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Ward, H., Radebach, A., Vierhaus, I., Fügenschuh, A., & Steckel, J. C. (2017). Reducing global CO 2 emissions with the technologies we have. Resource and Energy Economics, 49, 201–217. https://doi.org/10.1016/j.reseneeco.2017.05.001

Reducing global CO_2 emissions with the technologies we have

Abstract

The energy intensities of the various industrial sectors differ considerably across countries. This suggests a potential for emissions reductions through improved accessibility to efficient technologies. This paper estimates an upper-bound CO_2 emission mitigation potential that could theoretically be achieved by improved access to efficient technologies in industrial sectors. We develop a linear optimization framework that facilitates the exchange of sectoral production technologies based on the World Input-Output Database (WIOD), assuming perfect substitutability of technologies and homogeneity within economic sectors, while ignoring barriers to technological adoption and price driven adjustments. We consider the full global supply chain network and multiple upstream production inputs in addition to energy demand. In contrast to existing literature our framework allows to consider supply chain effects of technology replacements. We use our model to calculate emission reduction potentials for varying levels of access to technology. If best practice technologies were made available globally, CO_2 emissions could theoretically be reduced by more than 10 gigatons (Gt). In fact, even second-tier production technologies would create significant global reduction potentials. We decompose sectoral emission reductions to identify contributions by changes in energy intensity, supply chain effects and changes in carbon intensities. Excluding the latter, we find that considering supply chain effects increases total mitigation potentials by 14%. The largest CO_2 emission reduction potentials are found for a small set of developing countries.

Keywords: GHG mitigation potential, sectoral energy intensities, technology transfer, multi-regional input output data, optimization, multiple production inputs, supply chain effects

JEL Codes: C61, C39, Q54, O14, Q5

1. Introduction

In order to meet the goals of the Paris Agreement (United Nations, 2015), global greenhouse gas (GHG) emissions will need to be reduced considerably (IPCC, 2014a). This can only be achieved if today's developing countries participate in this overall effort (Jakob and Steckel, 2014; Paltsev et al., 2012) or even, according to some, "leapfrog" the historic patterns of energy use and GHG emissions of the industrialized world (Goldemberg, 1998). Yet, far from leapfrogging to a greener future, developing countries are largely reproducing said pattern (Jakob et al., 2014, 2012). Indeed, in recent years, the fast-growing energy demand in developing countries (Saygin et al., 2011) has been increasingly met with carbon-intensive coal (Steckel et al., 2015). The resulting lock-in effects in the energy infrastructure will impede long-term mitigation efforts (Davis et al., 2010; Unruh, 2000).

Truth be said, the global energy intensity[a] has been steadily declining since the early 1970s (Csereklyei et al., 2016). Past improvements have already been manifesting in lower annual GHG emission increases (IPCC, 2014b; Voigt et al., 2014). Some countries have even managed to decouple their rise in the per capita GDP from an increase in the per capita energy demand (Csereklyei et al., 2016). However, the pace of improvement will need to be accelerated even more, namely for three main reasons: the ambitious mitigation goals of the Paris Agreement; the projected increase in global industrial energy use by 2050 (Saygin et al., 2011); and the ongoing carbonization of energy systems (IPCC, 2014a; Steckel et al., 2015). Consequentially, in order to significantly deviate from business as usual scenarios that foresee energy supply related CO_2 emissions to double or even tripe until 2050 (IPCC, 2014b), next to reducing the carbon intensity of electricity generation energy intensity improvements will need to be

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[a] Understood as the energy intensity of the GDP, measured in joule per monetary output, whereby the carbon intensity of energy is measured in kilogram of CO_2 emissions per joule.

significantly accelerated, making it an important cornerstone in global mitigation efforts (IPCC, 2014b).

One important step in achieving energy intensity reductions is to understand the underlying drivers of energy intensity improvements (Löschel et al., 2015). Although the global energy intensity has been continuously decreasing, significant differences exist in the energy intensities across sectors and economies (Csereklyei et al., 2016; Kim and Kim, 2012; Mulder and de Groot, 2012; Voigt et al., 2014), as also shown in Figure 1. This points to differences in the production technologies of those sectors, and to considerable potential for climate change mitigation by focusing on those sectors exhibiting high energy intensities.

The diffusion of energy-efficient technologies from developed to developing countries is slow to take place, despite the significant cost savings this would incur, sometimes referred to an energy efficiency paradox (Jaffe and Stavins, 1994; Kim and Kim, 2012). The large reliance of developing countries on energy-inefficient production technologies offers considerable potential to cut down global energy consumption and thus CO_2 emissions.

[Figure 1]

Methods for estimating this potential have thus far focused on benchmarking the energy intensities in all industrial sectors with the most efficient one, being the so-called best practice technology (BPT). Based on this method, the energy consumption reduction potential is approximately 27% of the total global energy consumption[b],[c], (IEA, 2012; Saygin et al., 2011).

A serious limitation of these approaches is that these estimations do not take account of the energy, raw materials (including chemicals) and technology inputs that are required up- or

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[b] This translates into approximately 32.5 exajoules

[c] The same method was applied by Kim and Kim (2012)when estimating the potential for the relative improvement of the carbon intensity of production sectors.

downstream of the supply chain of a given production sector (Schenker et al., 2014). In this paper we argue that methods for estimating emission reduction potentials through technology exchange that focus solely on sectoral energy or carbon intensities overlook important constraints—and that this omission leads to missing out on relevant reduction potentials. Thus, to maximize emission (or energy) savings, the exchange of production technologies needs to consider the entire production network and the modification of multiple production inputs.

Using the World Input-Output Database (WIOD), a multi-regional input-output (MRIO) database (Dietzenbacher et al., 2013), for the year 2009, assuming sectoral homogeneity, disregarding barriers to technology transfer and price driven effects[d], we demonstrate that many of the technologies that would be considered "best practice" in terms of energy intensity do not have the highest emission mitigation potentials (due to their less efficient use of other upstream inputs). Our results show that indirect effects in upstream production stages, achieved by changing input coefficients in downstream industries, comprise substantial emission mitigation potentials that have not been considered thus far in the literature. We also show that significant CO_2 emissions reductions can already be achieved when replacing the most inefficient industrial technologies with moderately efficient production technologies.

This work contributes to the literature in three ways: i) it estimates a theoretical upper-bound CO_2 emission reduction potential that arises from improved distribution of efficient technologies; ii) it considers indirect effects resulting from technology exchanges in upstream and downstream supply chains, iii) it introduces an analytical tool for MRIO data, allowing for simultaneous replacement of multiple technologies in an optimal manner.

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[d] Such as rebound-, leakage or substitution effects

2. Methodological Framework and Data

We propose a methodological framework that considers the supply chain effects of all industrial technology exchanges taking place across the globe. We use multi-regional input-output (MRIO) data that allow us to map supply chains. We apply linear optimization on data derived from an MRIO table with the goal to minimize global CO_2 emissions in the global production network while still satisfying the final demand in each region. We consider single production technologies that are (potentially) exchanged and distributed across regions in an optimal way. The linear optimization is designed in such a way that the outcome results in an MRIO framework. To adequately consider emissions by international transportation, we adopt the framework by Cristea et al. (2013).

The linear optimization framework we apply allows to simultaneously exchange multiple interacting sectoral technologies[e]. Our approach differs from standard analyses using computable general equilibrium (CGE) modeling, applied regularly for evaluating comparable settings (e.g., Lu et al., 2010 and Schenker et al., 2014). Generally, CGE models use nested production functions with constant elasticities of substitution (Koesler and Pothen, 2013; Löschel et al., 2007), which are solved by optimizing this nested production structure (see Zha and Zhou (2014), Schenker (2014) and Alexeeva-Talebi (2012) for examples). Determining the (optimal) nested production structure (structure of elasticities), which has an influence on the results, see Zha and Zhou (2014), can be challenging when considering large amounts of inputs, as it is the case for our analysis[f]. In addition, it is not clear in how far elasticities (and

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[e] Supply chains in MRIO tables partially have circular dependencies, which we can reproduce with our approach.

[f] In our case, reflecting all 39 production inputs and a 38-level elasticity would imply 38!/2 possible configurations.

Armington elasticities (Armington, 1969)) would change, if production technologies are exchanged or multiple technologies are applied. Concerning CGE modeling, already moderate changes in elasticities can change the sign of resulting effects at sectoral level (Alexeeva-Talebi et al., 2012). Our approach hence omits potential challenges related to the use of specific elasticities and their structures[g].

However, using MRIO data in our context also needs to rely on specific assumptions (Lenzen, 2000; Steen-Olsen et al., 2015; Suh et al., 2004). For example, it requires assuming proportionality of monetary- and underlying physical flows. We thus interpret technologies as depending on underlying physical flows (referring to the initial state of WIOD) and assume homogeneity of sectoral output within economic sectors across countries. We make use of these assumptions for our analysis in so far as we neglect potential price- and midterm market effects, by ensuring market equilibria at each stage of the global supply chains. In other words, there is no sectoral overproduction and inputs to production are sufficiently provided. If we allowed for changes in prices, we could not keep the initial ratio of monetary- to physical flows that represents the underlying technologies.

To prevent violating real world restrictions, such as distribution of fertile land or oil wells, we implement constraints. For instance, we do not allow for changes in the regional energy infrastructure and reduce changes in local production structures to a necessary minimum. A complete overview of side constraints is given in the subsequent section.

Using WIOD for the year 2009 (Dietzenbacher et al., 2013; Timmer et al., 2015), which is its most recent release that considers labor and energy data, we derive highly detailed local production technologies for each of the 41 regions' 35 sectors. WIOD includes the EU27

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[g] For a discussion how our approach could be transformed into a CGE modeling structure also see the discussion part of this article.

countries (i.e., the European Union without Croatia) as well as major economies, including most OECD countries (Australia, Canada, Japan, South Korea, Mexico, United States), newly industrializing economies (i.e., Brazil, China, Indonesia, India, Turkey, Taiwan and Russia), and an aggregated residual region referred to as the “Rest of the World” (RoW). Additionally, WIOD provides highly detailed socio-economic satellite data on hours worked by persons engaged (labor input), including their qualification level, as well as on greenhouse gas emissions. In a subsequent step, standard procedures (Miller and Blair, 2009) allow to calculate the energy, commodity input and labor intensities. It is the energy intensities that are then taken as an indicator of the sectoral production technologies of a region.

3. Mathematical framework and underlying scenarios

This section gives an overview of the methodology applied for enabling multiple simultaneous technology replacements within a linear optimization framework. It is structured as follows: i) it discusses the production functions and energy infrastructure, ii) it introduces the constraints necessary to calculate minimal CO_2 emissions; iii) it discusses how changing transportation flows and related emissions are taken into account; iv) it introduces the minimization problem. The appendix provides full mathematical details.

3.1 Production functions and energy infrastructure

Our optimization framework applies Leontief production functions, derived for each regional sector, see equation (1), (for more details, see (Miller and Blair, 2009)). WIOD data expresses information on regions (R) and sectors (S) in sets, which are $R \coloneqq \{1,2,\dots,41\}$ and $S \coloneqq \{1,\dots,35\}$. The set of sectors consists of agricultural sectors ($s \in S_{Agr} \subset S$), of extraction sectors ($s \in S_{Ext} \subset S$), of manufacturing sectors ($s \in S_{Man} \subset S$), and of services sectors ($s \in$

$S_{Ser} \subset S$). We indicate parameters and values derived from datasets with a bar to distinguish them from (optimization) variables (those do not have a bar).

The final demand matrix $\bar{Y}$ that consists of elements $\bar{Y}_{r,s}^{r'}$, which denote the aggregated monetary flow from region $r \in R$, sector $s \in S$ into the final demand of region $r' \in R$. For the inter-industry matrix $\bar{Z}$, its elements are given by $\bar{Z}_{r,s}^{r',s'}$, denoting the monetary flow from region r, sector s to region r', sector $s' \in S$. WIOD accounts for five different types of final demand (see the Supplementary Information (SI) for further details).

We assume that the outputs of foreign and domestic production of one and the same sector are perfect substitutes for one another. To derive sectoral production technologies (Leontief production functions), consisting of input intensities, for each sector s and in each region r, total sectoral inputs of commodity s', being $\bar{I}_{r,s}^{s'}$ $(= \sum_{r'} \bar{Z}_{r',s'}^{r,s})$are divided by the corresponding total sectoral output $\bar{O}_{r,s} = \sum_{r'} \sum_{s'} \bar{Z}_{r,s}^{r',s'} + \sum_{r'} \bar{Y}_{r,s}^{r'}$. Thus, the production function is represented by vector $\bar{P}_{r,s}^{s'}$ of sector s, region r:

$$\bar{\boldsymbol{P}}_{r,s}^{s'} = \left\{ {\bar{\boldsymbol{I}}_{r,s}^{s'}} \big/ {\bar{\boldsymbol{O}}_{r,s}} \right\} \quad \boldsymbol{r} \in \boldsymbol{R}, \boldsymbol{s}, \boldsymbol{s}' \in \boldsymbol{S} \qquad \textbf{(1).}$$

Analogously, labor input and direct energy requirements are considered as additional production inputs. WIOD accounts for labor input and distinguishes between three different levels of labor qualification (q). By $\bar{L}_{r,s}^{q}$ we denote labor hours, with qualification level q used as production input in sector s of region r. Hence, for each unit of output, $\bar{LI}_{r,s}^{q} = {\bar{L}_{r,s}^{q}} \big/ {\bar{O}_{r,s}}$ needs to be provided as input.

For each regional sector the energy usage is given in WIOD, which we denote by $\bar{E}_{r,s}$; analogously, energy commodities consumed in each region with corresponding CO$_2$ emissions $(\bar{C}_r)$ are given. Those values allow considering energy use, namely as a production input (energy intensity ($\overline{EI}_{r,s}$)), as well as the regional carbon intensity[h] ($\overline{CI}_r$) of the regional energy infrastructure:

$$\boldsymbol{\overline{EI}_{r,s} = \frac{\overline{E}_{r,s}}{\overline{O}_{r,s}}}, \qquad \boldsymbol{r \in R, s \in S}, \tag{2}$$

$$\boldsymbol{\overline{CI}_r = \frac{\overline{C}_r}{\sum_s \overline{E}_{r,s}}}, \qquad \boldsymbol{r \in R, s \in S} \tag{3}$$

sectoral CO_2 emissions by sector s, in region r, thus result in:

$$\boldsymbol{\overline{C}_{r,s} = \overline{O}_{r,s} \times \overline{EI}_{r,s} \times \overline{CI}_r}, \qquad \boldsymbol{r \in R, s \in S} \tag{4}.$$

3.2 Scenario constraints

In order to approximate real world properties and ensure consistency in supply chains, when investigating CO_2 emission reduction potentials, we introduce specific constraints. Further, the set of all implemented constraints aims at reducing shifts in the regional production structure that cannot be entirely prevented when technologies are exchanged, also see SI; it also aims at approximating an equilibrium. No (or very few) constraints would result in extreme economic solutions. For example, economies would experience huge changes in their GDP, large-scale unemployment or considerable export and import imbalances. In the following, we describe the implemented constraints to find optimal solutions for modified matrices, please see the Appendix for more and mathematical detail.

Constraints:

i. The regional *final demand* is fixed for each commodity according to WIOD 2009 values[i].

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[h] As indicated by Equation (2) we use the term carbon intensity for CO2 intensity of energy throughout this paper.

[i] Even when fixing global production it is possible that because of more efficient technologies labor stocks are not completely used.

ii. We do not allow for changes in *regional GDP*, which is ensured by fixed regional *import* (*Imp*) and *export values* (*Exp*).

iii. To consider the possibility of technological exchange, we build on the traditional MRIO notation by defining the matrix $\boldsymbol{Q}$, which allows to consider *multiple production technologies* in a single regional sector[j]. $\boldsymbol{Q}$'s entries $\boldsymbol{Q}_{r,s}^{r'}$ account for the amount of sector s output in region r being produced with the technology of region r'. Thus, $\boldsymbol{Q}$ in principle allows each regional sector in each region to rely on a pool of 41 different technologies that exist within the 41 countries of the WIOD. We will partially limit the availability of technologies in the following.

We do not allow for technology exchanges within *service sectors*. To prevent an "indirect" exchange by way of production leakage, we further limit the export values of services to their original (WIOD 2009) values.

iv. The regional $\overline{\boldsymbol{CI}_r}$ is fixed and we do not allow for a technology exchange in the sectors "electricity, gas and water supply."

v. The total amount of *available energy* in a region is further limited to the WIOD 2009 level.

vi. We disable technological exchange for *agricultural and extraction sectors*, prohibit expansions and limit the regional production of these sectors to the WIOD 2009 levels.

vii. We further consider limited *labor stocks* and no *workers' mobility* across countries.

viii. Sectors that do not provide the necessary data for calculating *labor intensities* as well as regions without reported *labor stocks* cannot expand their production or change their production technology. Furthermore, their production technology is excluded from transfer[k].

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[j] This actually happens, see Table S4 in the SI.

[k] Sectors related to this issue are listed in the SI.

ix. Some *energy intensities* appear to be extraordinarily small (see Figure 1). We address this (potential) caveat by i) ranking sectoral energy intensities among regions (see Figure S3 in the SI), and ii) allowing technology exchange or local production expansion only for technologies that are less efficient than a specific percentile that guarantees to represent realistic technologies. The introduced threshold allows for variation, leading to different scenarios (Section 3.5).

x. We ensure that the amount of sectoral inflows equals the output multiplied with the technology.

xi. We *prevent overproduction*, in other words, sectoral outputs plus the available usable stocks (see SI) have to match the corresponding demand (final consumption plus intermediate production).

3.3 International transportation

An optimization at the global scale needs to consider that international transportation flows change, and so do related emissions. Most MRIO tables consider different sectors that include international transportation. WIOD accounts for transportation in its sectors "Inland Transport," "Water Transport" and "Air Transport." However, applying an optimization algorithm complicates the treatment of international transportation, as these sectors would be treated as simple commodities. Like all other sectors, they are used as inputs to intermediate production or enter final demand[l].

To more appropriately consider international transportation, we construct an international transportation framework for WIOD by adapting results of (Cristea et al., 2013). These authors collected and provided detailed data on worldwide transportation for the Global Trade

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[l] If only sectors contained in WIOD were used for transport modeling, the LP would not be supplied with necessary information on distances and modes of transportation that apply when commodities are internationally traded.

Analysis Project (GTAP) database (partially aggregated sectors, GTAP 7 (Narayanan et al., 2012)), considering transportation modes, weight of commodity and transportation distances. These data allow to calculate average CO_2 emissions for the transportation of commodity types (without services) considering value and travelled distance of shipments. Thus, for each commodity, average transportation emissions can be expressed for the transportation of goods worth USD 1, namely per km and considering different transportation modes.

We use GTAP 8 (for the year 2007) to adapt the data to WIOD (for the year 2007), which allows to construct a transportation framework considering emissions attributed to the transportation of non-service commodities for each USD per kilometer. For simplicity, we fix the respective global average composition of transportation modes for each commodity (as identified by Cristea et al. 2013) and use that composition to calculate the standard transportation unit of one USD*km. We hence calculate sector-specific CO_2 emissions per USD*km, considering transportation modes (see SI). This methodology generates transportation data for the year 2007 applied on MRIO data of the year 2009. As transportation-related emissions have continuously dropped over the past decades (Hummels, 2007), the model derived for WIOD 2009 has the tendency to overestimate transport-related emissions per USD*km in 2009 and is thus suitable to provide a conservative estimate. We approximate transportation distances pair by pair, calculating great-circle distances of the region's capitals[m], whose coordinates were computed by GeoHack ("GeoHack," n.d.).

Combining distances, commodity value and emissions per USD*km, transport-related emissions can thus be considered in the optimization framework. Transport-related emissions result as the sum of all commodities, where the product of commodity values in USD is

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[m] For Australia, Sydney was taken; for RoW, Pretoria, South Africa.

multiplied with their calculated emissions per USD*km and the distance between the origin and destination. When applying this transportation model to WIOD 2007, results reveal a total of 2.4 Gt of CO_2 emissions due to international transportation. This is close to the 2.5 Gt of total CO_2 emissions by transportation sectors in WIOD 2007. As transportation sectors in WIOD also consider domestic transportation[n], our approach hence ensures that CO_2 emission reduction potentials are not overestimated because of too low emissions by transportation. We conclude that the derived transportation model sufficiently matches our demand and can be applied within the optimization, see the SI for information on how average transportation distances changed within the optimization.

3.4 Solving the minimization problem

With all constraints introduced, we define the minimization problem of CO_2 emissions as a Linear Program (LP) (Dantzig, 1963). It can be expressed as:

$$\mathbf{min}\ \left(\sum_{\boldsymbol{r}\in\boldsymbol{R}}\sum_{\boldsymbol{r'}\in\boldsymbol{R}}\sum_{\boldsymbol{s}\in\boldsymbol{S}}\left[\left(\boldsymbol{Q}_{\boldsymbol{r},\boldsymbol{s}}^{\boldsymbol{r'}}\times\overline{\boldsymbol{EI}}_{\boldsymbol{r'},\boldsymbol{s}}\times\overline{\boldsymbol{CI}}_{\boldsymbol{r}}\right)+\boldsymbol{T}_{\boldsymbol{r},\boldsymbol{s}}^{\boldsymbol{r'}}\right]\right). \tag{5}$$

Hereby, $T_{r,s}^{r'}$ denotes the total emissions related to the international transportation of commodities of sector s from region r to region r', for Q according to Section 3.3.

The basic equations and the constraints we have formulated are linear. Our LP tries to minimize CO_2 emissions that are associated to production. Considering the constraints of 3.2 Please see Appendix and SI for more detail and evidence why an optimal solution exists.

3.5 Defining and implementing scenarios

We define scenarios based on specific technology thresholds—the level of technology efficiency made accessible—resulting in different "common technology pools." The technological efficiency is approximated by the corresponding energy intensities, which we select to define different technology thresholds. First we rank sectoral technologies across

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[n] Domestic transportation in WIOD accounts for approximately 1 Gt of CO_2 emissions.

countries according to their energy intensities. Second we choose a specific global percentile τ. Sectoral technologies with energy intensities above τ are made available for all countries. Thus, they are allowed to replace —or coexist with—existing or other technologies of the pool in the optimization framework. All technologies that are more efficient than τ are only locally available, in other words, they can only be used by the region of origin since they are not part of the technology pool. We implement a further restriction for these technologies as their production level cannot be expanded. This is a necessary constraint that prevents efficient technology from being transferred indirectly via trade.

We implement three different thresholds and related scenarios. As an approximation of the best available technology, we choose the 15th percentile, which ensures excluding potential positive outliers (see Figure 1). We intend to avoid that technologies with extremely low energy intensities are made accessible, prohibiting extremal solutions. We further choose a high threshold scenario with $\tau = 85^{th}$, where only few technologies are made accessible, in order to investigate the effects of a moderate improvement to the access to technologies. Finally, we choose $\tau = 50^{th}$ to be the reference scenario (“REF”), where the median-efficient technology is made available.

4 Results

In this section we evaluate the results of the different scenarios. We further provide outcomes for a simple energy intensity exchange to give an idea of how the consideration of supply chains and multiple inputs can influence results. Additionally, we apply a decomposition to the results in order to exclude any relative shift in average carbon intensities (see SI).

The solutions of the optimization scenarios are summarized in Table 1, see Table S4 in the SI for exemplary information on how applied technologies, sectoral inputs and the origin of inputs changed. They reveal that access to more efficient industrial technologies combined with a partial reconfiguration of the economic flow network could hypothetically lead to large reductions of global CO_2 emissions. Depending on the underlying scenario, we find reductions ranging between 5.7 and 10.9 Gt (see Table 1).

[Table 1]

For $\tau = 50^{th}$, emissions reductions of approximately 8.3 Gt compared to WIOD 2009 are realized. We contrast this result with a scenario where supply chain effects and multiple inputs are not considered, in other words, a scenario where solely energy intensities are exchanged (energy intensities worse than the 50th percentile are replaced by corresponding median energy intensities). In this case, the CO_2 emissions reductions are estimated to be 4.27 Gt—nearly 4 Gt less than the reduction achieved with the REF scenario (see Table 1 for the simple EI exchange scenario).

The optimization considering the transportation model also influences the global transportation network, see Figure 2, which depicts the average transportation distance for transported goods. Especially energy intensivesectors and sectors that reveal high relative transportation emissions are on average trasported on shorter distances, see SI 1.

[Figure 2]

The optimized technology matrix[o] $\hat{Q}$ allows identifying which elements of the sectoral common technology pools were selected by the algorithm most frequently. We compare their energy intensity with the best available energy intensity in the common pool, i.e., the median energy intensity, their relative differences are depicted in Figure 3. For some sectors, such as “Coke, Refined Petroleum and Nuclear Fuel,” “Chemicals and Chemical Products” or “Basic Metals and Fabricated Metal,” the best available technologies in terms of energy efficiency

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[o] This is the solution of the optimization problem.

are implemented. In contrast, we observe that generally the most efficient available technologies in terms of energy intensities remain unconsidered. They are hence not the most efficient technologies in terms of CO_2 emissions mitigation when considering the network characteristics of the economy.

[Figure 3]

Further, investigating results shows that emissions reductions are unevenly distributed across sectors. For the REF scenario, “Coke, Refined Petroleum and Nuclear Fuel” is the sector with the highest absolute CO_2 emissions reduction, accounting for total reductions of approximately 3.3 Gt (see Figure 4). Other sectors with large emission reductions potentials are “Chemicals and Chemical Products,” “Rubber and Plastics” as well as different metal and minerals sectors. In contrast, the sector with the second largest emissions reductions is “Electricity, Gas and Water supply,” for which technology exchange has been disabled. These reductions result from reductions in demand by downstream industries, caused by technology changes in other sectors and relative delocalization changes in downstream production sectors.

[Figure 4]

We further assess in which countries the largest *absolute* emissions reductions are located (see Figure 5). Highest reduction potentials can be found predominately in China (4.6 Gt), India (1.23 Gt) and the United States (0.51 Gt), note that results are partially influenced by underlying energy infrastructure. Furthermore, substantial amounts of the resulting reductions are located in the residual region RoW, accounting for more than 2.4 Gt. As the RoW has no accounted labor inputs, its industrial technologies have been treated as described in Section 3; reductions are hence caused by changes in the downstream intermediate demand. Highest *relative* reductions occur for India (81.8%) and China (74%). For both countries identified magnitudes of hypothetical CO_2 emissions reductions approximately match the magnitudes of differences in sectoral energy intensities to most efficient countries as identified by Voigt et al. (2014).

[Figure 5]

The regional analysis indicates that the existing energy infrastructure has an influence on the optimization results, as regions with high reductions have relatively high carbon intensities in their energy infrastructure. The algorithm considers higher carbon intensities and thus strives to reduce the energy demand in such regions as much as possible within the given constraints. These effects clearly limit results regarding the actual potential emissions reductions achieved by improved upwards industrial technologies. In order to separate various effects, we apply a factor decomposition, please see the SI for more detail.

[Figure 6]

We identify three driving factors (Figure 6) for emissions reductions: i) relative energy intensity changes related to technology exchange and relative production shifts; ii) technology exchanges in downstream industries leading to lower demand for intermediate commodities; and iii) changes in the relative composition of the energy infrastructure and related changes in carbon intensity caused by shifts in production sites. We find that for most sectors, observed relative reductions are mainly driven by reductions in average energy intensities. In contrast, some sectors, such as leather products, show increasing energy intensities. This indicates that relevant reduction in other inputs more than countervail higher consumption of energy per output. Changes in carbon intensities generally play a minor role; however, they are still relevant for some energy-intensive industries (e.g., metal production). It is important to note that these are not (directly) caused by access to better technologies.

The decomposition factor ”Change due to reduced demand by downstream industries,” which accounts for indirect changes in supply chains due to technology exchange, contributes to reducing emissions for all sectors. Large effects are identified for extraction, manufacturing, transportation equipment and wood products sectors.

Combining the information of the factor decomposition shown in Figure 6 with total reductions shown in Figure 4 allows calculating the absolute reduction potential to be gained from technology exchange, excluding relative shifts in the energy infrastructure. We do this for the REF scenario (see Figure 7). We find that the CO_2 emissions reductions by global access to mid-level technology could be as high as 5.9 Gt. These CO_2 reductions still exceed reductions resulting from a simple energy intensity exchange scenario (see Table 3) by approximately 1 Gt, underlining that considering multiple inputs and supply chains is important and justifying the chosen framework.

[Figure 7]

5 Discussion

In this paper we estimate an upper bound for CO_2 emission mitigation potentials by improved access to efficient technologies. We develop a methodology that enables to simultaneously exchange multiple technologies in a framework considering MRIO data. This type of analysis allows to consider multiple production inputs for each sector while ensuring consistency in global production chains. It also allows for optimal endogenous technology replacements without requiring to determine beforehand which replacements take place. Furthermore, our framework tolerates the application of multiple technologies in a single production sector.

Even though our approach – to the best of our knowledge – allows to go beyond the existing literature by allowing to consider supply chain effects, it is also subject to various caveats. In this section we discuss how our results are potentially biased by i) oppressing technology induced feedbacks on GDP, ii) the level of sectoral aggregation and sectoral heterogeneity, and iii) effects of technological adaptation. We further give explanations why developing countries could fail to adopt efficient technologies.

Technology induced feedbacks on GDP and price effects

The optimization approach is subject to constraints in order to prevent extremal solutions. Unlike CGE modeling, our approach cannot map price effects. To compensate for this constraint, we artificially approximate market equilibria. This is done by ensuring that demand equals supply and by assuming a proportionality between the monetary value of a flow and the underlying quantity (Koesler and Pothen, 2013). It is theoretically conceivable that an exchange of technology also leads to changes in regional GDP, which can be positive for regions using more efficient technologies and negative for regions exporting fossil fuels. To consider such increases (decreases) and hence larger (smaller) consumption within our model, detailed knowledge on technology induced feedbacks on growth – or more specifically, induced feedbacks by the exchange of multiple technologies - would be necessary. Ignoring those effects is a caveat. We justify our approach as changes in the consumption structures would disable a comparison between resulting- and initial WIOD emissions, which is – however – relevant for our paper. It should be noted, though, that introducing price effects, e.g. by applying a CGE modeling approach would likely reduce the observed reduction potentials, as reduced prices can be expected to lead to higher demand. However, such a rebound is expected to be of rather minor relevance (Gillingham et al., 2016, 2013).

A representation of price effects could be achieved by using a CGE model. Even though the computational requirements would be large, a reshuffling of production technologies using a CGE model should be feasible. Single sectoral technology exchanges that consider a subset of sectoral inputs has been done in the past (Böhringer and Rutherford, 2008). A first step to implement our input output based approach in a CGE type of analysis, left to future research, could start from utilizing some type of KLEM production structure that considers energy and non-energetic raw materials explicitly next to capital and labor (such as in Koesler and Schymura, 2015). Assuming that elasticities of substitutions are zero would allow to consider all sectoral commodity inputs, which could be stepwise added.

Sector aggregation and homogeneity

By using WIOD we necessarily assume homogeneity of the sectoral outputs across regions, and use aggregated sectors. Both are strong assumptions that likely have an influence on our results (cf. Steen-Olsen et al., 2015 for a detailed discussion). For a similar case, disaggregating specific energy intensive sectors of the GTAP MRIO (Andrew and Peters, 2013; Narayanan et al., 2012), Alexeeva-Talebi et al. (2012) show that relevant heterogeneity within sectors across countries exists. However, a priori it is not clear how more sectoral detail, either by better data or generated by a disaggregation algorithm, e.g. Wenz (2015), will impact results of our optimization, given that the quality of data is sufficient.[p] On the one hand, more disaggregation, i.e., a larger amount of sectors for which technologies can be exchanged, potentially increases the reduction potential, which is observable for single sectors, see Figure S12 in the SI. On the other hand, for sufficiently inhomogeneous sectors, a disaggregation could prevent that products with low energy intensities are used to replace energy intensive products, hence reducing reduction potentials.

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[p] Low data quality in energy-, commodity input-, or labor intensity possibly caused by insufficient (national) accounting can determine unrealistic extremal solutions. In this respect, it is an asset that WIOD accounts for largest and advanced economies with sufficient reporting capacities. In addition only one region is being estimated (Steen-Olsen et al., 2015).

To investigate how aggregation and homogeneity affect our results, we disaggregate the four WIOD sectors “Coke, Refined Petroleum and Nuclear Fuel” (“Fuels”), “Chemicals and Chemical Products” (“Chemicals”), “Basic Metals and Fabricated Metal” (“Metals”), “Other Non-Metallic Minerals” (“Minerals”), which rank among the sectors revealing the highest reduction potentials, using Exiobase 2.0 (Wood et al., 2015) that accounts for 163 sectors. We assume that regional sums of subsectors in Exiobase 2.0 (2007) and regional sectors in WIOD (2009) are approximately proportional. Doing so, we can disaggregate “Fuels” and “Chemicals” into three, “Minerals” into seven and “Metals” into thirteen subsectors. For the optimization (REF scenario), we account how frequently regional technologies are applied. These frequency shares are multiplied with the regional subsector shares of Exiobase 2.0. Figure 8 shows global sub-sectoral shares before and after optimization. For “Fuels” and “Chemicals” the sub-sectoral composition does not change significantly, which implies that using the higher sectoral resolution for the optimization would not have influenced overall results significantly, see Figures S10 and S11 in the SI for further detail.

[Figure 8]

The picture changes when looking at “Minerals” and “Metals”. While Exiobase 2.0 allows for a higher level of disaggregation than “Fuels” and “Chemicals”, resulting disaggregated sectors also show higher variations in relative shares before and after the optimization. To understand the implications for our overall results it is therefore important to look more into the details of sub-sectoral deviations. As consequence of the optimization for “Basic Metals and Fabricated Metal” the sub-sectoral share of steel decreases, while the one of copper increases (see also two middle bars in Figure 9). This change can be explained by the different sectoral compositions of the Dutch metal sector, which becomes the majorly applied technology after optimization, to the Chinese one, which dominates prior to optimization (see Figure 9).

However, when comparing energy intensities it should be noted that energy consumption for producing steel and copper is approximately comparable (Norgate et al., 2007). We hence do not expect a massive bias of overall results due to aggregation. In case of “Other Non-Metallic Mineral” the global share of “Cement, Lime and Plaster” increases, while all other shares decrease. This – again – can be explained by the change of the relative composition of global technology (see Figure 9). As this sector is one of the most energy- and CO_2 intense industries (Alexeeva-Talebi et al., 2012), we conclude that the observed changes do not lead to an overestimation of reduction potentials, rather the opposite might be true.

[Figure 9]

It would of course be desirable to run the entire analysis with an increased sectoral disaggregation. As Exiobase 2.0 is not compatible with the applied transportation model, understanding how heterogeneity and aggregation issues influence the optimization results is hence not possible. In order to estimate the effect of (dis)aggregation on optimization results with respect to total emissions we artificially merge WIOD sectors “Chemicals and Chemical Products” and “Rubber and Plastics”, as well as “Basic Metals and Fabricated Metals” and “Other Non-Metallic Minerals”. We then calculate corresponding (output-weighted) energy intensities, input intensities and transportation emissions. The new MRIO (which now only has 33 instead of 35 sectors), is used to re-run the optimization described in section 3. We find that emission reduction potentials increase by 750 Mt (a difference of 4.5%) compared to the original REF scenario, see Table 2, with small differences regarding the sign for the two aggregated sectors under consideration.

[Table 2]

In this example, emission reducing- and emission increasing effects occur in parallel. It is hence hardly possible to – a priori – say that aggregation will lead to large scale deviations of our results. We emphasize that in both cases reduction potentials in the supply chains play an important role that need to be regarded in any future estimates of mitigation potentials that arise when replacing outdated, inefficient (production) technologies. Replicating our analysis with higher disaggregation would however be an interesting field of future research.

Effects of and limits to technological adoption

Our static approach neglects dynamic effects that might influence overall developments. For example, the adaptation of new technologies in single sectors might lead to various spill-over effects on other sectors (Hirschman, 1958; Javorcik, 2004) and in turn lead to further efficiency gains. Results should hence be seen as indicative of an upper-bound reduction potential, keeping the above-mentioned restrictions in mind. The question of whether countries with relevant reduction potentials have the political, societal and technological capabilities or the necessary infrastructure to successfully adopt advanced technologies (Arnold et al., 2016) is arguably open to debate. Indeed, many developing countries are not able to do so, also identified as one explanation for the energy efficiency paradox mentioned before (Kim and Kim, 2012). Among others, a possible explanation could be insufficient capacities to absorb new technologies and limited research and technology development capacities in developing countries (Dechezleprêtre et al., 2013, 2011). For successful adaptation of more efficient technologies also financing costs in developing countries, as observed for the energy sector, could hinder necessary capital investments (Hirth and Steckel, 2016; Waissbein et al., 2013). Considering the points discussed, a definite statement on the amount of total emissions reductions induced by technological exchange is always connected to constraints and subject to some uncertainty. Nevertheless, our results reveal the importance to consider supply chain- and network effects, when investigating most efficient technologies.

6 Conclusion

Our analysis suggests that the potential for mitigating climate change by means of making more efficient production technologies available across the globe might be even larger than previously estimated, as supply chain effects have not been considered thus far. The existing literature estimates that there is a potential to reduce current production-related GHG emissions by 25 to 27% by way of reducing industrial energy consumption (see also (IPCC, 2014b)). By contrast, our results point to a CO_2 emission reduction potential of 23-43%, depending on the efficiency level of technology that is made available, see Table 1. Our results underline the importance of considering multiple inputs and entire production networks where cascading effects perpetuate. We find that even second-tier, less-than-best technologies allow for substantial GHG reduction potentials, even when controlling for changes in the energy infrastructure.

The largest CO_2 emissions reductions occur in a limited set of regions and sectors. In particular developing countries as well as the United States show large CO_2 emission reduction potentials[q], indicating the use of rather inefficient technologies in some sectors. Given that supply chains are interwoven, the unambiguous assigning of reductions to specific sectors (or regions) is challenging. Future research could hence aim to identify which single-sector technology replacements in which regions might contribute the most to exploiting the mitigation potentials. One promising avenue would be to combine the approach presented in this paper considering multiple technology exchanges with more advanced structural path decomposition analyses, e.g. Yang et al. (2015).

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[q] This result is partially influenced by underlying carbon intensity the decomposition at country level (Figure 6) is not possible, since global sectors are considered.

Our results hold some implications for climate policy. Given that the larger demand-side reduction potentials can be expected to decrease the pressure for energy system transformation on the supply side, our results imply lower mitigation costs than previously assumed. Our results can help to identify key sectors - or in other words mitigation hotspots - where sectoral mitigation efforts would be especially fruitful. Knowledge of those hotspots derived from this analysis could support agreements that provide selected sectors in developing countries with tailor-made access to efficient technologies, particularly when first-best, globally targeted climate policy (e.g., global carbon pricing) is not available. In addition, the provision of technology and cooperated technology development constitute alternative and potentially cheap tools to reducing global GHG emissions (El-Sayed and Rubio, 2014; Fraunhofer ISI, 2015; Kriegler et al., 2014). In this sense, due to efficiency consideration such knowledge would also allow to identify the sectors to be given priority in the distribution of funding in international climate finance. Nevertheless, resulting reductions would be smaller, as our solution represents a *cooperative* optimal solution that can only be achieved when multiple technologies are replaced simultaneously.

The newly estimated mitigation potentials arguably do not address the question of how the necessary technology exchanges might be implemented. As a reminder, technological innovation takes place mainly in developed countries, whereas the highest mitigation potentials exist in developing economies (Peterson, 2008). Meeting this challenge will require finding ways to overcome factors that are responsible for the observed efficiency differences in production technologies in addition to ensure that patent holders are compensated and that global competitiveness is maintained (Mowery and Oxley, 1995). In this respect, it should be of interest that a high level of mitigation can already be achieved by replacing the most polluting technologies with moderately efficient technology, in other words, with technology that is not top-tier and less than best practice.

Given that differences in production technologies are highly relevant for productivity differences (Acemoglu et al., 2007), there is a good chance that more efficient technologies, in terms of CO_2 emissions reductions, will pay off in monetary terms. In this respect it is important to consider that the costs incurred in overcoming the barriers of technology adoption (Parente and Prescott, 1994) constitute, themselves, a lock-in barrier. In the future, research on climate change mitigation through increased access to technology should attempt to better understand how technologies can be most successfully transferred considering necessary preconditions and potential barriers, also accounting for coordinated action[r]. In addition, understanding how financial constraints can be overcome is of importance. If international climate finance was used as catalyst to create incentives for private capital to invest in efficient production technologies, this could probably realize large leverage effects. Our research shows that investments do not need to be cutting-edge technologies, but state of the art technology investments could be a huge step forward.

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[r] It has been indicated for a simple technology exchange model (technology only depending on energy intensity) that uncoordinated unilateral providence of efficient technologies by developed countries might be countervailed by rebound and leakage effects (Stephan and Müller-Fürstenberger, 2015).

References

Acemoglu, D., Antràs, P., Helpman, E., 2007. Contracts and Technology Adoption. American Economic Review 97, 916–943.

Alexeeva-Talebi, V., Boehringer, C., Löschel, A., Voigt, S., 2012. The value-added of sectoral disaggregation: Implications on competitive consequences of climate change policies. Energy Economics 34, 127–142.

Andrew, R., Peters, G.P., 2013. A Multi-Region Input–Output Table Based on the Global Trade Analysis Project Database (GTAP-MRIO). Economic Systems Research 25, 99–121.

Ang, B.W., Wang, H., 2015. Index Decomposition Analysis with Multidimensional and Multilevel Energy Data. Energy Economics 51, 67–76.

Armington, P.S., 1969. A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers 16, 159–178.

Arnold, J.M., Javorcik, B., Lipscomb, M., Mattoo, A., 2016. Services reform and manufacturing performance: evidence from India. The Economic Journal 126, 1–39.

Böhringer, C., Rutherford, T.F., 2008. Combining bottom-up and top-down. Energy Economics 30, 574–596.

Cristea, A., Hummels, D., Puzzello, L., Avetisyan, M., 2013. Trade and the greenhouse gas emissions from international freight transport. Journal of Environmental Economics and Management 65, 153–173.

Csereklyei, Z., Rubio Varas, M. d. M., Stern, D.I., 2016. Energy and Economic Growth: The Stylized Facts. The Energy Journal 37, 223–255.

Dantzig, G., 1963. Linear programming and extensions. Princeton University Press and RAND Corporation.

Davis, S.J., Caldeira, K., Matthews, H.D., 2010. Future CO2 Emissions and Climate Change from Existing Energy Infrastructure. Science 329, 1330–1333.

Dechezleprêtre, A., Glachant, M., Hascic, I., Johnstone, N., Meniere, Y., 2011. Invention and Transfer of Climate Change–Mitigation Technologies: A Global Analysis. Review of Environmental Economics and Policy 5, 109–130.

Dechezleprêtre, A., Glachant, M., Ménière, 2013. What Drives the International Transfer of Climate Change Mitigation Technologies? Empirical Evidence from Patent Data. Environment and Resource Economics 54, 161–178.

Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., de Vries, G., 2013. The construction of world input-output tables in the WIOD project. Economic Systems Research 25, 71–98. doi:10.1080/09535314.2012.761180

El-Sayed, A., Rubio, S.J., 2014. Sharing R&D investments in cleaner technologies to mitigate climate change. Resource and Energy Economics 38, 168–180.

Fraunhofer ISI, 2015. How energy efficiency cuts costs for a 2-degree future.

GeoHack [WWW Document], n.d. URL https://tools.wmflabs.org/geohack (accessed 9.22.14).

Gillingham, K., Kotchen, M.J., Rapson, D.S., Wagner, G., 2013. The rebound effect is overplayed. Nature 493, 475–476.

Gillingham, K., Rapson, D., Wagner, G., 2016. The Rebound Effect and Energy Efficiency Policy. Review of Environmental Economics and Policy 10, 68–88. doi:10.1093/reep/rev017

Goldemberg, J., 1998. Leapfrog energy technologies. Energy Policy 26, 729–741.

Hirschman, A.O., 1958. The Strategy of Economic Development, Yale Studies in Economics. Yale University Press, New Haven, CT, USA.

Hirth, L., Steckel, J.C., 2016. The role of capital costs in decarbonizing the electricity sector. Environmental Research Letters 11. doi:doi:10.1088/1748-9326/11/11/114010

Hummels, D., 2007. Transportation Costs and International Trade in the Second Era of Globalization. Journal of Economic Perspectives 21, 131–154.

IEA, 2012. Energy Technology Perspectives - Pathways to a Clean Energy System - Executive Summary. OECD Publishing.

IPCC, 2014a. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

IPCC, 2014b. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jaffe, A.B., Stavins, R.N., 1994. The energy-efficiency gap: what does it mean? Energy Policy 22, 804–810.

Jakob, M., Haller, M., Marschinski, R., 2012. Will history repeat itself? Economic convergence and convergence in energy use patterns. Energy Economics 34, 95–104. doi:10.1016/j.eneco.2011.07.008

Jakob, M., Steckel, J.C., 2014. How climate change mitigation could harm development in poor countries. WIREs Climate Change 5, 161–168. doi:10.1002/wcc.260

Jakob, M., Steckel, J.C., Klasen, S., Lay, J., Grunewald, N., Martínez-Zarzoso, I., Renner, S., Edenhofer, O., 2014. Feasible Mitigation Actions in Developing Countries. Nature Climate Change 4, 961–968. doi:10.1038/nclimate2370

Javorcik, B., 2004. Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages. American Economic Review 94.

Kim, K., Kim, Y., 2012. International comparison of industrial CO2 emission trends and the energy efficiency paradox utilizing production-based decomposition. Energy Economics 34, 1724–1741.

Koesler, S., Pothen, F., 2013. The Basic WIOD CGE Model: A Computable General Equilibrium Model Based on the World Input-Output Database. ZEW Dokumentation NR. 13-04.

Koesler, S., Schymura, M., 2015. SUBSTITUTION ELASTICITIES IN A CONSTANT ELASTICITY OF SUBSTITUTION FRAMEWORK – EMPIRICAL ESTIMATES USING NONLINEAR LEAST SQUARES. Economic Systems Research 27, 101–121.

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S.K., Tavoni, M., van Vuuren, D.P., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climate Change 123, 353–367.

Lenzen, M., 2000. Errors in Conventional and Input-Output—based Life—Cycle Inventories. Journal of Industrial Ecology 4, 127–148.

Löschel, A., Otto, V., Dellink, R., 2007. Energy Biased Technical Change – A CGE Analysis. Resource and Energy Economics 29, 137–158.

Löschel, A., Pothen, F., Schymura, M., 2015. Peeling the onion: Analyzing aggregate, national and sectoral energy intensity in the European Union. Energy Economics 52, 63–75.

Lu, C., Tong, Q., Liu, X., 2010. The impacts of carbon tax and complementary policies on Chinese economy. Energy Policy 38, 7278–7285.

Miller, R.E., Blair, P.D., 2009. Input-Output Analysis, Second Edition. ed. Cambridge University Press.

Mowery, D.C., Oxley, J.E., 1995. Inward technology transfer and competitiveness: the role of national innovation systems. Cambridge Journal of Economics 19, 67–93.

Mulder, P., de Groot, H.L.F., 2012. Structural change and convergence of energy intensity across OECD countries, 1970-2005. Energy Economics 34, 1910–1921.

Narayanan, B.G., Dimaranan, B.V., McDougall, R., 2012. Guide to the GTAP Data Base. Center for Global Trade Analysis, Purdue University.

Norgate, T.E., Jahanshahi, S., Rankin, W.J., 2007. Assessing the environmental impact of metal production processes. Journal of Cleaner Production 15, 838–848.

Paltsev, S., Morris, J., Cai, Y., Karplus, V., Jacoby, H., 2012. The role of China in mitigating climate change. Energy Economics 34, 444–450.

Parente, S.L., Prescott, E.C., 1994. Barriers to Technology Adoption and Development. Journal of Political Economy 102, 298–321.

Peterson, S., 2008. Greenhouse gas mitigation in developing countries through technology transfer?: a survey of empirical evidence. Mitigation and Adaptation Strategies for Global Change 13, 283–305.

Saygin, D., Worrell, E., Patel, M.K., Gielen, D.J., 2011. Benchmarking the energy use of energy-intensive industries in industrialized and in developing countries. Energy 36, 6661–6673.

Schenker, O., Koesler, S., Löschel, A., 2014. On the Effects of Unilateral Environmental Policy on Offshoring in Multi-Stage Production Processes. ZEW Discussion Paper No. 14-121.

Steckel, J.C., Edenhofer, O., Jakob, M., 2015. Drivers for the renaissance of coal. Proceedings of the National Academy of Sciences 112, E3775–E3781. doi:10.1073/pnas.1422722112

Steen-Olsen, K., Owen, A., Hertwich, E.G., Lenzen, M., 2015. Effects of sector aggregation on CO2 multipliers in multiregional input–output analyses. Economic Systems Research 26, 284–302.

Stephan, G., Müller-Fürstenberger, G., 2015. Global Warming, Technological Change and Trade in Carbon Energy. Environmental and Resource Economics 62, 791–809.

Suh, S., Lenzen, M., Treloar, G., Hondo, H., Horvath, A., Huppes, G., Jolliet, O., Klann, U., Krewitt, W., Moriguchi, Y., Munksgaard, J., Norris, G., 2004. System Boundary Selection for Life Cycle Inventories using hybrid approaches. Environmental Science & Technology 38, 657–664.

Timmer, M., Dietzenbacher, E., Los, B., Stehrer, R., Vries, G.J., 2015. An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. Review of International Economics 23, 575–605.

United Nations, 2015. Adoption of the Paris Agreement.

Unruh, G.C.U., 2000. Understanding carbon lock-in. Energy Policy 28, 817–830.

Voigt, S., De Cian, E., Schymura, M., Verdolini, E., 2014. Energy intensity developments in 40 major economies: Structural change or technology improvement? Energy Economics 41, 47–62.

Waissbein, O., Glemarec, Y., Bayraktar, H., Schmidt, T.S., 2013. Derisking Renewable Energy Investment. A Framework to Support Policymakers in Selecting Public Instruments to Promote Renewable Energy Investment in Developing Countries. United Nations Development Programme, New York, NY, USA.

Wenz, L., Willner, S.N., Radebach, A., Bierkandt, R., Steckel, J.C., Levermann, A., 2015. Regional and sectoral disaggregation of multi-regional input-output tables – a flexible algorithm. Economic Systems Research 27, 194–212. doi:10.1080/09535314.2014.987731

Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., de Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., Simas, M., Ivanova, O., Weinzettel, J., Schmidt, J.H., Merciai, S., Tukker, A., 2015. Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability 7, 138–163.

Yang, Z., Dong, W., Xiu, J., Dai, R., Chou, J., 2015. Structural Path Analysis of Fossil Fuel Based CO2 Emissions: A Case Study for China. PLOS ONE. doi:10.1371/journal.pone.0135727

Zha, D., Zhou, D., 2014. The elasticity of substitution and the way of nesting CES production function with emphasis on energy input. Applied Energy 130, 793–798.

Figures

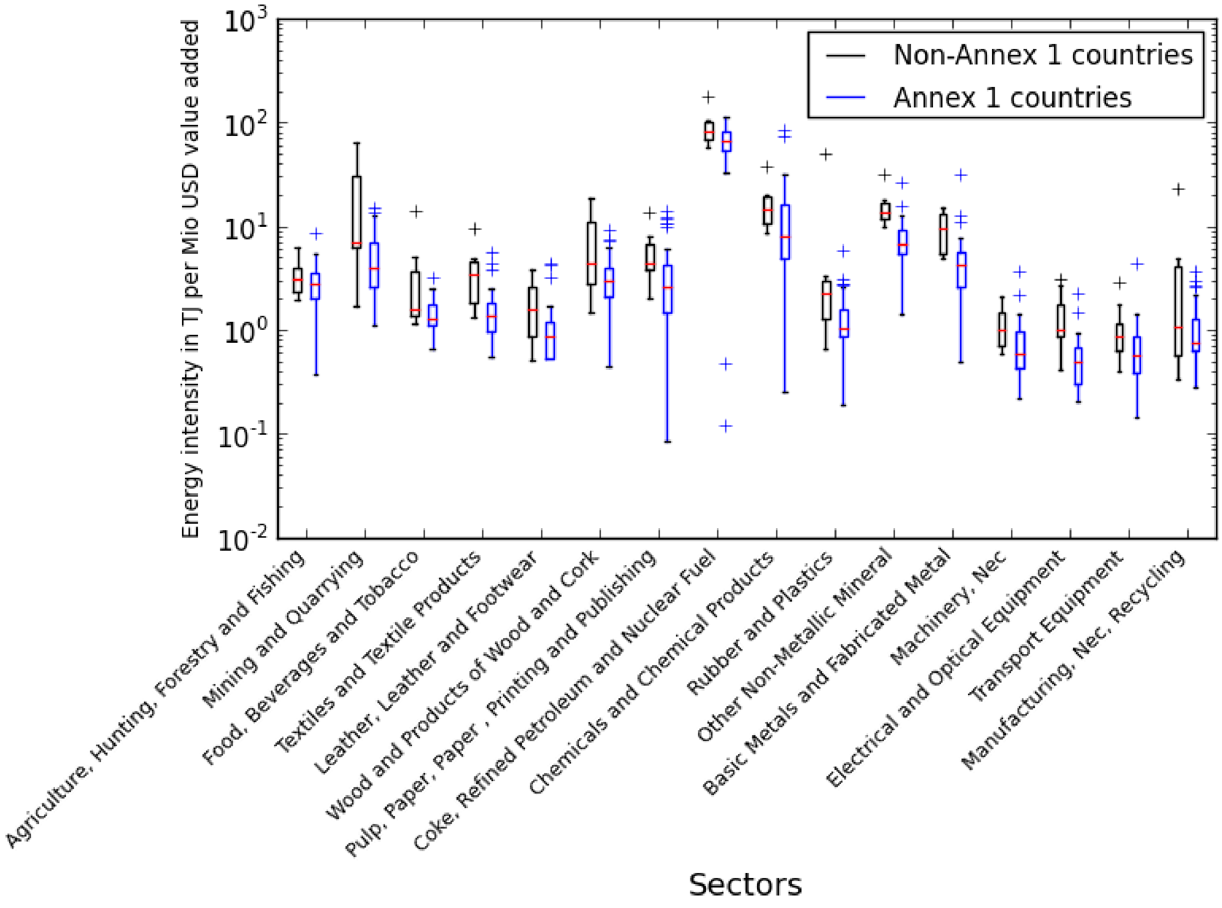


Figure 1: Distribution of energy intensity of industrial sectors across the 40 regions represented in the World Input Output Database (WIOD 2009), excluding the residual region "Rest of the World". Boxes represent 25th to 75th percentiles; red lines refer to medians; whiskers in each direction correspond to 1.5 times the interquartile range; black boxplots represent non-Annex I regions of the UNFCCC; blue boxplots correspond to Appendix I regions; and crosses represent outliers.

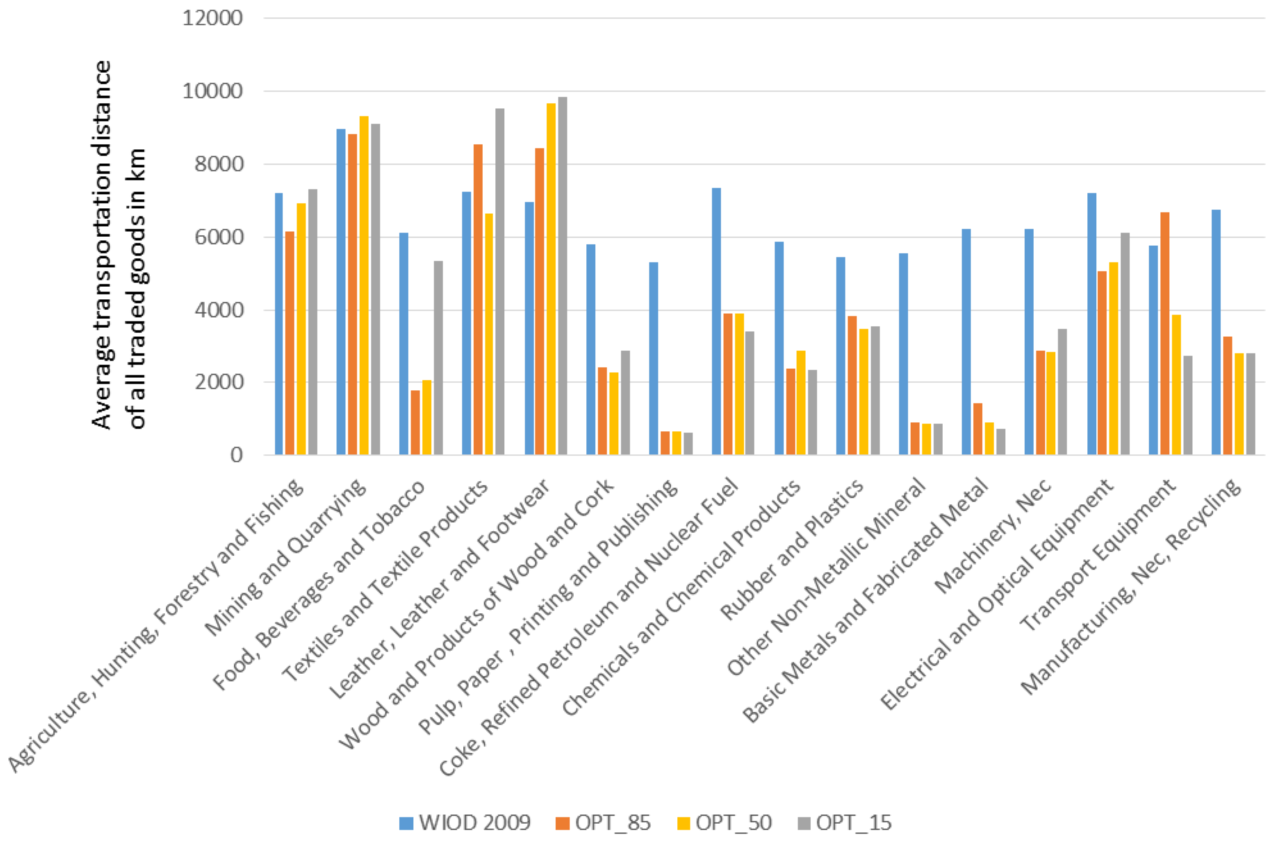


Figure 2: Average transportation distance for all goods in WIOD 2009 and for the optimization scenarios.

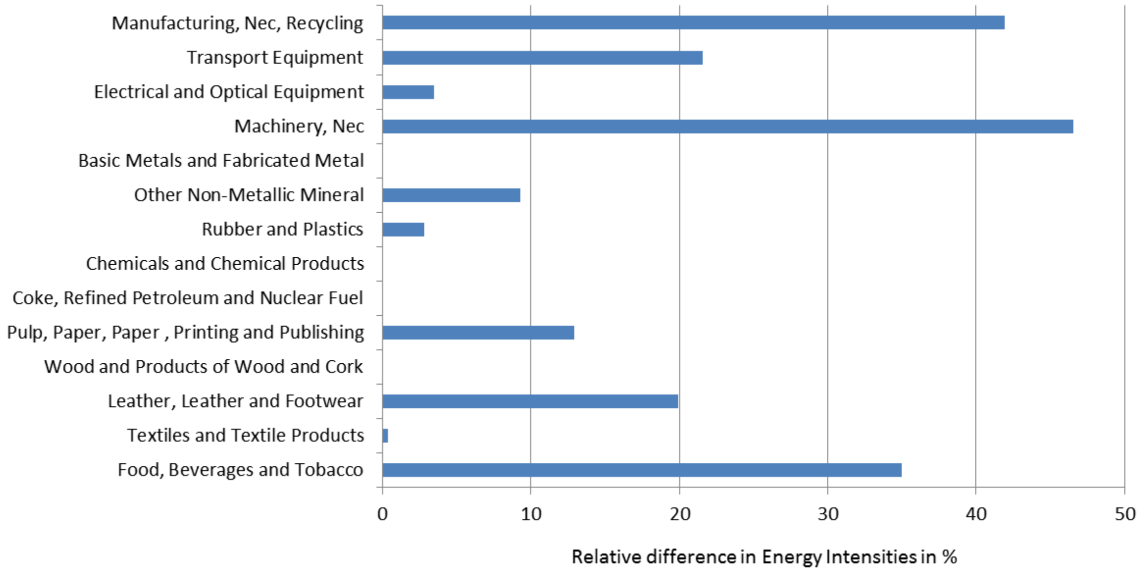


Figure 3: Relative differences in sectoral energy intensities between (mainly) implemented sectoral technologies for the REF scenario and the best available technology pool in terms of energy efficiency, in other words, the 50th energy intensity percentile. No differences occur if the most energy-efficient technology was primarily implemented.

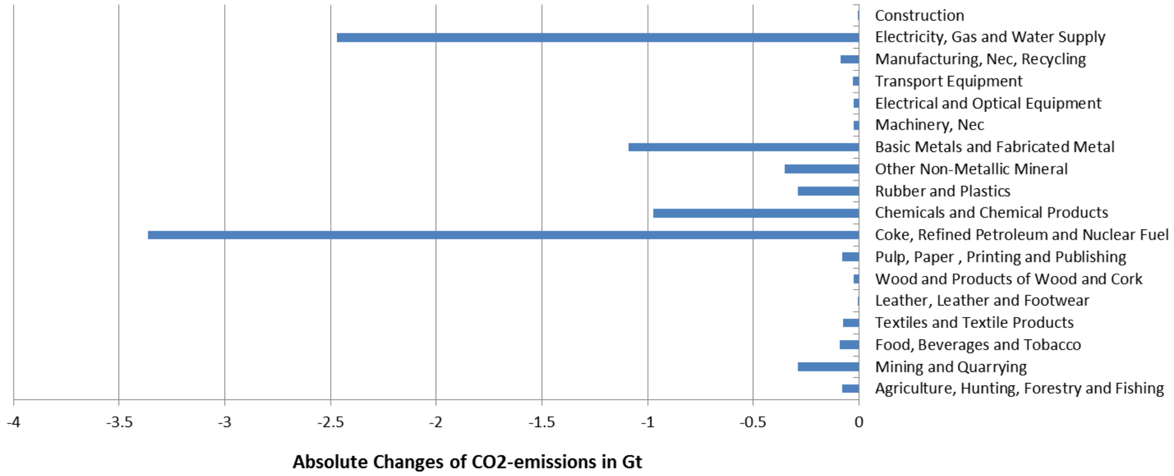


Figure 4: Total sectoral CO_2 emissions changes for the REF scenario in Gt CO_2 at the global scale.

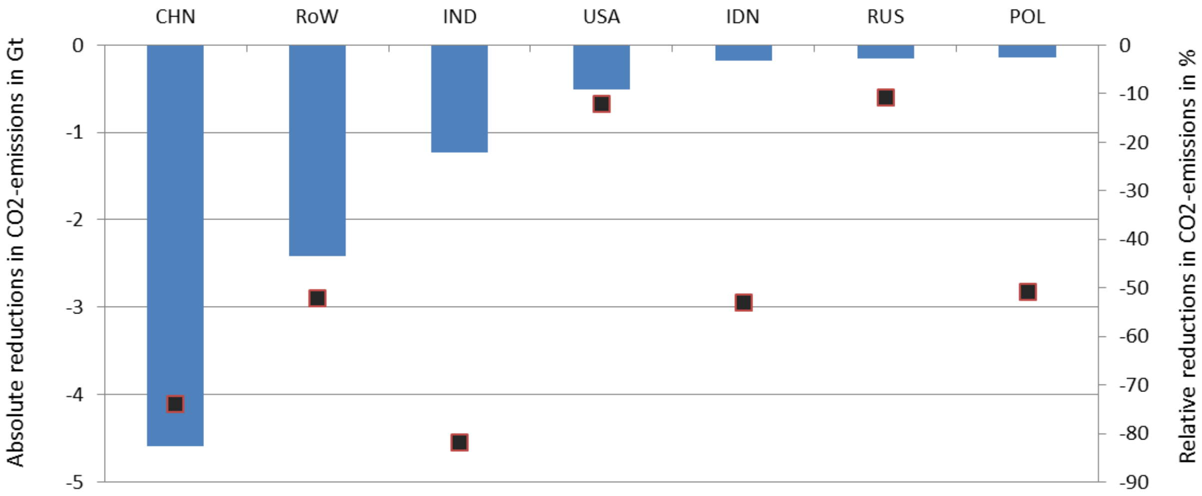


Figure 5: Resulting absolute and relative regional emissions changes in Gt (left axis, bars) of CO_2 and %, respectively (right axis, squares), for the REF scenario. We show regions with changes larger than 0.1 Gt Note that countries' absolute CO_2 emissions reductions do not consider emissions from International transport, which are accounted for in a separate term (see (14)).

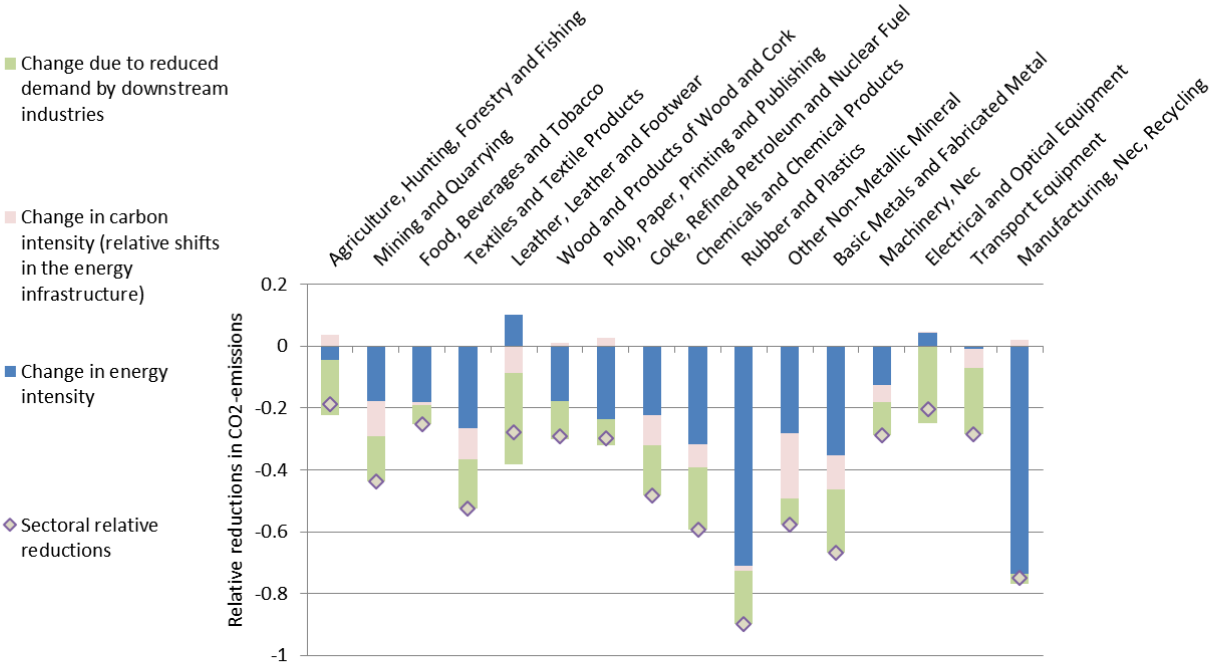


Figure 6: Factor decomposition of resulting relative changes of CO_2 emissions for the REF scenario. For global industrial sectors, relative reductions are decomposed into contributions of i) relative changes in carbon intensities (related to relative shifts in the energy infrastructure), ii) relative changes in energy intensities, and iii) changes in total outputs due to reduced demand in downstream industries following technology exchange. Changes in carbon intensity can be attributed to (relative) shifts in the production location, as this changes the relative composition of the underlying energy system.

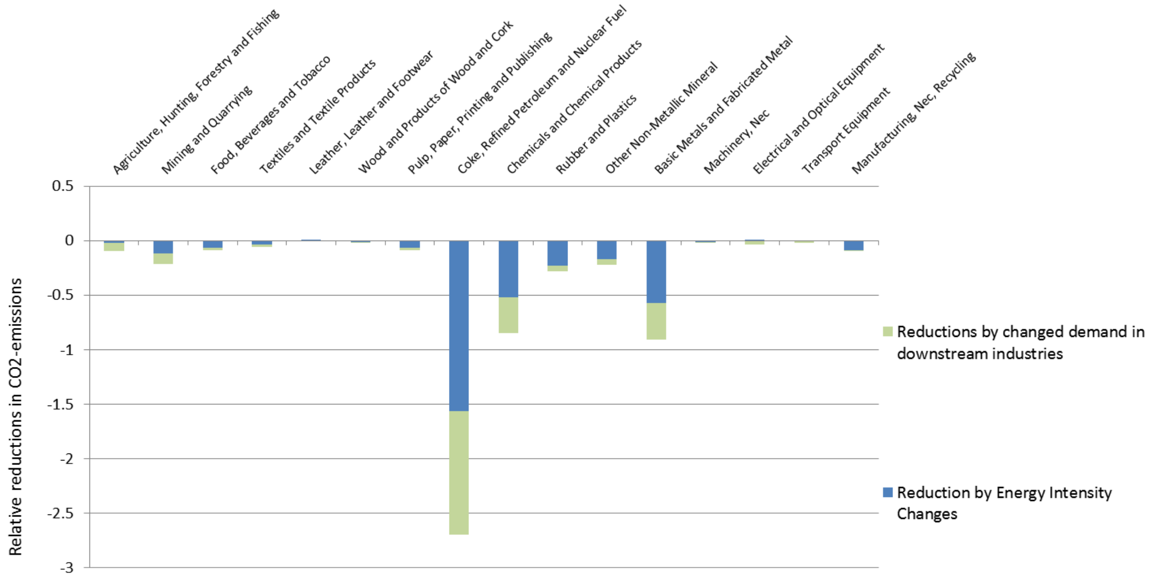


Figure 7: Absolute sectoral CO$_2$ emissions reductions, adjusted for relative changes in energy infrastructure (changes in carbon intensity) in Gt for the REF scenario, decomposed into direct energy intensity changes and changes in demand for intermediate goods by technology exchanges in downstream industries. Results are obtained by combining information from Figure 6 and Figure 4.

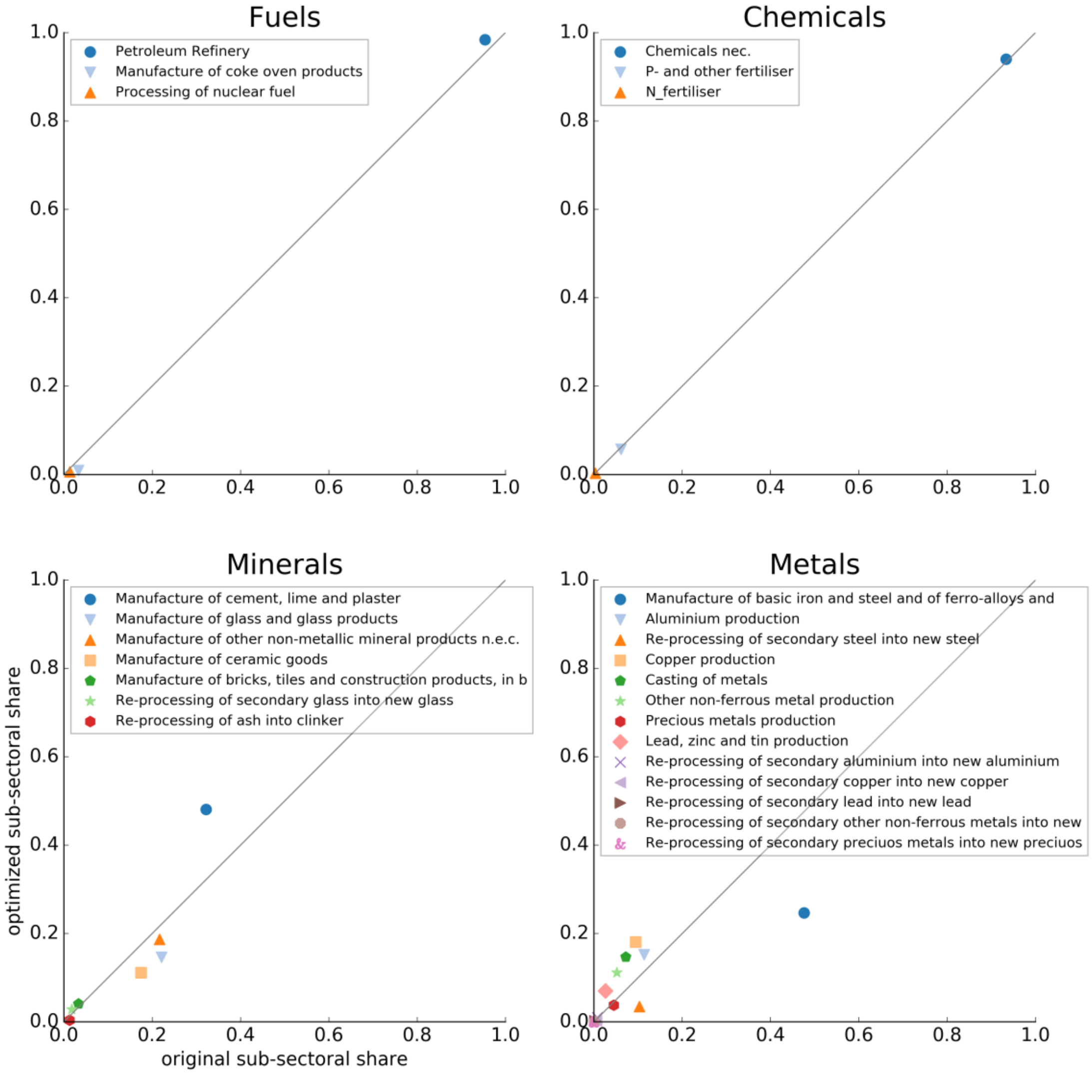
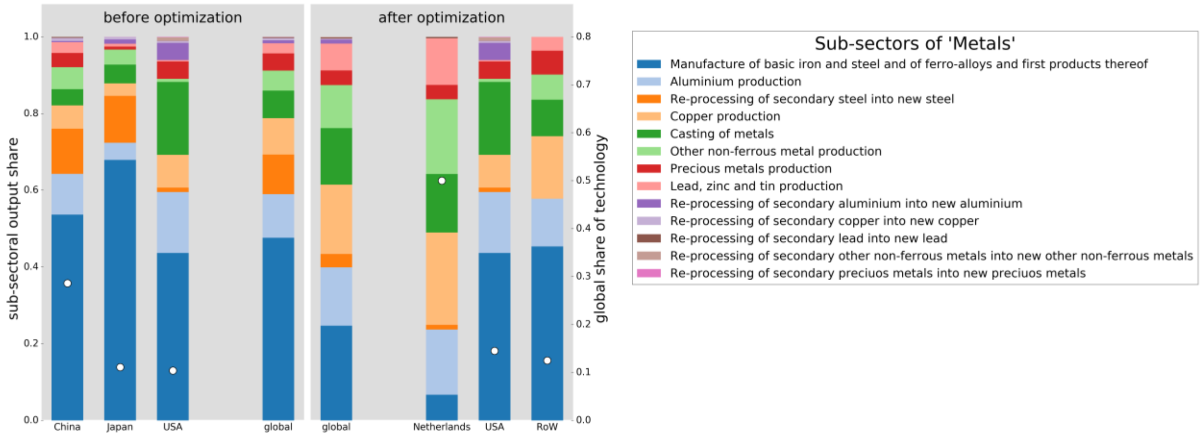


Figure 8: Subsector shares of the global sectors before and after the optimization (REF scenario). Colored nodes correspond to Exiobase 2.0 sectors. Note that the color coding is harmonized with Figure 9 and Figures S10, S11 in the SI.

A) Basic Metals and Fabricated Metals



B) Other Non-Metallic Minerals

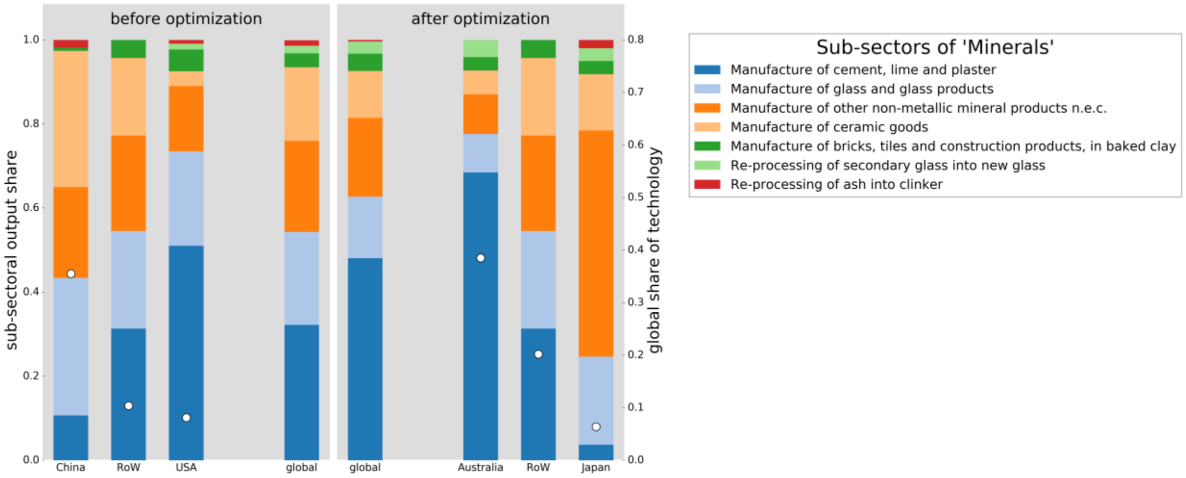


Figure 9: Relative composition of regional- and the global technology of WIOD sectors A) "Basic Metals and Fabricated Metals" and B) "Other Non-Metallic Minerals" disaggregated to corresponding EXIOBASE 2.0 sectors. The left side depict the initial state, the right side depicts technological composition after optimization. Bars in the middle directly compare global sectoral composition before and after optimization. For both cases the three most frequent applied regional technologies are depicted with their corresponding share (white squares). Results for other sectors can be found in the SI.

Tables

Scenario	WIOD 2009	$\tau = 15^{th}$	$\tau = 50^{th}\ (REF)$	$\tau = 85^{th}$	Simple EI exchange for $\tau = 50^{th}$
CO_2 emissions in Gt	24.87	13.98	16.55	19.20	20.60
Absolute reduction in Gt compared to WIOD 2009	N/A	10.89	8.32	5.67	4.27
Relative reduction in % compared to WIOD 2009	N/A	43%	33%	23%	17%
Total emissions related to transportation in Gt	1.5	2.6	2.7	2.6	1.5

Table 1: Total CO_2 emissions and reductions related to production for implemented scenarios. We further show the WIOD 2009 emissions (first column) and emissions resulting from a simple exchange of energy intensities (last column). Note that for the optimization scenarios an artificial transportation model is applied, in addition to considered transportation sectors.

Scenario	**WIOD 2009**	**OPT_50**	**OPT_50_aggregated**
Total emissions	24.9	16.5	15.8
Total sectoral emissions	24.9	15.1	14.7
“Coke, Refined Petroleum and Nuclear Fuel”	1.05	0.36	0.32
“Chemicals and Chemical Products” + “Rubber and Plastics”	0.32	0.07	0.08
“Other Non-Metallic Minerals” + “Basic Metals and Fabricated Metals”	0.43	0.08	0.07

Table 2: Impact of using aggregated sectors within the optimization on CO_2 emissions (given in Gt). For different scenarios relevant sectors are depicted. For Opt_50_aggregated, “Chemicals and Chemical Products, Rubber and Plastics” have been aggregated before the optimization, for the other two, these sectors have been aggregated after optimization. For more detail, see Figure S12 in the SI.

Appendix: Extended mathematical framework

i. The regional *final demand* is fixed for each commodity according to WIOD 2009 values[s]. However, we allow for changes in the *production location*, in other words, the place where final demand goods are produced:

$$\sum_r \overline{\boldsymbol{Y}}_{r,s}^{r'} = \sum_r \boldsymbol{Y}_{r,s}^{r'}, \quad \boldsymbol{r}', \boldsymbol{r} \in \boldsymbol{R} \text{ and } \boldsymbol{s} \in \boldsymbol{S}. \tag{6}$$

ii. We do not allow for changes in *regional GDP*, which is ensured by fixed regional *import* (*Imp*) and *export values* (*Exp*). In combination with Equation (6), this guarantees the intended outcome[t]:

$$\boldsymbol{Exp}_{\boldsymbol{r}} = \overline{\boldsymbol{Exp}_{\boldsymbol{r}}} \qquad r \in \boldsymbol{R} \tag{7}$$

$$\boldsymbol{Imp}_{\boldsymbol{r}} = \overline{\boldsymbol{Imp}_{\boldsymbol{r}}} \qquad \boldsymbol{r} \in \boldsymbol{R} \tag{8}$$

The idea behind these constraints is that we want to ensure comparability of WIOD 2009 data with the optimization result.

iii. To consider the possibility of technological exchange, we build on the traditional MRIO notation by defining the matrix $\boldsymbol{Q}$, which allows to consider *multiple production technologies* in a single regional sector[u]. $\boldsymbol{Q}$'s entries $\boldsymbol{Q}_{r,s}^{r'}$ account for the amount of sector s output in region r being produced with the technology of region r'. Thus, $\boldsymbol{Q}$ in principle allows each regional sector in each region to rely on a pool of 41 different technologies that exist within the 41 countries of the WIOD. We will partially limit the availability of technologies in the following. The total sectoral output of a region for the optimization problem will result as the sum of $\boldsymbol{Q}_{r,s}^{r'}$ over $\boldsymbol{r}'$:

---

[s] Even when fixing global production it is possible that because of more efficient technologies labor stocks are not completely used.

[t] GDP=C+I+G+Exp-Imp, where C refers to consumption, I to investments and G to government spending. In our case, C+I+G refers to overall consumption—which corresponds to the sum of entries of vector Y, respectively Y* which are fixed by equation (4). It suffices to simply keep the trade balance fixed in order to achieve a constant GDP.

[u] This actually happens, see Table S4 in the SI.

$$\boldsymbol{O_{r,s} = \sum_{r'} Q_{r,s}^{r'}}, \qquad \boldsymbol{r', r \in R} \textbf{ and } \boldsymbol{s, s' \in S} \tag{9}$$

We focus on efficiency gains from access to more efficient industrial technologies. As a consequence, we do not allow for technology exchanges within *service sectors*, which are often country specific (military services). To prevent an "indirect" exchange by way of production leakage, we further limit the export values of services to their original (WIOD 2009) values. Thus, for a service sector s,

$$\boldsymbol{Q_{r,s}^{r'} = 0, for\ r \neq r',\ s \in S_{Ser},\ r', r \in R} \tag{10}$$

and

$$\boldsymbol{Exp_{r,s} \leq \overline{Exp}_{r,s} \qquad s \in S_{Ser}, r \in R} \tag{11}$$

have to be fulfilled.

iv. We aim to assess CO_2 emission reduction potentials by technology exchange without changing *energy systems,* as these are slow to adopt (Davis et al., 2010; Unruh, 2000). Therefore, the regional $\boldsymbol{\overline{CI}_r}$ is fixed and we do not allow for a technology exchange in the sectors "electricity, gas and water supply."

v. The total amount of *available energy* in a region is further limited to the WIOD 2009 level, preventing the expansion of emission-efficient energy production. This, in turn, limits the estimated emissions reductions and excludes even better solutions.

vi. Localized *natural endowments*, such as fertile soil or oil reservoirs, cannot be transferred. They influence local sectoral production technologies, in other words, the Leontief coefficients of these sectors are influenced by local endowments and hide the "real" efficiency of technologies. As a consequence, we disable technological exchange for *agricultural and extraction sectors*, prohibit expansions and limit the regional production of these sectors to the WIOD 2009 levels:

$$\boldsymbol{O_{r,s} \leq \overline{O}_{r,s}, \quad s \in S_{Agr} \cup S_{Extr}, r \in R} \tag{12}$$

$$\boldsymbol{Q}^{r'}_{r,s} = \mathbf{0}, \qquad \boldsymbol{r} \neq \boldsymbol{r}', \boldsymbol{r}, \boldsymbol{r}' \in \boldsymbol{R}, \boldsymbol{s} \in \boldsymbol{S}_{Agr} \cup \boldsymbol{S}_{Extr}. \tag{13}$$

vii. We further consider limited *labor stocks* and no *workers' mobility* across countries. Labor use in the optimization is not allowed to exceed available labor hours (stocks) $\bar{L}^q_r$ in any region r and for any level of qualification $\boldsymbol{q}$.

$$\bar{\boldsymbol{L}}^{\boldsymbol{q}}_{\boldsymbol{r}} \geq \sum_{\boldsymbol{r}'} \sum_{\boldsymbol{s}} \boldsymbol{Q}^{r'}_{r,s} \times \overline{\boldsymbol{LI}}^{\boldsymbol{q}}_{r',s} \qquad \boldsymbol{r}, \boldsymbol{r}' \in \boldsymbol{R}, \boldsymbol{s} \in \boldsymbol{S} \tag{14}$$

viii. Sectors that do not provide the necessary data for calculating *labor intensities* as well as regions without reported *labor stocks* cannot expand their production or change their production technology. Furthermore, their production technology is excluded from transfer[v]. This constraint is implemented in order to prevent extremal solutions.

ix. Analyzing WIOD's sectoral energy intensities reveals significant regional differences (see Figure 1). Some *energy intensities* appear to be extraordinarily small. This might not be due to highly efficient processes but to the data collection itself. We address this (potential) caveat by i) ranking sectoral energy intensities among regions (see Figure 3 the SI), and ii) allowing technology exchange or local production expansion only for technologies that are less efficient than a specific percentile that guarantees to represent realistic technologies. The introduced threshold allows for variation, leading to different scenarios (to be described in Section 3.5).

x. In order to secure consistency within the resulting optimized MRIO table, when technologies are exchanged, we ensure a provision of *sufficient inputs.* In other words, we ensure that the amount of sectoral inflows equals the output multiplied with the technology. For each sector s of region r, the following condition holds:

$$\sum_{\boldsymbol{r}'} \boldsymbol{Z}^{r',s'}_{r,s} = \sum_{\boldsymbol{r}'} \boldsymbol{Q}^{r'}_{r,s} \times \bar{\boldsymbol{P}}^{s'}_{r',s}, \ \boldsymbol{r}, \boldsymbol{r}' \in \boldsymbol{R}, \ \boldsymbol{s}, \boldsymbol{s}' \in \boldsymbol{S}. \tag{15}$$

---

[v] Sectors related to this issue are listed in the SI.

xi. We *prevent overproduction*, in other words, sectoral outputs plus the available usable stocks $\overline{\boldsymbol{St}}_{\boldsymbol{r,s}}$ (i.e., negative "changes in inventories," see SI) have to match the corresponding demand (final consumption plus intermediate production):

$$\sum_{\boldsymbol{r'}}\sum_{\boldsymbol{s'}}\boldsymbol{Z}_{\boldsymbol{r,s}}^{\boldsymbol{r',s'}} + \sum_{\boldsymbol{r'}}\boldsymbol{Y}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} = \overline{\boldsymbol{St}}_{\boldsymbol{r,s}} + \boldsymbol{O}_{\boldsymbol{r,s}}\,, \boldsymbol{r}, \boldsymbol{r'} \in \boldsymbol{R},\ \boldsymbol{s}, \boldsymbol{s'} \in \boldsymbol{S}. \qquad \textbf{(16)}$$

Thus, stocks $\overline{\boldsymbol{St}}_{\boldsymbol{r,s}}$ are considered for Z and Y and are available without additional costs (same treatment as in WIOD and in (Koesler and Pothen, 2013)).

Optimization problem

$$\mathbf{min}\ (\ \sum_{\boldsymbol{r}\in\boldsymbol{R}}\sum_{\boldsymbol{r'}\in\boldsymbol{R}}\sum_{\boldsymbol{s}\in\boldsymbol{S}}\left[\left(\boldsymbol{Q}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} \times \overline{\boldsymbol{EI}}_{\boldsymbol{r',s}} \times \overline{\boldsymbol{CI}}_{\boldsymbol{r}}\right) + \boldsymbol{T}_{\boldsymbol{r,s}}^{\boldsymbol{r'}}\right] \qquad (5)$$

$$\textbf{subject to} \qquad \sum_{\boldsymbol{r}}\overline{\boldsymbol{Y}}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} = \sum_{\boldsymbol{r}}\boldsymbol{Y}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} \qquad (6)$$

$$\boldsymbol{Exp}_{\boldsymbol{r}} = \overline{\boldsymbol{Exp}}_{\boldsymbol{r}} \qquad (7)$$

$$\boldsymbol{Imp}_{\boldsymbol{r}} = \overline{\boldsymbol{Imp}}_{\boldsymbol{r}} \qquad (8)$$

$$\boldsymbol{Exp}_{\boldsymbol{r,s}} \leq \overline{\boldsymbol{Exp}}_{\boldsymbol{r,s}} \qquad \boldsymbol{s} \in \boldsymbol{S}_{\boldsymbol{Ser}} \qquad (11)$$

$$\boldsymbol{O}_{\boldsymbol{r,s}} \leq \overline{\boldsymbol{O}}_{\boldsymbol{r,s}} \quad \boldsymbol{,} s \in S_{Agr} \cup S_{Extr}, \qquad (12)$$

$$\boldsymbol{Q}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} = \mathbf{0}, r \neq r', s \in S_{Agr} \cup S_{Extr} \cup S_{Ser} \qquad (13+10)$$

$$\overline{\boldsymbol{L}}_{\boldsymbol{r}}^{\boldsymbol{q}} \geq \sum_{\boldsymbol{r'}}\sum_{\boldsymbol{s}}\boldsymbol{Q}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} \times \overline{\boldsymbol{LI}}_{\boldsymbol{r',s}}^{\boldsymbol{q}} \qquad (14)$$

$$\sum_{\boldsymbol{r'}}\boldsymbol{Z}_{\boldsymbol{r,s}}^{\boldsymbol{r',s'}} = \sum_{\boldsymbol{r'}}\boldsymbol{Q}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} \times \overline{\boldsymbol{P}}_{\boldsymbol{r',s}}^{\boldsymbol{s'}} \qquad (15)$$

$$\sum_{\boldsymbol{r'}}\sum_{\boldsymbol{s'}}\boldsymbol{Z}_{\boldsymbol{r,s}}^{\boldsymbol{r',s'}} + \sum_{\boldsymbol{r'}}\boldsymbol{Y}_{\boldsymbol{r,s}}^{\boldsymbol{r'}} = \overline{\boldsymbol{St}}_{\boldsymbol{r,s}} + \boldsymbol{O}_{\boldsymbol{r,s}} \qquad (16)$$

with $\boldsymbol{r}, \boldsymbol{r'} \in \boldsymbol{R}\ \boldsymbol{and}\ \boldsymbol{s}, \boldsymbol{s'} \in \boldsymbol{S}$

Linear optimization problems are numerically solved by using the simplex algorithm (Dantzig, 1963). In the case of our particular problem, one feasible solution is given by the original setup (matrices Z and Y). It follows that our solution space is non-empty. Moreover, it cannot be unbounded from below, since all variables are non-negative and have positive coefficients in the objective function. Therefore it has an optimal solution.

Supplementary Information for online publication only (SI)

Content:

- SI 1 Construction of the transport model
- SI 2 Decomposition analysis
- SI 3 Technology adoption
- SI 4 Comparison analysis of the different scenarios
- SI 5 Differences in sectoral energy intensities
- SI 6 Treatment of final demand vector
- SI 7 Impact of the optimization on emissions in Annex I and Non-Annex I countries
- SI 8 List of sectors without labor intensity
- SI 9 Changes in average transportation distances
- SI 10 Changes in Production inputs, production technology and sectoral composition of regions
- SI 11 Disaggregating of “Chemicals” and “Fuels”
- SI 12 Counterfactual analysis with aggregated sectors

SI 1. Construction of the transportation model

The following steps were taken to construct the underlying transportation model: We matched Cristea et al.’s (2013) aggregated GTAP non-service sectors to WIOD’s non-service sectors (see Table Appendix 1 and Figure Appendix 1). Generally, the chosen matchings concord, whereby discrepancies tend to exist in the Agricultural, Electrical and Optical Equipment, and Machinery sectors. Since data on transportation and commodity weights are available only for aggregated GTAP sectors, it is indispensable to assess the fraction of WIOD sectors that are allocated to a different sector in the GTAP model.

We believe that the two pairs “Electrical and Optical Equipment” and “Machinery nec.” and “Agriculture-Hunting-Forestry and Fishing” and “Food Beverages and Tobacco” need to be examined, as their pairwise sums of aggregated GTAP sectors and WIOD sectors match. We therefore performed a corrective calculation. Comparing differences of pair elements between aggregated GTAP and WIOD, we concluded that 45% of WIOD’s “Agriculture-Hunting-Forestry and Fishing” sector is contained in the GTAP’s “Food, Beverages and Tobacco” sectors, and thus consider this share to have the higher corresponding weight per

USD of GTAP's "Food, Beverages and Tobacco." The same procedure was applied to the pair "Electrical and Optical Equipment" and "Machinery nec."

We thus derive specific weighted commodity weights, corresponding transportation mode (weighted by weight of commodities) shares and weight-value factors for WIOD. We finally end up with $CO_2 emissions\ per\ (USD * km)$, as shown in Table 2 of the Appendix. Combining these data with pairwise distances of the regions' capitals (data taken from ("GeoHack," n.d.)) enables considering emissions related to international transportation within the optimization framework.

Bulk agriculture
Processed agriculture
Forestry
Fishing
Minerals
Oil
Gas
Textiles
Wearing apparel
Leather products
Wood products
Paper products, publishing
Petroleum, coal products
Chemical, rubber, plastic products
Mineral products nec.
Ferrous metals
Metals nec.
Metal products
Motor vehicles and parts
Transport equipment nec.
Electronic equipment
Machinery and equipment, nec.
Manufactures nec

Agriculture, Hunting, Forestry and Fishing
Mining and Quarrying
Food, Beverages and Tobacco
Textiles and Textile Products
Leather, Leather and Footwear
Wood and Products of Wood and Cork
Pulp, Paper, Paper , Printing and Publishing
Coke, Refined Petroleum and Nuclear Fuel
Chemicals and Chemical Products
Rubber and Plastics
Other Non-Metallic Mineral
Basic Metals and Fabricated Metal
Machinery, Nec
Electrical and Optical Equipment
Transport Equipment
Manufacturing, Nec; Recycling

Table S1: Matching of aggregated GTAP sectors (Cristea et al. 2013) (left) with WIOD sectors (right). Colors indicate matchings of sector groups.

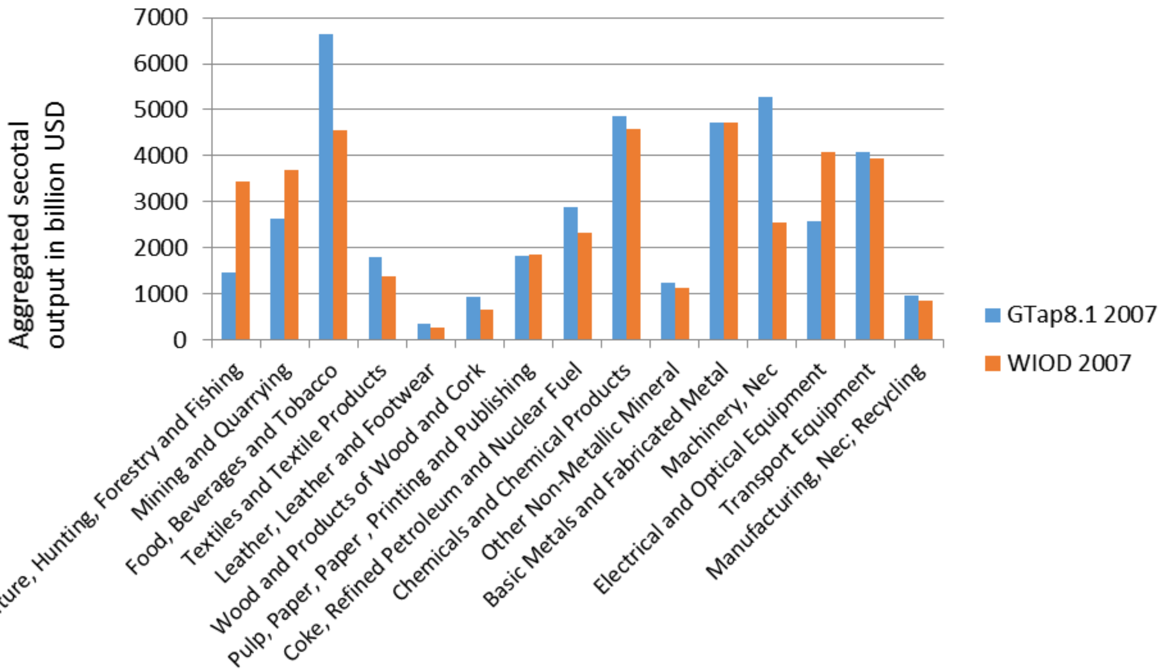


Figure S1: Assessing the sector matching of Cristea et al.'s (2013) sectors of GTAP 8.1. 2007 and WIOD sectors for the year 2007. The plot shows total aggregated outputs. Large deviations occur for Agriculture, Hunting, Forestry and Fishing, Machinery NEC., Electrical and Optical Equipment and Food, Beverages and Tobacco.

Agriculture, Hunting, Forestry and Fishing	30.47
Mining and Quarrying	54.91
Food, Beverages and Tobacco	27.87
Textiles and Textile Products	15.21
Leather, Leather and Footwear	14.50
Wood and Products of Wood and Cork	29.88
Pulp, Paper, Paper , Printing and Publishing	36.00
Coke, Refined Petroleum and Nuclear Fuel	78.54
Chemicals and Chemical Products	20.98
Rubber and Plastics	20.98
Other Non-Metallic Mineral	41.78
Basic Metals and Fabricated Metal	42.70
Machinery, Nec	18.60
Electrical and Optical Equipment	15.26
Transport Equipment	8.81
Manufacturing, Nec; Recycling	12.33

Table S2: Calculated CO_2 emissions in gram per $1000 * \mathrm{USD} * \mathrm{km}\left[\frac{gram}{1000*\$*km}\right]$ for WIOD's industrial commodities.

SI 2 Decomposition analysis

To understand which factors influence the optimization results, we perform a factor decomposition. For examples in the literature, see the Kaya decomposition (IPCC, 2014b), Ang and Wang (2015) or Voigt et al. (2014).

We consider as relevant variables:

World average sectoral energy intensity "old" (before optimization) for sector s:

$$EI_{old\_s} := \frac{\sum_r O_{r,s} \times EI_{r,s}}{\sum_r O_{r,s}}$$

World average sectoral energy intensity "new" (after optimization) for sector s:

$$EI_{new\_s} := \frac{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}} \times EI_{r',s}}{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}}}$$

World average sectoral carbon intensity "old" for sector s:

$$CI_{old\_s} := \frac{\sum_r O_{r,s} \times EI_{r,s} \times \boldsymbol{CI_r}}{\sum_r O_{r,s} \times EI_{r,s}}$$

World average sectoral carbon intensity "new" for sector s:

$$CI_{new\_s} := \frac{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}} \times EI_{r',s} \times \boldsymbol{CI_r}}{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}}}$$

Changes in total sectoral production-related CO$_2$ emissions for sector s:

$$\Delta CO_{2s} := \frac{\sum_r O_{r,s} \times EI_{r,s} \times \boldsymbol{CI_r}}{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}} \times EI_{r',s} \times \boldsymbol{CI_r}}$$

We then calculate relevant factors:

$$\Delta CI_s = {}^{CI_{new\_s}}\!\Big/_{CI_{old\_s}}$$

$$\Delta EI_s = {}^{EI_{new\_s}}\!\Big/_{EI_{old\_s}}$$

$$\Delta Output_s = {}^{\sum_r O_{r,s}}\!\Big/_{\sum_r \sum_{r'} \boldsymbol{Q}^{*r'}_{\boldsymbol{r,s}}}$$

All possible changes in sectoral CO$_2$ emissions can be necessarily explained by the above-mentioned factors. The relation $\Delta CO_{2s} = \Delta CI_s \times \Delta EI_s \times \Delta Output_s$ holds. To get the factor decomposition shown in Figure 5 with a=b+c+d, where we account for relative changes in sectoral emissions, a logarithmic transformation has to be applied.

We use

$$a = \Delta CO_{2s} - 1$$

$$b = \log(\Delta Output_s)/\log(\Delta CO_{2_s}) \times (\Delta CO_{2_s} - 1)$$

$$c = \log(\Delta EI_s)/\log(\Delta CO_{2_s}) \times (\Delta CO_{2_s} - 1)$$

$d = log(\Delta CI_s)/\log(\Delta CO_{2_s}) \times (\Delta CO_{2_s} - 1)$,

for which the desired equation holds.

SI 3 Technology adaptation

When evaluating technologies that were exchanged, we can show with Appendix, Table 3 that, in part, technologies from the common technology pools replaced technologies that have an even better energy intensity than the chosen threshold. Exemplarily, let x denote the fraction that is chosen as a threshold in a specific scenario (in the case of the reference (REF) scenario, x equals 0.50). If every non-accessible technology was better than the best pool technology in terms of emissions reductions, it would be expected that at most $(1 - x) * 41$ regions adapt new technologies. However, in the case of $\tau = 85^{th}$, at least 22 regions adapted common technology pools for "Food, Beverages and Tobacco," by far exceeding the common expectation of only 8 regions ($(1 - 0.8) * 41 \approx 8$). Nevertheless, there are also some sectors where the adaptation rate is lower than expected.

Scenario	$\tau = 85^{th}$	$\tau = 50^{th}$	$\tau = 15^{th}$
Food, Beverages and Tobacco	22	27	36
Textiles and Textile Products	15	30	32
Leather, Leather and Footwear	12	27	29
Wood and Products of Wood and Cork	1	14	18
Pulp, Paper, Paper, Printing and Publishing	4	13	19
Coke, Refined Petroleum and Nuclear Fuel	9	19	25
Chemicals and Chemical Products	8	12	21
Rubber and Plastics	12	22	22
Other Non-Metallic Mineral	6	7	15
Basic Metals and Fabricated Metal	4	10	17
Machinery, Nec	26	26	31
Electrical and Optical Equipment	7	25	25
Transport Equipment	18	26	28
Manufacturing, Nec, Recycling	16	24	33

Table S3: Approximation of the number of regions that changed their sectoral production technologies in different scenarios. A regional sector is considered as having changed its production technology if at least 50% of its WIOD 2009 output was produced in the optimized solution and less than 10% was produced with its original technology.

SI 4 Sectoral composition of output and emissions

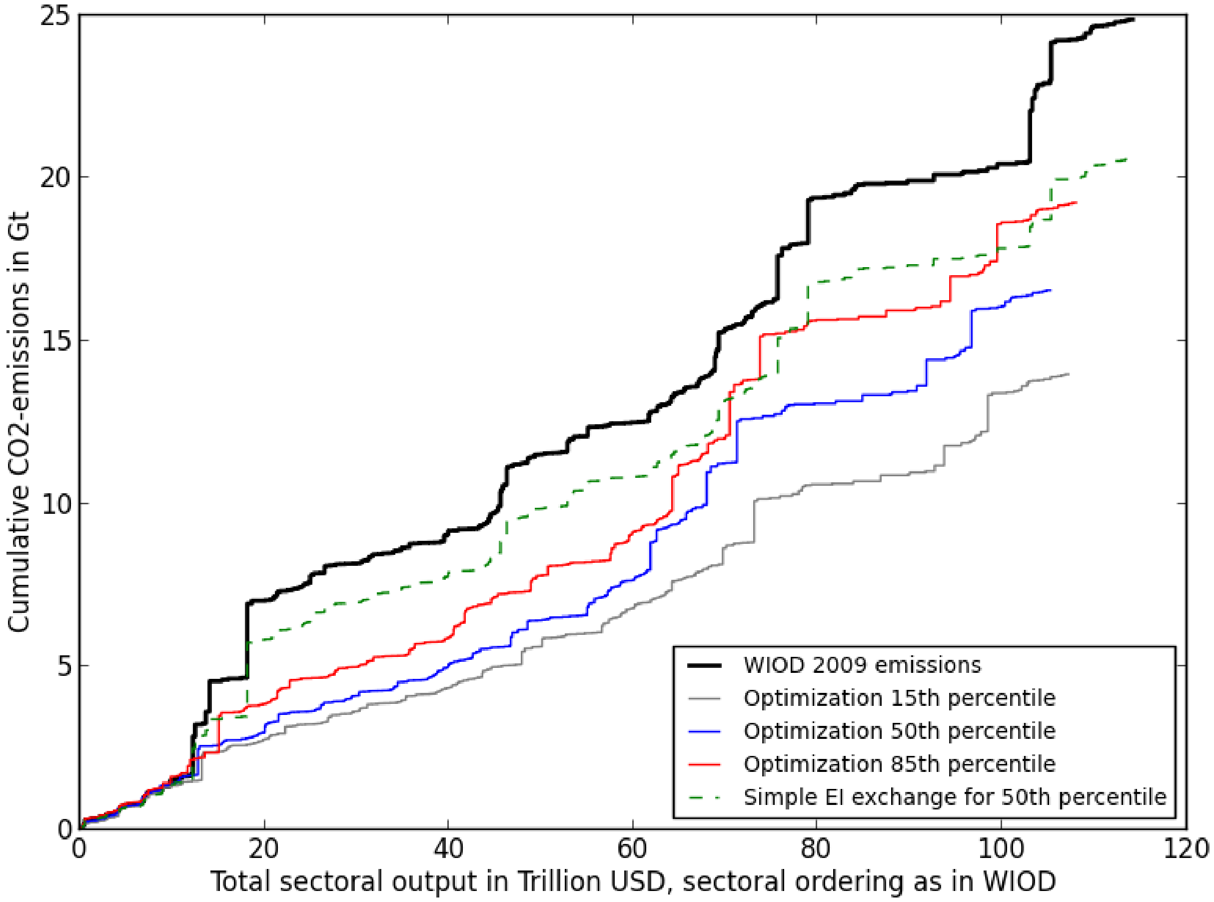


Figure S2: Cumulative sectoral outputs and cumulative sectoral CO_2 emissions for implemented optimization scenarios, WIOD 2009 and a simple energy intensity exchange, omitting effects in supply chains. Regional and sectoral ordering is according to WIOD, i.e. beginning with Australia, sector 1, ending with RoW, sector 35.

SI 5 Differences in regional sectoral energy intensities

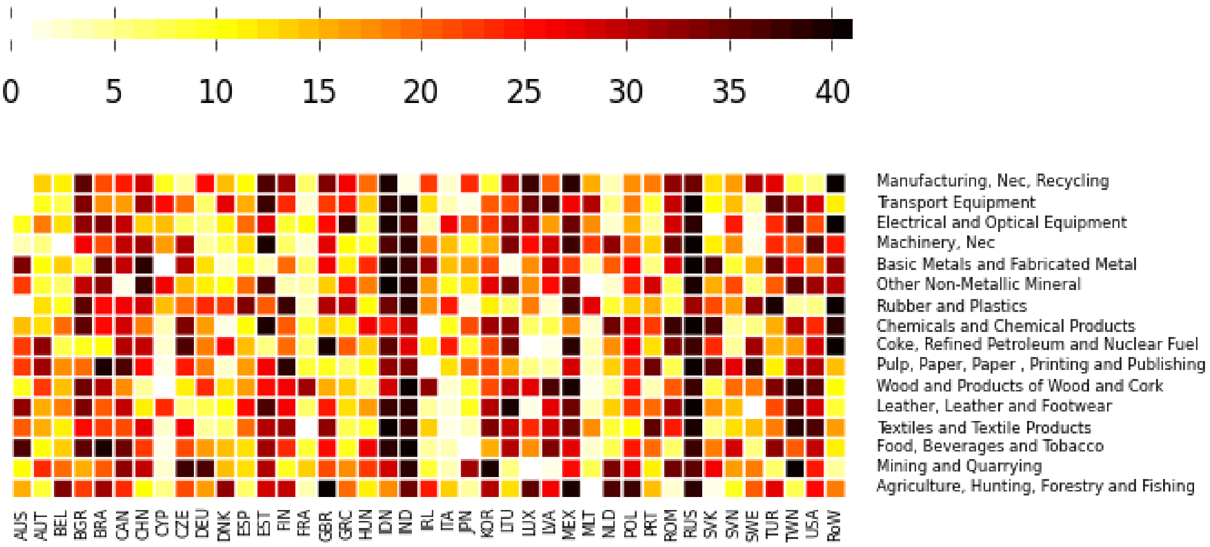


Figure S3: Ranking of sectoral energy intensities among regions for sectors with technological exchange. Additionally, the sectors "Mining and Quarrying" and "Agriculture, Hunting, Forestry and Fishing" are shown. The white color corresponds to best-energy intensity, while brown corresponds to worst-energy intensity (in joule per USD).

SI 6 Treatment of final demand in WIOD

WIOD distinguishes five different types of final demand:

1) Final consumption expenditure by households,
2) final consumption expenditure by non-profit organizations serving households,
3) final consumption expenditure by governments,
4) gross fixed capital formation, and
5) changes in inventories and valuables.[w]

The demand category "Changes in inventories and valuables" needs a special treatment (Koesler and Pothen, 2013) as it influences the amount of commodities that are available for further production processes.

If WIOD's "Changes in inventories and valuables" shows a positive sign, stocks are increased, implying additional duties, such as that more goods need to be produced. In this case, the category is treated as an ordinary final demand. Otherwise, if the sign is negative, all other types of final demands, except "Changes in inventories and valuables," are summed up and refer to $Y_{i,l}^{j}$. In this case, available stocks are reduced. Thus, a fraction of "Changes in

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[w] For "Changes in Inventories" a special treatment is applied (see Section 3.2).

inventories and valuables" enters the market and is available as a pre-product for production or consumption. We denote these available stocks in region i, commodity l, by St_i^l, since these goods are available for an intermediate consumption or final demand without production costs.

SI 7 Visualization of aggregated reduction for country groups

The following figure, shows how the different scenarios, i.e., more ambitious technological accessibility, influence mitigation potentials in Annex I and Non Annex I regions.

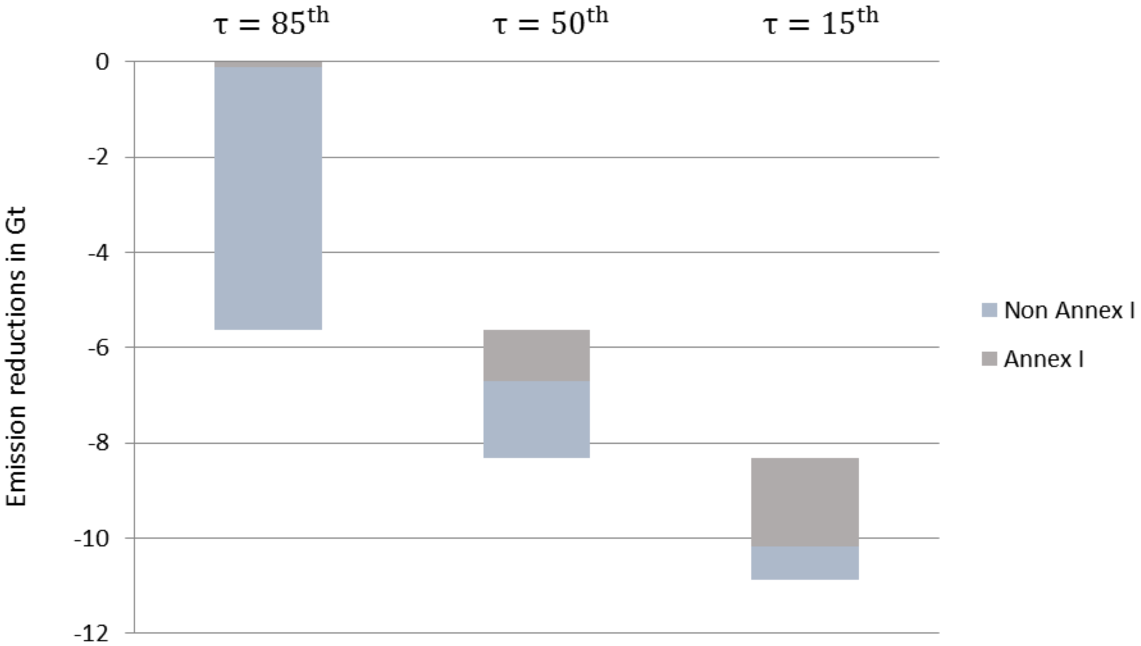

Figure S4: Accumulated CO_2 emissions reductions depending on the scenario and on the country group in which they occur. The cheap scenario corresponds to $\tau = 85^{\text{th}}$, the moderate one to $\tau = 50^{\text{th}}$ and expensive one to $\tau = 15^{\text{th}}$.

SI 8 List of sectors without labor intensity

We take abbreviations from WIOD. Qualification level 0 refers to low qualified labor, 1 to medium qualified labor, while 2 refers to high qualified labor. The data reads as country, sector, labor qualification level.

AUS , Private Households with Employed Persons , qualification level 0

AUS , Private Households with Employed Persons , qualification level 1

AUS , Private Households with Employed Persons , qualification level 2

BGR , Private Households with Employed Persons , qualification level 0

BGR , Private Households with Employed Persons , qualification level 1

BGR , Private Households with Employed Persons , qualification level 2

BRA , Private Households with Employed Persons , qualification level 0

BRA , Private Households with Employed Persons , qualification level 1

BRA , Private Households with Employed Persons , qualification level 2

CHN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 0

CHN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 1

CHN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 2

CHN , Private Households with Employed Persons , qualification level 0

CHN , Private Households with Employed Persons , qualification level 1

CHN , Private Households with Employed Persons , qualification level 2

CYP , Coke, Refined Petroleum and Nuclear Fuel , qualification level 0

CYP , Coke, Refined Petroleum and Nuclear Fuel , qualification level 1

CYP , Coke, Refined Petroleum and Nuclear Fuel , qualification level 2

ESP , Private Households with Employed Persons , qualification level 0

ESP , Private Households with Employed Persons , qualification level 1

ESP , Private Households with Employed Persons , qualification level 2

EST , Private Households with Employed Persons , qualification level 0

EST , Private Households with Employed Persons , qualification level 1

EST , Private Households with Employed Persons , qualification level 2

HUN , Private Households with Employed Persons , qualification level 0

HUN , Private Households with Employed Persons , qualification level 1

HUN , Private Households with Employed Persons , qualification level 2

IDN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 0

IDN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 1

IDN , Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel , qualification level 2

IDN , Private Households with Employed Persons , qualification level 0

IDN , Private Households with Employed Persons , qualification level 1

IDN , Private Households with Employed Persons , qualification level 2

JPN , Private Households with Employed Persons , qualification level 0

JPN , Private Households with Employed Persons , qualification level 1

JPN , Private Households with Employed Persons , qualification level 2

KOR , Private Households with Employed Persons , qualification level 0

KOR , Private Households with Employed Persons , qualification level 1

KOR , Private Households with Employed Persons , qualification level 2

LUX , Leather, Leather and Footwear , qualification level 0

LUX , Leather, Leather and Footwear , qualification level 1

LUX , Leather, Leather and Footwear , qualification level 2

LUX , Coke, Refined Petroleum and Nuclear Fuel , qualification level 0

LUX , Coke, Refined Petroleum and Nuclear Fuel , qualification level 1

LUX , Coke, Refined Petroleum and Nuclear Fuel , qualification level 2

LVA , Coke, Refined Petroleum and Nuclear Fuel , qualification level 0

LVA , Coke, Refined Petroleum and Nuclear Fuel , qualification level 1

LVA , Coke, Refined Petroleum and Nuclear Fuel , qualification level 2

MEX , Private Households with Employed Persons , qualification level 0

ROM , Private Households with Employed Persons , qualification level 0

ROM , Private Households with Employed Persons , qualification level 1

ROM , Private Households with Employed Persons , qualification level 2

RUS , Private Households with Employed Persons , qualification level 0

RUS , Private Households with Employed Persons , qualification level 1

RUS , Private Households with Employed Persons , qualification level 2

SVK , Private Households with Employed Persons , qualification level 0

SVK , Private Households with Employed Persons , qualification level 1

SVK , Private Households with Employed Persons , qualification level 2

SWE , Leather, Leather and Footwear , qualification level 0

SWE , Leather, Leather and Footwear , qualification level 1

SWE , Leather, Leather and Footwear , qualification level 2

and all sectors of "Rest of the World"

SI 9 Chances in Average transporting distances

The following two Figures show how the average transport distance of all goods and the average distance of transported goods changes as consequence of the optimization.

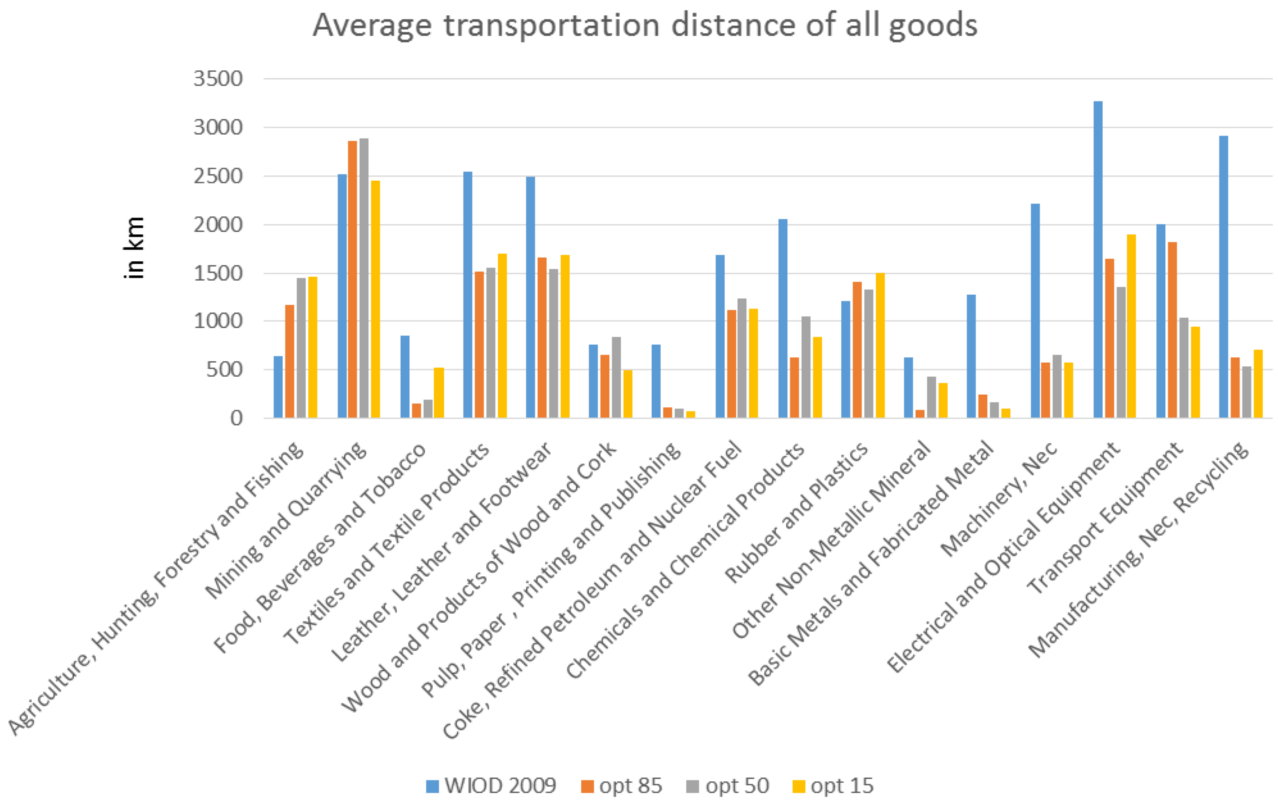

Figure S5: Average distance of transported goods for WIOD 2009 and the different scenarios in km.

SI 10 Changes in technology, sectoral input composition and the structural composition of regions

The follow table gives evidence for 4 exemplary sectors, how technology, inputs and origin of inputs changed in consequence of the optimization (REF scenario).

US Transport equipment

100% US technology		100% DK technology	
Sectoral output level relative to WIOD 2009	100%		57%
10 Most important input sectors (WIOD 2009)	share	10 Most important input sectors in Opt 50	share
US Transport Equipment	25.6	US Basic Metals and Fabricated Metal	19.2
US Basic Metals and Fabricated Metal	15.06	US Wholesale Trade and Commission Trade,	16.6
US Renting of M&Eq and Other Business Activities	11.2	Except of Motor Vehicles and Motorcycles	
US Wholesale Trade and Commission Trade,	5.8	US Machinery, Nec	11.8
Except of Motor Vehicles and Motorcycles		MEX Transport Equipment	11.3

US Electrical and Optical Equipment	4.4	US Electrical and Optical Equipment	8.3
US Rubber and Plastics	2.8	US Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	7.6
US Machinery, Nec	2.5	US Renting of M&Eq and Other Business Activities	5.6
US Financial Intermediation	2.3	US Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel	2
US Inland Transport	1.5	JP Financial Intermediation	1.7
MEX Transport Equipment	1.4	US Rubber and Plastics	1.5

China Chemicals nec.

Output level relative to WIOD 2009	100%		4.10%
100% Chinese technology		100% Finish technology	
10 Most important input sectors (WIOD 2009)	share	10 Most important input sectors in Opt 50	share
CHN Chemicals nec.	33.8	TWN Chemicals nec.	35.6
CHN Mining and Quarrying	8	CHN Renting of M&Eq and Other Business Activities	9.4
CHN Coke, Refined Petroleum and Nuclear Fuel	7.2	CHN Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	8.5
CHN Electricity, Gas and Water Supply	6.6	TWN Coke, Refined Petroleum and Nuclear Fuel	6
CHN Agriculture, Hunting, Forestry and Fishing	3.8	CHN Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	5.6
CHN Rubber and Plastics	3.8	CHN Inland Transport	4.5
CHN Renting of M&Eq and Other Business Activities	3.5	ROW Mining and Quarrying	3.8
CHN Food, Beverages and Tobacco	3	FRA Other Supporting and Auxiliary Transport Activities, Activities of Travel Agencies	2.8
CHN Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	2.8	US Electricity, Gas and Water Supply	2.6
CHN Basic Metals and Fabricated Metal	2.1	CHN Pulp, Paper, Paper , Printing and Publishing	2.4

Germany Manufacturing nec.

Output level relative to WIOD 2009	100%		161.00%
100% German technology		100% Canadian technology	
10 Most important input sectors (WIOD 2009)	share	10 Most important input sectors in Opt 50	share
Renting of M&Eq and Other Business Activities	11.50%	AUT Wood and Products of Wood and Cork	17.00%
DEU Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	7.60%	NLD Basic Metals and Fabricated Metal	12.70%
DEU Basic Metals and Fabricated Metal	7.50%	DEU Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	7.60%
DEU Manufacturing, Nec, Recycling	6.90%	CZE Rubber and Plastics	7.60%
DEU Wood and Products of Wood and Cork	6.90%	DEU Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	6.00%
DEU Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	6.60%	CZE Textiles and Textile Products	5.60%
DEU Real Estate Activities	3.20%	DEU Renting of M&Eq and Other Business Activities	5.60%
DEU Inland Transport	2.40%	NLD Chemicals and Chemical Products	5.50%
DEU Rubber and Plastics	2.30%	ROW Mining and Quarrying	5.30%
		CZE Manufacturing, Nec, Recycling	5.20%

Denmark Food, Beverages and Tobacco

Output level relative to WIOD 2009	100%		137.00%
100% Danish technology		72.7% Danish technology, 20.1% Finish technology, 7.1% British technology	
10 Most important input sectors (WIOD 2009)	share	10 Most important input sectors in Opt 50	share
DNK Agriculture, Hunting, Forestry and Fishing	27.10%	DEU Food, Beverages and Tobacco	18.10%
DNK Food, Beverages and Tobacco	12.60%	CHN Agriculture, Hunting, Forestry and Fishing	13.90%
DNK Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	11.20%	DEU Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	11.01%
DNK Renting of M&Eq and Other Business Activities	6.40%	FIN Agriculture, Hunting, Forestry and Fishing	10.20%
DNK Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	5.30%	SWE Agriculture, Hunting, Forestry and Fishing	8.50%
DNK Inland Transport	3.10%	DNK Renting of M&Eq and Other Business Activities	7.80%
NLD Agriculture, Hunting, Forestry and Fishing	2.10%	DNK Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods	5.70%
ROW Food, Beverages and Tobacco	2.10%	DNK Inland Transport	4%
DNK Financial Intermediation	1.70%	DEU Pulp, Paper, Paper , Printing and Publishing	2.00%
DEU Agriculture, Hunting, Forestry and Fishing	1.60%	JPN Financial Intermediation	1.80%

Table S4: Changes in applied technology, sectoral input composition and origins of inputs for exemplary sectors.

Changes in structural composition of countries

The following 4 figures give evidence on how the sectoral composition of 4 exemplary countries changed as consequence of the optimization.

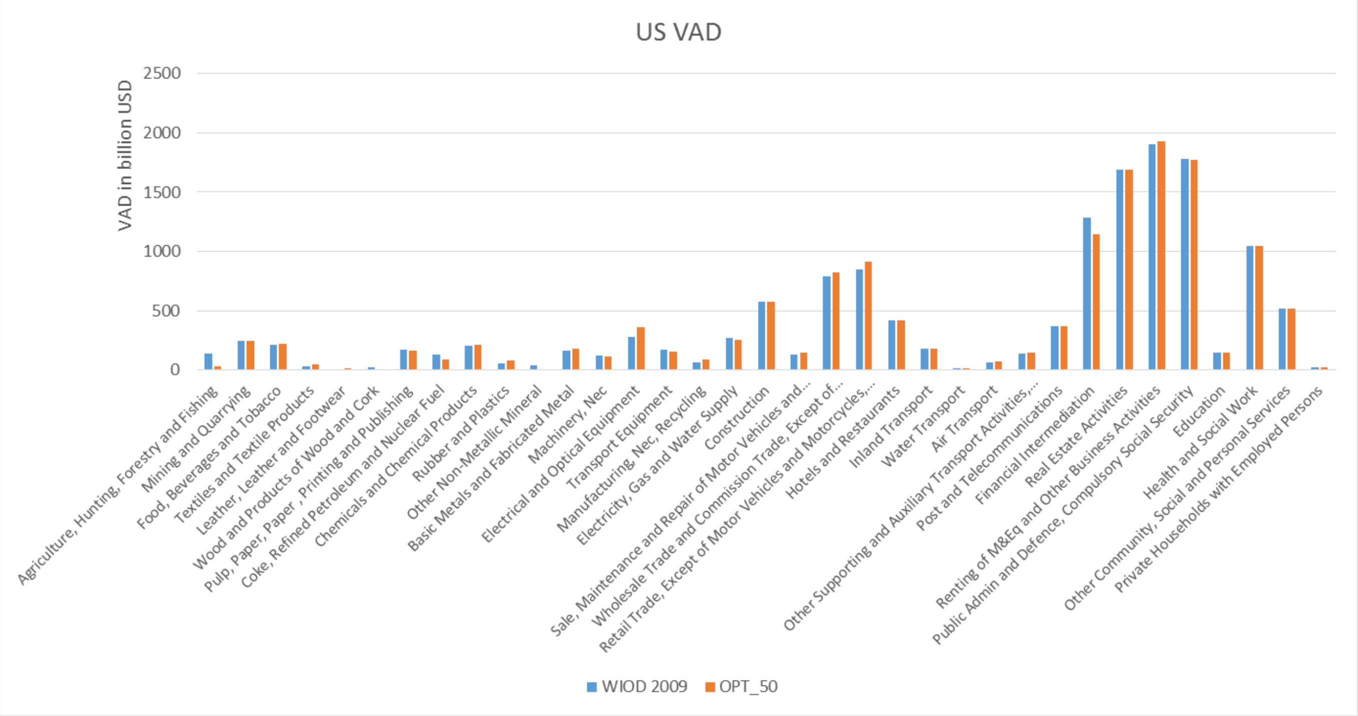

Figure S7: Structural composition of the USA in VAD for WIOD 2009 and OPT 50 in billion USD.

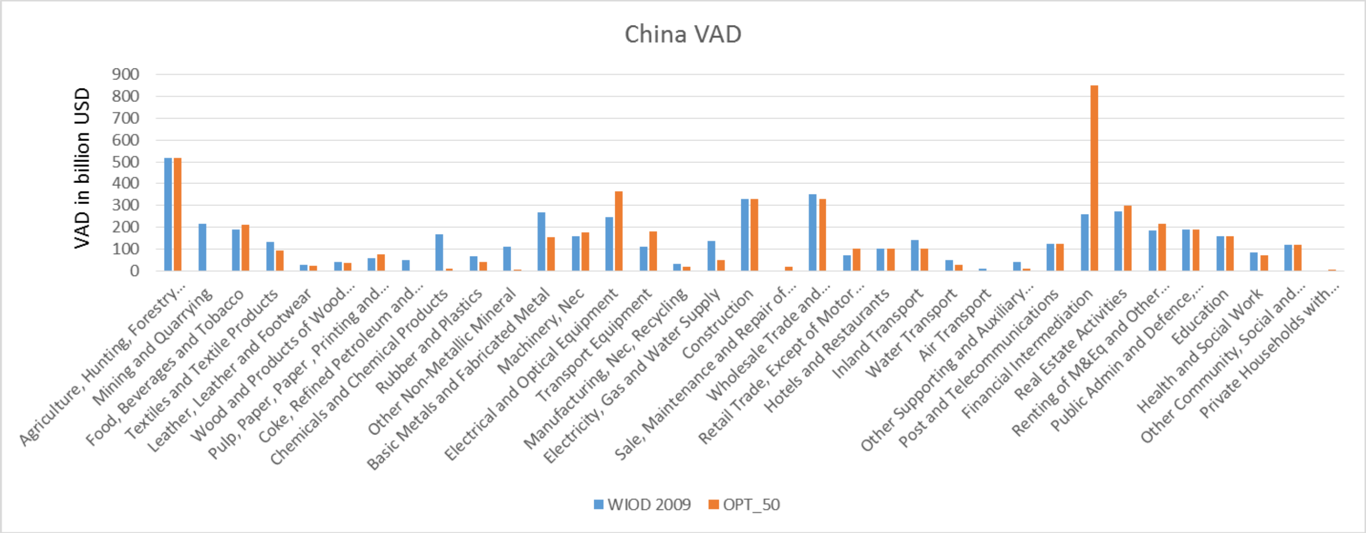

Figure S8: Structural composition of China in VAD for WIOD 2009 and OPT 50 in billion USD.

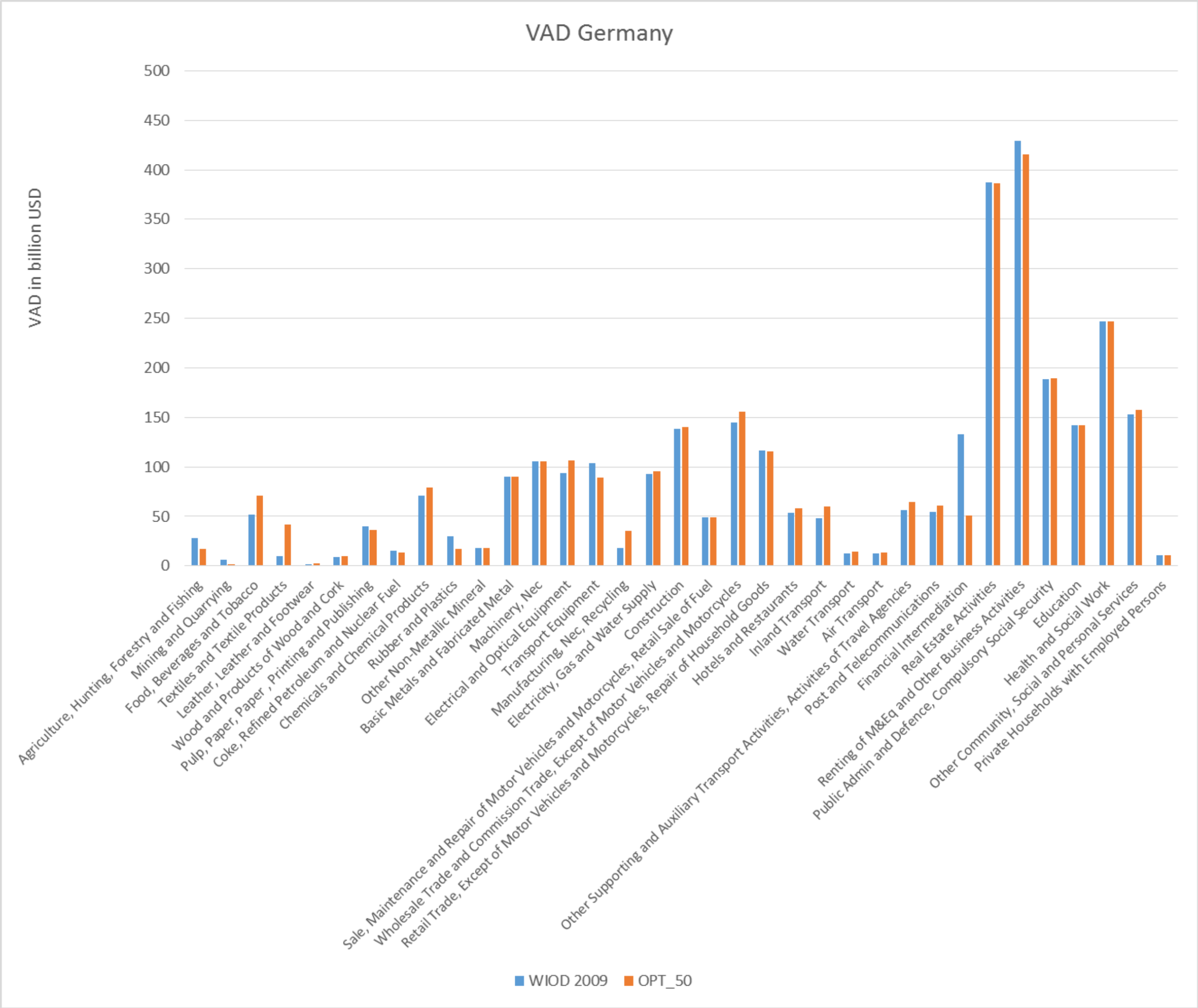

Figure S9: Structural composition of Germany in VAD for WIOD 2009 and OPT 50 in billion USD.

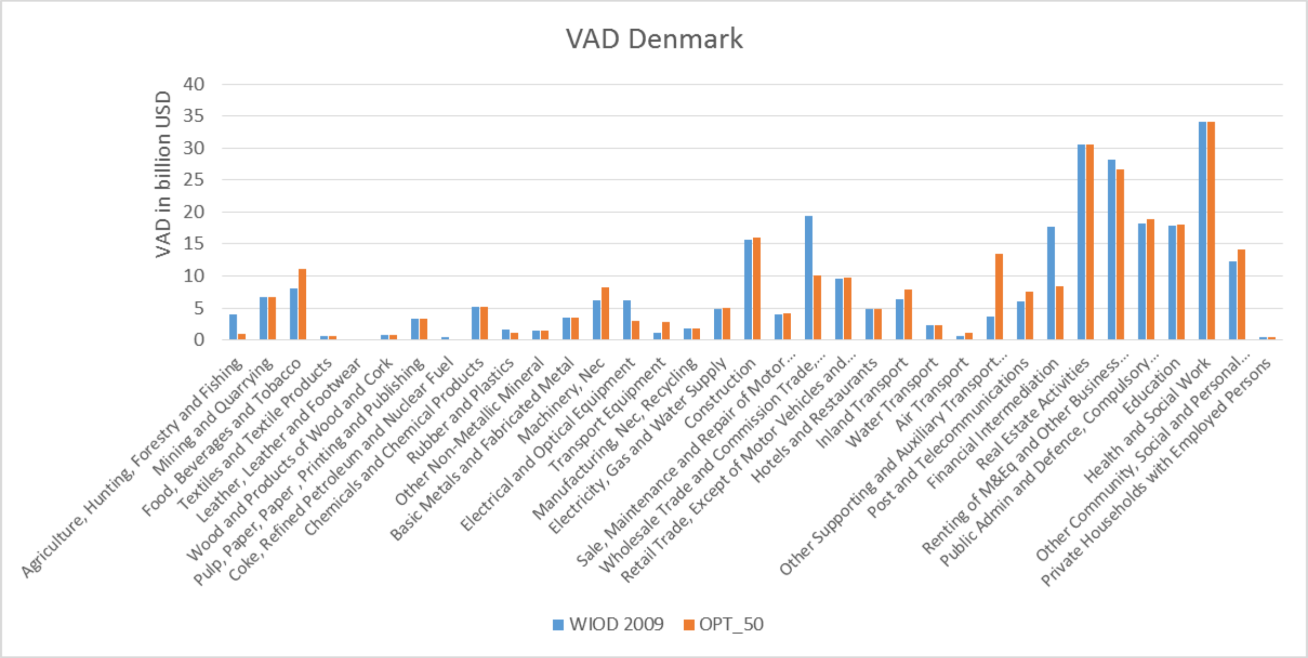

Figure S10: Structural composition of Denmark in VAD for WIOD 2009 and OPT 50 in billion USD.

SI 11 Disaggregating of “Chemicals” and “Fuels”

The following two figures give evidence on how the (sub-) sectoral composition of “Chemicals and Chemical Products” (“Chemicals”) and “Coke, Refined Petroleum and Nuclear Fuels” (“Fuels”) changed as consequence of the optimization. Evidence is gained by decomposing sector shares with the help of Exiobase 2.0.

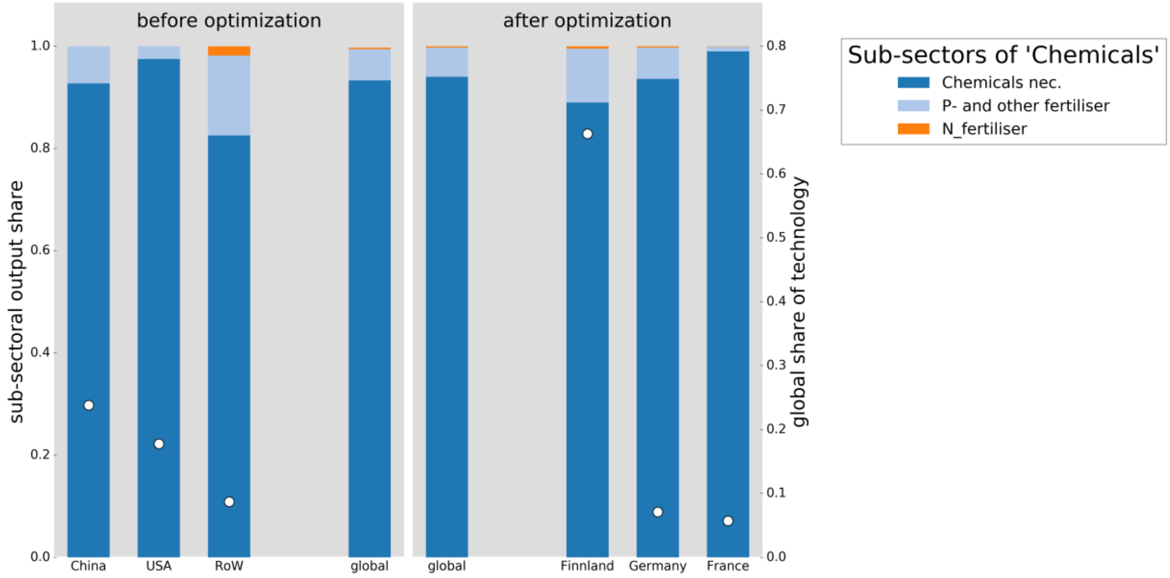

Figure S11: Relative composition of regional- and the global technology of “Chemicals and Chemical Products”, when disaggregating WIOD (2009) to the corresponding EXIOBASE 2.0 sectors (2007). The upper half depicts WIOD 2009 average technology and the most frequently used technologies (global production shares, white dot). The lower half depicts most frequently used technologies after optimization and the resulting new average technology. For both cases the most frequent applied technologies are depicted.

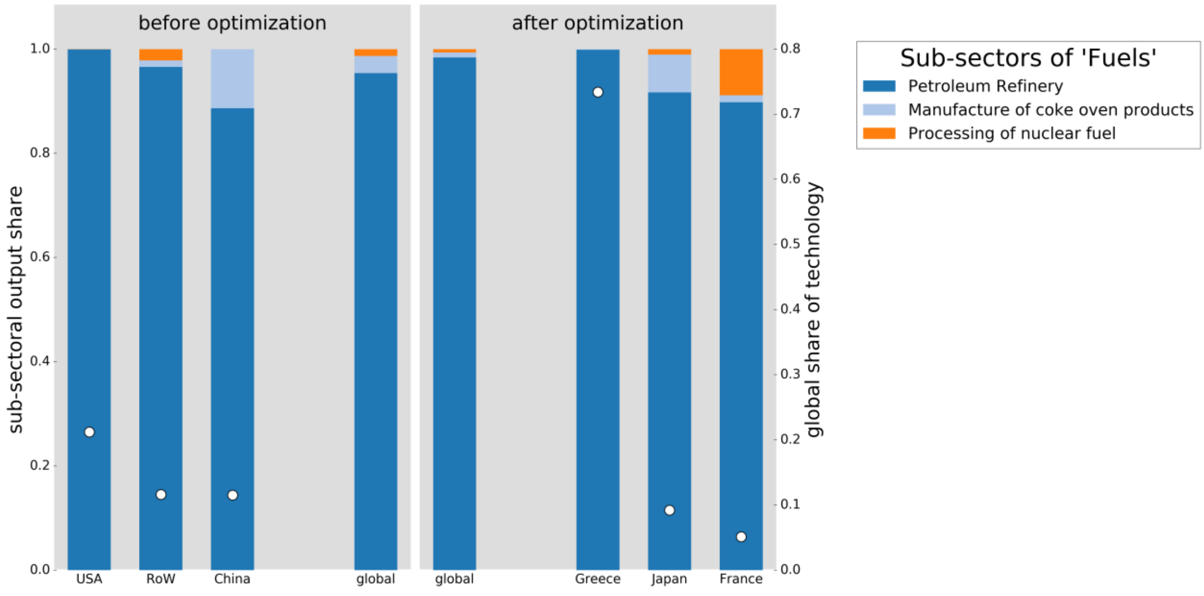

Figure S12: Relative composition of regional- and the global technology of “Coke, Refined Petroleum and Nuclear Fuel”, when disaggregating WIOD (2009) to the corresponding EXIOBASE 2.0 sectors (2007). The left side depict the initial state, the right side depicts technological composition after optimization. For both cases the three most frequent applied technologies are depicted with their corresponding share (white squares).

SI 12 Counterfactual analysis with aggregated sectors

SI 12 gives evidence, on how a further aggregation of sectors influenced optimization results For analyzing the impacts, we aggregated WIOD to 33 sectors and performed the optimization analysis please see the discussion for more detail.

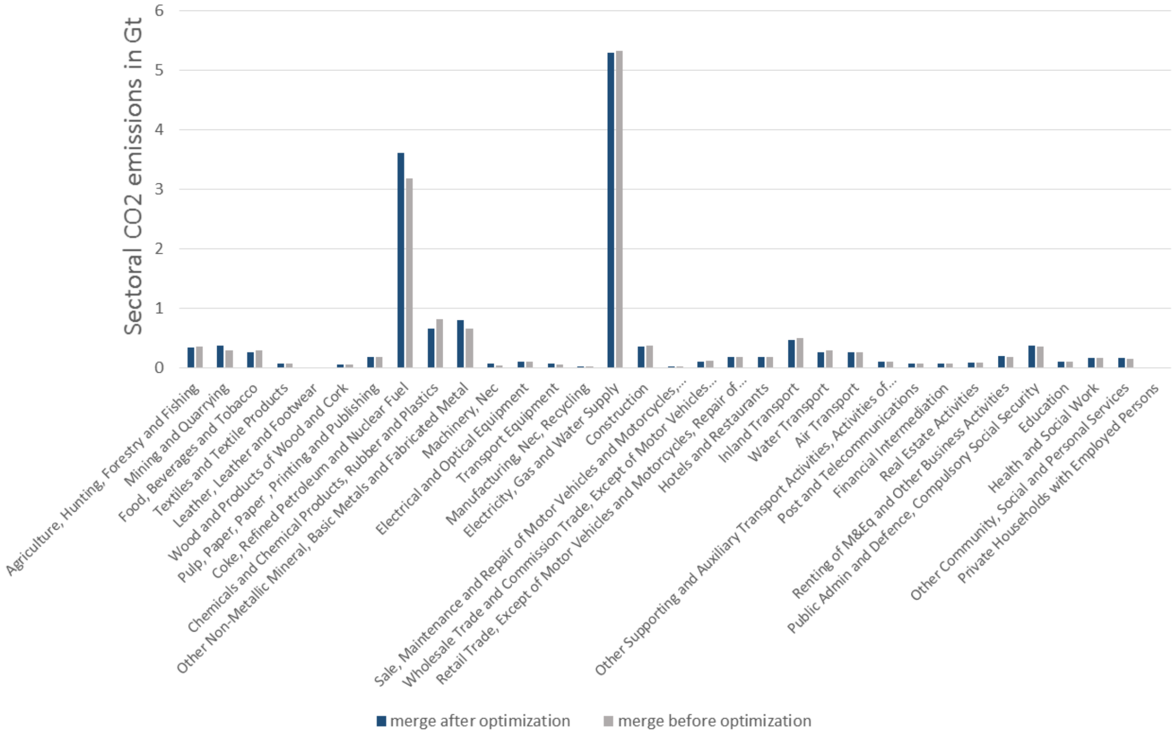

Figure S13: Evaluating the influence of sectoral aggregation on optimization results. For a counterfactual analysis “Chemicals and Chemical Products” and “Rubber and Plastics” as well as “Other Non-Metallic Minerals” and “Basic Metals and Fabricated Metals” have been merged before the optimization, results are given as grey bars. Blue color

represent the considered REF scenario where sectors have been merged after the optimization. The total amount of sectoral emissions is 15.2 Gt for the left (blue) case and 14.7 Gt for the right (grey) case.

Ang, B.W., Wang, H., 2015. Index Decomposition Analysis with Multidimensional and Multilevel Energy Data. Energy Econ. 51, 67–76.

Cristea, A., Hummels, D., Puzzello, L., Avetisyan, M., 2013. Trade and the greenhouse gas emissions from international freight transport. J. Environ. Econ. Manag. 65, 153–173.

GeoHack [WWW Document], n.d. URL https://tools.wmflabs.org/geohack (accessed 9.22.14).

IPCC, 2014. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Koesler, S., Pothen, F., 2013. The Basic WIOD CGE Model: A Computable General Equilibrium Model Based on the World Input-Output Database. ZEW Dok. NR 13-04.

Voigt, S., De Cian, E., Schymura, M., Verdolini, E., 2014. Energy intensity developments in 40 major economies: Structural change or technology improvement? Energy Econ. 41, 47–62.