpassing the mining and quarrying sectors. Basic metals (D24) also increases substantially, overtaking non-metallic mineral products (D23). However, relative movements of the production EF over time for any given sector tend to follow the pattern of direct EFs.

4.6 Transition Risk

We now present our findings transition risk using EF gap analysis. In particular, we are interested in differences in transition risk across income categories and whether there is evidence of movement towards lower risk tiers.

4.6.1 EF Gaps across countries - Levels

Our transition risk measure combines two elements, EF gap levels and convergence of EF gaps. Figure 7 presents EF gaps calculated by country and sector for our final period of 2015–2018. To calculate the gap thresholds, we take the standard deviation of the global distribution of EFs for a given sector and add it to the frontier (the 25th percentile value). Countries at or below the 25th percentile value are considered to have ‘no gap’, countries between the 25th percentile value and one standard deviation above the 25th percentile value are considered to be ‘low gap’, and countries with EFs above the 25th percentile value plus one standard deviation are considered to be ‘high gap’. These categories carry over to the first portion of our transition risk rating (i.e., no gap = lowest transition risk, high gap = highest transaction risk).

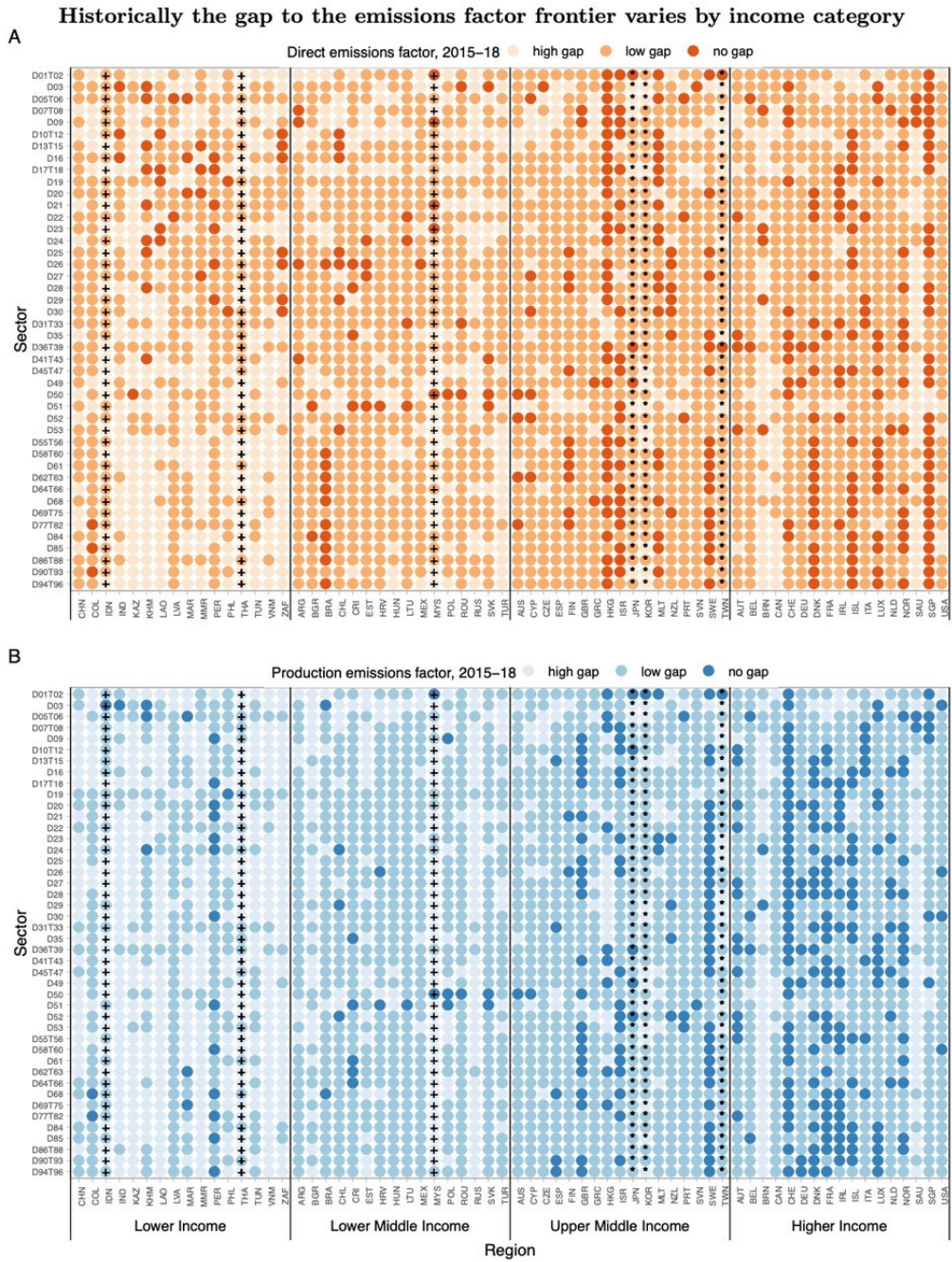


Figure 7: Gap to the emission factor frontier by region and sector, 2015–2018 (low gap threshold = frontier + std)

Note: Sectors are listed on the left axis. Countries are divided into our four per capita income quartiles (bottom of figure), with each country listed on the horizontal axis. We superimpose a ‘plus sign’ for the rapidly industrializing southeast Asian countries, Indonesia (IDN), Malaysia (MYS), and Thailand (THA). We superimpose an asterisk for Japan and the Newly Industrialized Economies (NIEs), South Korea and Taiwan. Mainland China (CHN) is found to the far left and the United States (USA) to the far right. Top panel A corresponds to direct emission factors while bottom panel B presents production emission factors. Instead of presenting precise numerical EF gaps, which is not warranted, we instead divide EF gaps into three buckets: high gap, low gap, and (effectively) no gap. The darker the dots, the smaller the gap. Thus, countries that have succeeded in reaching the EF frontier would have columns filled with the darkest dots.

Ignoring entrepôt nations (e.g., Hong Kong, Singapore) and Malta, each of which score very highly, the countries closest to the ideal among direct EFs in non-service sectors include Cambodia (KHM), Laos (LAO), Peru (PER), Iceland (ISL), Ireland (IRL), and Israel (ISR). The cleanest countries for production emissions include Denmark (DNK), France (FRA), Great Britain (GBR), Israel (ISR), Sweden (SWE), and Switzerland (CHE).

What about the countries identified with the ‘East Asian Miracle’? Did the rapid export-oriented industrialization strategies associated with China, Japan, the NIEs – South Korea, and Taiwan, or the second-wave ‘Asian Tiger’ economies – Indonesia, Malaysia, and Thailand, conflict with reduced emission factors? In terms of direct emissions, China does not look much different than Canada or the United States. Japan and NIE’s compare favorably in non-service sectors with high income economies (less so, Taiwan), as does Malaysia. The weakest performers are Indonesia and Thailand, who lag many of the other countries in the lowest income quartile.

However, it is hard to talk about these countries outside of their role in global supply chains. When we take production emissions into account, the second-wave economies perform poorly, as does China. On the other hand, Japan’s and the NIEs’ performance improves somewhat. These results suggest that domestically-oriented production in the second-wave Asian economies tilted more towards higher emissions processes (including reliance on electricity generation).

4.6.2 Convergence in EF Values

The second of our transition risk metrics, presented in Figure 8, is evidence of convergence towards the frontier. In either panel, convergence would be signaled by a darkening of each country column as one moves from the top period towards the bottom period. Somewhat clear examples of convergence are China (CHN) and Brazil (BRA), for direct emissions, Romania (ROU) and Slovakia (SVK), for production emissions, and Sweden (SWE) for both. Mindful of the fact that the EF frontier is a moving target, there is no overwhelming pattern of convergence that emerges from Figure 8. Many of the lowest income countries appear to have in fact diverged from the frontier in company with countries from other quartiles, including from the richest quartile (e.g., Brunei (BRN), Canada (CAN), and Saudi Arabia (SAU), for direct emissions). Of the non-entrepôt/petro-exporter nations in the wealthiest quartile, Canada (CAN) and the United States (USA) stand out for the paucity of sectors that fall into the ‘no gap’ category throughout all periods.

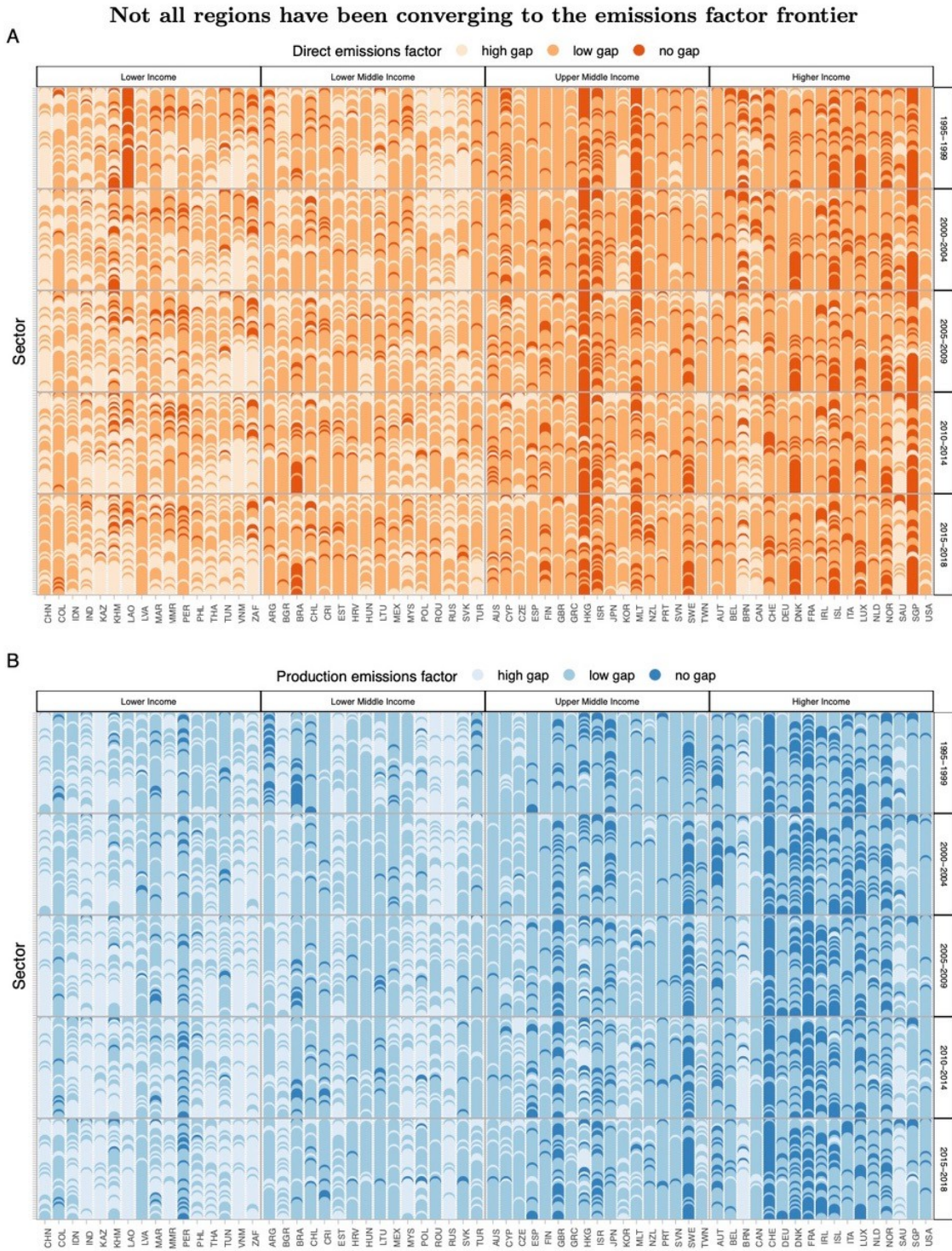


Figure 8: Evolution of the distance to the emission factor frontier by region and sector, 1995-2018

Note: Figure 8 presents the same information from Figure 7, but stacks all of our five time periods vertically for both direct and production emissions. Each panel from Figure 7 is essentially collapsed into the top fifth of each panel in Figure 8. The vertical axes of both figures contain the same sectors, only in Figure 8 they are repeated five times making the scale too small to label.

4.6.3 Composite Scores

The measures described in the preceding two subsections are now combined into the four rating tiers described in the introduction as Tier 1 to Tier 5. We take each country-sector dyad that appears in our sample, and divide them into each tier as follows:

Tier 1: No EF gap (in 2015–2018) - We place all dyads that fall at or below the 25th percentile into this category.

Tier 2: Low EF gap, converging (at least one “high gap” history with no “no gap” history) - We include dyads that fall into the ‘low gap’ category in the final period, and for which progress from one gap category to the next has occurred at least once over the past three periods with no divergence over these periods.

Tier 3: Low EF gap, non-converging - We include dyads that fall into the ‘low gap’ category in the final period, but for who there has been no progression from ‘high gap’ in the last three periods.

Tier 4: Low EF gap, diverging - (at least one “no gap” period in the dyads history) - We include dyads that fall into the ‘low gap’ category in the final period, but which experienced at least one “no gap period in its history.

Tier 5: High EF gap - This category includes dyads that are more than a standard deviation away from the frontier in the final period, regardless of history.

The number of dyads falling into each of these categories is given in Table 3 and the different tiers are shown for each country and sector in Figure 9.

Table 3: Number of dyads falling into each tier, by type of emissions, 2015-2018

	Direct Emissions	Production Emissions
Tier 1	376	355
Tier 2	437	351
Tier 3	1,229	1,182
Tier 4	215	256
Tier 5	691	804

Focusing on direct emissions (Figure 9A), we find that income matters for the composite score of our measure of climate transition risk: the highest income quartile of countries tends to have the largest number of Tier 1 dyads, and the lowest income quartile tends to have the largest number of Tier 5 dyads. At the same time, transition risk is dynamic and historically high-income levels are not a guarantee of a low transition risk and low incomes are not an impediment to lowering the transition risk. Tier 4 consists of dyads that have diverged from the “no gap” category to the “low gap” category,

which occurred frequently among dyads in wealthier countries. Tier 2 includes dyads that have moved up into the “low gap” category from the “high gap” category, as frequently occurring among poorer countries. In a global economy with low transition risk, there would be many “converging” dyads and few “diverging” ones. While the number of dyads in Tier 2 exceeds the number in Tier 4 (Table 3), the number of Tier 3 dyads is greater than the sum of dyads in Tiers 1, 2 and 4, which is not encouraging in terms of the global climate transition risk.

Moving from direct emissions to production emissions (from the top to the bottom panel of Figure 9), we find that accounting for supply chain effects only accentuates the direct emissions findings concerning the distribution of dyads within each tier. In addition, the number of dyads in the lowest income quartile Tier 5 rises when moving from direct to production emissions, with decreases in the number of dyads in every other tier except for Tier 4. Furthermore, although the number of dyads across all four income quartiles in Tier 1 decreases when moving to Panel B, the number of dyads in the top income quartile of Tier 1 increases. While we cannot rule out other drivers of compositional effects on the transition risk faced by lower income countries in our data, these observations raise the possibility that by “outsourcing” their GHG-emissions-intensive intermediate inputs to poorer countries, wealthier countries may also be offloading their climate transition risk.

Both of these observations appear to be consistent with the hypothesis that wealthier countries “outsource” GHG-emissions-intensive intermediate inputs to poorer countries.

Tiered transition risks as measured by convergence of emissions factor to frontier, by region (grouped by income) and sector

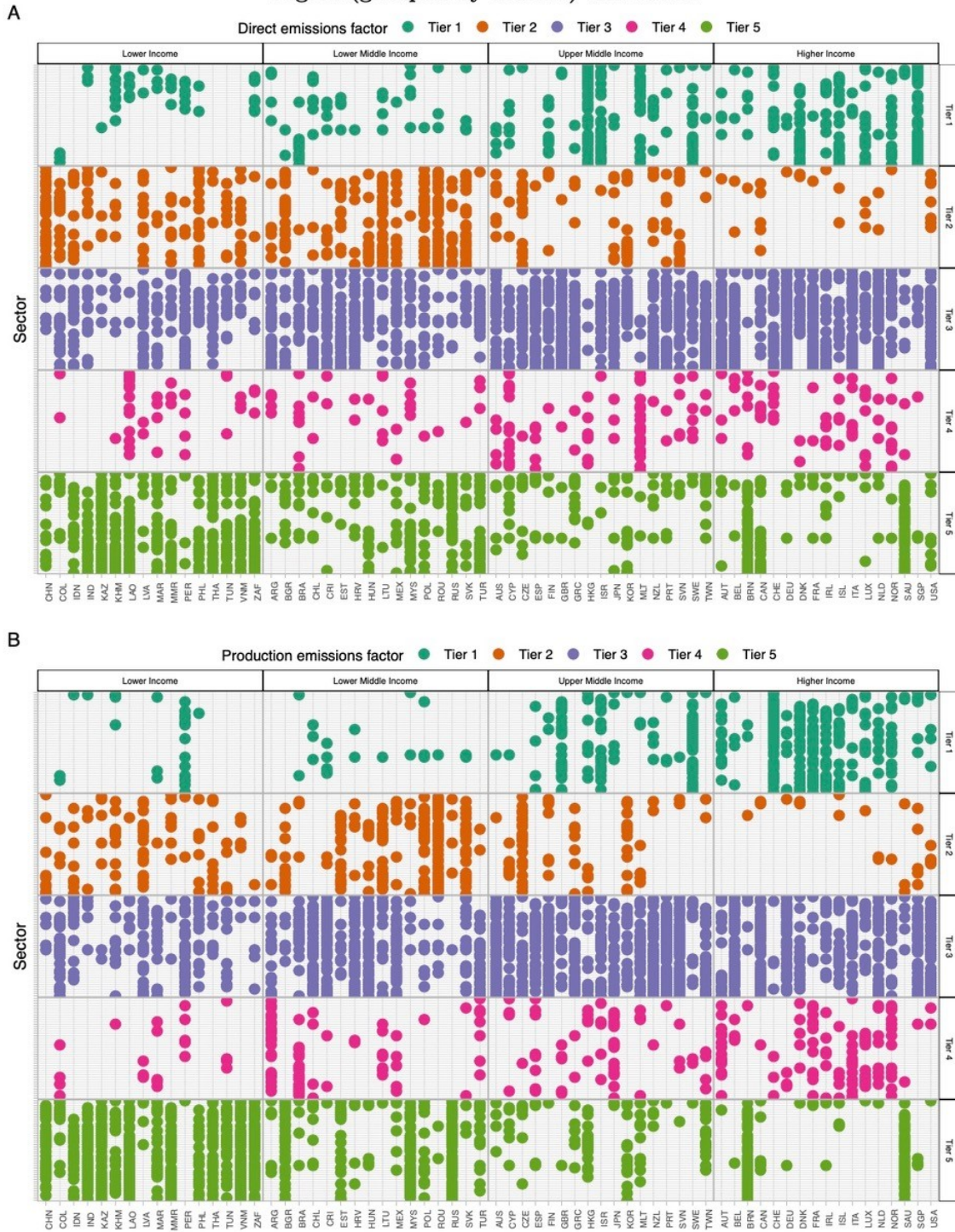


Figure 9: Tiered transition risks by dyad, 2015-2018

5 Conclusion

We describe a new method of calculating transition risk by country-sector dyad that accounts for both distance-to-the-frontier and demonstrated convergence towards lower emissions. Applying our method to publicly available data, we assign dyads to five transition risk tiers that assume that transition risk increases when a country’s sector falls far behind the emission factor frontier of peer countries, and is not converging. Overall, higher income countries tend to be closer to the frontier than lower income countries, but climate transition risk changes over time even across countries with substantially different levels of income. Nevertheless, progress in converging to the EF frontier has been limited. Partly, this is because the frontier itself has been moving ever towards lower emissions per unit monetary value of output, and partly this is because our measure imposes relative as opposed to absolute metrics.

Our comparison of the direct and production EF frontiers indicates the divergent scope for emissions policies focused on domestic facilities – such as restrictions on factory emissions – and emissions policies focused on imported inputs – such as carbon border taxes. Of course, not all intermediate inputs are imported. Domestic facility emissions restrictions will incentivize a move to net zero for both direct and production EFs, especially given the large amount of embodied emissions in electricity generation. However, the large volume of international trade in intermediate inputs is likely to be a significant contributor to production emissions in the manufacturing sector. A potential conflict can arise between the desire to reduce emissions by restricting high-emissions imported inputs and the desire to promote industrial development in low income economies. By allowing for different thresholds (based on peer performance), for economies of different per capita income groupings as outlined in our paper, we believe that this conflict can be mitigated.

We stress the following data limitations of our approach. The OECD intercountry input-output data that we rely most upon is lagged by several years from the present. The elevated level of data aggregation is another concern. A given sector’s emission factor might differ across countries not because the technology is less green, but because of differences in the composition of each sector. For example, agriculture, hunting and forestry (D01T02) covers a wide range of products that vary widely in their individual emission factors. Developing more granular datasets should be a priority. Lacking such granularity in our dataset, we choose to avoid precise estimates of EFs in our transition risk measure. Given that our sectoral transition risk measure is informative about the average risks of firms in that sector, it should be supplemented by the distribution of firm-level emissions whenever possible.

Of course, going from the transition risk in sectors to that in individual firms is not possible given public data. We believe that our sectoral transition risk measure is informative about the average risks of firms in that sector, but we have no way of knowing how large the distribution of firm-level emissions are. Nonetheless, we think our measure is a useful input for analysts concerned with the financial impact of transition risks.

Future work could prioritize the use of differences in demand elasticities and abatement costs by economic sector. Such data, together with structural modeling, would help characterize sectors

as: (1) sunset input sectors that provide a standardized intermediate input perfectly substituted for by other intermediate inputs, such as coke & petroleum; (2) sunset consumer sectors that produce final goods for which consumers may substitute away from, such as certain animal products; and (3) malleable sectors with scope for transitioning to lower-emissions production techniques but for which demand is relatively inelastic, such as electricity, heating and cooling, grain crops, and concrete. By accounting for income and policy differences across national economies and abatement cost differences across sectors, such models would then help interpret the observed EF gaps and provide a deeper understanding of climate transition risk.

Supplementary Material

A Data

We present all global estimates in units of gigatonnes of carbon equivalents (GtC, e15gC), which is the same as 1000 megatonnes of carbon (MtC, Table 4), the unit we use to calculate and report country and sector level estimates.

Table 4: Factors used to convert carbon in various units

Unit 1	=	Unit 2	×	Conversion	Source
Gigatonnes of carbon (GtC)		Megatonnes of carbon (MtC)		1000	SI unit convention
Gigatonnes of carbon (GtC)		Kilotonnes of carbon (KtC)		e6	SI unit convention

A.1 Methodology for calculating non-CO₂ emissions

We obtain non-CO₂ greenhouse gas (GHG) emissions data from the [data annex](#) of the U.S. (Environmental Protection Agency (EPA), 2022) report [Global Non-CO2 Greenhouse Gas Emission Projections & Mitigation Potential: 2015–2050](#). These data, excluding the projected estimates, cover the years 1995–2018. Explanations of the data calculations are given in associated methodological documentation on the report’s webpage. The report provides CO₂-equivalent – (CO₂e) using 100-year Global Warming Potentials (GWP100) – emissions for key sectors in units of millions of metric tonnes (megatonnes, Mt). For certain sectors these emissions can be directly added to the CO₂ emissions provided by the OECD. For others, emissions need to be distributed across different sectors using flow sector attribution modeling. We discuss these cases below.

EPA sectors that map directly into OECD sectors include:

- Sector Agriculture (all sources and subsources): maps into OECD sector D01T02 (Agriculture, hunting, forestry)
- Sector Energy – Source Combustion – Subsource Biomass: maps into OECD sector D35 (Electricity, gas, steam and air conditioning supply)
- Sector Energy – Source Coal (all subsources): maps into OECD sector D05T06 (Mining and quarrying, energy producing products)
- Sector Industrial Processes – Source Metals (all subsources): maps into OECD sector D24 (Basic Metals)
- Sector Industrial Processes – Source Electronics (all subsources): maps into OECD sector D26 (Computer, electronic and optical equipment)

- Sector Industrial Processes – Sources Nitric/Adipic and ODSSubs (all subsources): maps into OECD sector D20 (Chemical and chemical products)
- Sector Waste (all sources and subsources): maps into OECD sector D36T39 (Waste supply; sewerage, waste management and remediation activities)
- Sector Energy – Source NGO (all subsources): maps into OECD sector D19 (Coke and refined petroleum products)
- Sector Energy – Source OtherEnergy (all subsources): maps into OECD sector D05T06 (Mining and quarrying, energy producing products)

Emissions from Electric Power Systems (EPS) primarily involve sulfur hexafluoride, SF₆, which the EPA methodology documentation allocates between total global sales to replace emitted SF₆ (20 percent) and global sales to manufacturers of electrical equipment (60 percent), which is believed to have been mostly added in new equipment by the manufacturer ([Environmental Protection Agency \(EPA\), 2019](#), p.5-67). To raise the allocation to 100 percent, we take 30 percent of this category and allocate it to OECD sector D35 (Electricity, gas, steam and air conditioning supply) and allocate the remaining 70 percent to OECD sector D27 (Electrical equipment).

Sector Industrial Processes – Source OtherIPPU (Other Industrial Processes) contributes two greenhouse gasses – methane (CH₄) and nitrous oxide (N₂O) – which are allocated as follows. The EPA methodology documentation indicates that industrial processes emitting CH₄ are:

- chemical production (OECD sector D20: Chemical and chemical products)
- iron and steel production (OECD sector D24: Basic metals), metal production (OECD sector D24: Basic metals)
- mineral products (OECD sector D23: Other non-metallic mineral products)
- petrochemical production (OECD sector D19: Coke and refined petroleum products)
- silicon carbide production (OECD sector D20: Chemical and chemical products).

Those emitting N₂O are:

- metal production (OECD sector D24: Basic metals)
- solvent and other product use (OECD sector D20: Chemical and chemical products).

We use modeling to allocate CH₄ emissions from OtherIPPU across the four sectors using weights determined by their CO₂ emission shares (for each country and year from OECD TeCO2 2021 database). For example, for OECD sector D20 OtherIPPU CH₄ emissions, we calculate “D20/(D19 + D20 + D23 + D24)” all measured in CO₂ emissions from TeCO2 database to determine the share of OECD sector D20 out of reported OtherIPPU CH₄ emissions. (When total emissions from these four sectors is zero, we set the share equal to zero.) Multiplying this share (calculated for a country-year dyad) times the

value of OtherIPPU CH₄ emissions gives us the CH₄ CO₂e emissions for sector D20 for that country in that year. Likewise, N₂O emissions are calculated using the shares of OECD sectors D24 and D20 in OtherIPPU N₂O emissions.

Sector Industrial Processes – Source HCFC-22 (chlorodifluoromethane) covers a GHG that results from emissive applications (OECD sector D35: AC and refrigeration) as well as production of a feedstock for production of synthetic polymers (OECD sector D20: Chemical and chemical products). The Montreal Protocol calls for phasing out the emissive application of HCFC-22, but feedstock production is still permitted. To use modeling assumptions to apportion HCFC-22 emissions, we use Tables 5-56, “Portion of Total HCFC-22 Production that is Feedstock HCFC-22 for A1 Countries”, and 5-57, “Portion of Total HCFC-22 Production that is Feedstock HCFC-22 for Non-A1 Countries” (([Environmental Protection Agency \(EPA\), 2019](#), p.5-157)).

Sector Energy – Source Stationary and Mobile Combustion. This category consists of methane (CH₄) and nitrous oxide (N₂O) emissions from combustion of fossil fuels in vehicles; power plants; and residential, commercial, and industrial stationary sources (([Environmental Protection Agency \(EPA\), 2019](#), p.5-25)). It is calculated by applying an emission factor (by fuel type) to total annual consumption of coal, oil, and gas. Because this category could apply to every OECD sector plus the household consumption of road transport, and home heating and cooling, we calculate the shares of each sector in CO₂ emissions by country and year and apply this shares to distribute the CH₄ and N₂O emissions across sectors including households based on the OECD estimates of HCE_{*j*}. For example, if OECD sector D20 in country *R* accounts for *y* percent of production-based CO₂ emissions (plus *HCE*) in 2005, we multiply CH₄ and N₂O emissions by *y* to get sector D20’s non-CO₂ emissions from stationary and mobile combustion.

EPA does not provide non-CO₂ GHG data on Hong Kong, China, and Chinese Taipei (OECD region names). We use ([Food and Agriculture Organization \(FAO\), 2023](#)) data on non-CO₂ GHG emissions (in CO₂e measured in kilotonnes: 1 kilotonne = 1000 metric tonne = 0 Mt) that are immediately attributed to agriculture (OECD sector D01T02), which include

- F1 Crop residues: N₂O emissions from the decomposition of nitrogen in crop residues left on managed soils;
- F2 Burning crop residues: CH₄ and N₂O emissions produced by the combustion of a percentage of crop residues burnt on-site;
- F3 Rice cultivation: CH₄ emissions from the anaerobic decomposition of organic matter in paddy fields;
- F4 Enteric fermentation: CH₄ gas produced in digestive systems of ruminants and to a lesser extent of non-ruminants;
- F5 Manure management: CH₄ and N₂O emissions from aerobic and anaerobic processes of manure decomposition; and
- F6 Manure left on pasture: N₂O emissions from nitrogen of manure left by grazing livestock on pasture.

EPA reports Agriculture sector emissions as follows (source followed by subsource, when applicable, and then separately for each gas):

- E1 Enteric fermentation: Livestock; Enteric; CH₄
- E2 Agricultural soils: AgSoils; NA; N₂O
- E3 Manure management: Livestock; Manure; CH₄ and N₂O
- E4 Rice cultivation: Rice; NA; CH₄
- E5 Other agricultural sources: OtherAg; NA; CH₄ and N₂O

Since we only need agriculture sector total emissions, we do not disaggregate them into EPA sources and subsources.

For these two regions and other emissions sources, emission values are set to zero.

A.2 Land-use change and agricultural process GHG emissions

Human activities lead to land-use change GHG emissions, which include ([Food and Agriculture Organization \(FAO\), 2023](#)):

- F1 Drained organic soils: CO₂ and N₂O emissions associated with the mineralization and oxidation of the organic matter in organic soils that are drained for agriculture (cropland and grassland) (item 6729);
- F2 Forests: CO₂ emissions and removal corresponding to forest carbon stock changes inclusive of aboveground and belowground living biomass (items 6751 Forestland and 6750 Net forest conversion); and
- F3 Fires: CH₄ and N₂O emissions from biomass burning in a range of vegetation types and from fires in organic soils (items 69921 Fires in humid tropical forests, and 6993 Fires in organic soils).

Agriculture sector processes lead to GHG emissions which include ([Environmental Protection Agency \(EPA\), 2022](#)):

- E1 Cropland soils: N₂O emissions from cropland soils due to the application of synthetic fertilizer;
- E2 Enteric fermentation: CH₄ emissions from enteric fermentation of livestock;
- E3 Manure management: CH₄ and N₂O emissions from manure management;
- E4 Rice cultivation: CH₄ emissions from rice cultivation;
- E5 Field burning of agricultural residues: CH₄ and N₂O emissions from agricultural residue burning (source: UNFCCC database); and
- E6 Prescribed burning of savannas: CH₄ and N₂O emissions from savanna burning (source: UNFCCC database).

Whereas GHG emissions from agriculture sector processes are allocated to OECD sector D01T02, emissions from land-use change are allocated to an “investment” account for the whole economy in the year they occur because these emissions are due to changes in the carbon stock and are not an immediate by-product of a production process. For land-use change emissions we use ([Food and Agriculture Organization \(FAO\), 2023](#)) and Intergovernmental Panel on Climate Change (IPCC) Tier 1 methodology in units of kilotonnes (= 0 Mt). We do not use higher-resolution spacial methods that account for GHG emissions due to certain components of land-use changes ([Hong et al., 2021](#)), which otherwise also rely on FAOSTAT database, because we cannot link GHG emissions to individual products for all OECD sectors.

A.3 Calculating GHG Emission Factor

To determine the emission factors by region-year-sector triads, we add EPA non-CO₂ GHG emissions measured in CO₂e to the corresponding OECD non-CO₂ emissions and divide the sum by total output to obtain an emission factor for both CO₂ and non-CO₂ GHG emissions. Total output data are from the 2021 edition of the OECD Intercountry Input-Output tables dataset and corresponds to gross output in the OECD methodology.

We directly calculate the production-based CO₂ emissions (PRODCO2) using the CO₂emission factor (EFCO2) from OECD TeCO2 2021 database and total output (GROUTPUT) from OECD ICIO 2021 database

$$\text{PRODCO2} = \text{GROUTPUT} \times \text{EFCO2}.$$

The OECD portal can be used to retrieve PRODCO2. However, in this case the number of PRODCO2 observations with zeros exceeds the number of observations with zero EFCO2. The reason appears to be due to the fact that the portal censors production CO₂ emissions below kilotonnes.

We also have cases in which non-CO₂ GHG emissions by a region-year-sector triad is non-zero, yet total output corresponding to that triad is zero. There are 91 such instances arising from the allocation of “NGO” to OECD sector D19 and “OtherEnergy” to D05T06, for

- D19: LUX (1995–2018)
- D05T06: BEL (1995–2018); PRT (1995–2018); SGP (2000–2018)

We reallocate these non-CO₂ GHG emissions to the household sector in the corresponding country and year.

Finally, we have instances of

$$\text{GROUTPUT} = 0 \text{ and } \text{PRODGHG} = 0,$$

in which case we set $\text{EFCO2} = 0$.

A.4 Deflators for Constant Price Gross Output Dollar Values

We use Production (Gross Output) deflators from the OECD iSTAN database (“Deflator_USD”) to obtain 2015 US constant dollars by country, sector, and year. Unfortunately, Deflator_USD is not populated for all the countries in our dataset and is occasionally missing for the years 1995 and 1996. Where Deflator_US is missing, we substitute the USA counterpart.

iSTAN reports separate deflators for sectors D17 and D18, but these sectors are combined in TeCO2 as D17T18. To calculate the D17T18 deflator, we combine the individual deflators using their value-added shares as weights but only for the US deflator. For all other countries for which we have Deflator_USD, we use a simple average.

A.5 Additional data

- GDP per head, constant international prices (base year 2017): World Bank, [World Development Indicators \(WDI\)](#), accessed 24 April 2023. Missing Taiwan and Canada 1995 and 1996.
- Population: FAO, [FAOSTAT](#), supplemented with OECD, [OECD.Stat](#), Historical Population Data for Belgium and Luxembourg, accessed 24 April 2023.

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