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Notes

Abstract

Complying with the goals of the Paris Agreement on climate protection will require a substantial decarbonization of the global energy system by the second half of the century. Developing countries and emerging economies already account for more than half of global energy related emissions. Strong economic and demographic growth in these countries will drive future power sector expansions. At the same time, solar photovoltaics has experienced massive cost reductions in recent years. Despite substantially lower demand growth for electricity and comparably lower solar potentials, eight out of ten countries with the largest additions of solar PV installations in the last decade are highly developed countries. In this paper, we analyze the perspective towards solar PV integration by country development level. We firstly apply Kaya decomposition analysis to analyze emission dynamics by country groups. We find renewable energies to play a minor role in countries of low human development. Combining financing data and country specific solar irradiation potentials, we find that for many countries in the Global South, comparably inferior financing conditions overcompensate the higher irradiation potentials, making capital intensive renewable energy projects unviable. Our results highlight the importance of access to affordable finance for capital intensive renewable energy technologies, such as solar PV, and suggest that climate policies in countries of low human development should more decidedly focus on reducing risk premiums, if these are to represent an economically viable option for climate mitigation.

Contents

1 Introduction

Developing countries and emerging economies, the Global South[1], is home to 6 billion people, 79% of world population, and account for 53% of global energy related CO_2 emissions (Enerdata 2021). Comparably higher economic growth rates and a rising electricity demand will lead the power sector of these countries to substantially expand in future years (IEA 2018; IEA 2019, 2021a, 2021b). To a large extent, countries of lower human development have satisfied their rising energy demand through fossil fuels, leading to an increasing carbonization, visible in the increasing CO_2 intensity in primary energy supply (Figure 1). In the power sector, electricity demand growth in the has likewise primarily been satisfied by fossil fuels, most outstandingly coal, creating committed emissions during decades of operation of fossil-related power infrastructure (IEA 2019, Erickson 2015, Tong et al. 2019).

Complying with the goals of the Paris Agreement to keep global average temperature increase above pre-industrial levels well below 2°C will require substantially decarbonizing the global energy supply by the second half of the century, restricting cumulative greenhouse gas emissions (GHG) below a certain limit (IPCC 2018). The intergovernmental panel for climate change estimates this total carbon budget to be in the range of 300 Gt CO_2 and 900 Gt CO_2 for a 1.5°C or 2°C temperature increase stabilization target, respectively (83% likelihood) (IPCC 2021). While the global power sector currently represents the largest single GHG emitting sector, its relevance for climate change mitigation goes beyond its own emissions. The decarbonization of other sectors such as the transport, industry or building sector will rely – to different extent depending on technological pathways chosen – on a carbon neutral power sector. Key technologies to decarbonize the transport, industrial or buildings sector, such as electric vehicles, green hydrogen, or heat pumps will only reduce GHG emissions if powered by carbon neutral electricity. There are several alternatives to decarbonize the global power sector: Using fossil fuels with carbon capture and storage or direct air capture technologies represents a possibility, but these technologies still partly lack technological maturity and economic viability to be rolled out at a Paris-compatible pace at global scale (IPCC 2014). Nuclear energy also represents an option, its use is however associated with specific risks which often undermine its acceptance, while consideration of storage costs of nuclear waste, increased safety requirements and long permitting procedures make newly built plants uncompetitive (IPCC 2014). On the other hand, renewable energies (RE) for power generation represent a carbon-neutral, low risk and technologically mature power generation alternative. In the past decades, sharp cost reductions for key renewable energy technologies, most outstandingly for onshore and offshore wind turbines and solar photovoltaics (PV) have been observed, bringing their levelized costs of electricity (LCOE) to a competitive range with fossil fuels (see methods for further elaboration on LCOE) (IRENA 2020b). To a large extent, cost reductions are commonly attributable to lower equipment costs due to learning effects in their manufacturing. This decrease is explained by the learning rate, the well-understood relationship between cumulative installed volumes of a given technology and its LCOE (IRENA 2018). Most outstanding reductions have been observed for solar PV, for which a doubling in total installed capacities has led to a 37% decrease of its costs in the 2000-2010 timeframe, a rate substantially higher than onshore wind (23%) and offshore (10)% wind (IRENA 2020b). However, achieving low LCOE for capital intensive renewable energy projects, such as solar PV, requires financing capital expenditures at low interest rates, as

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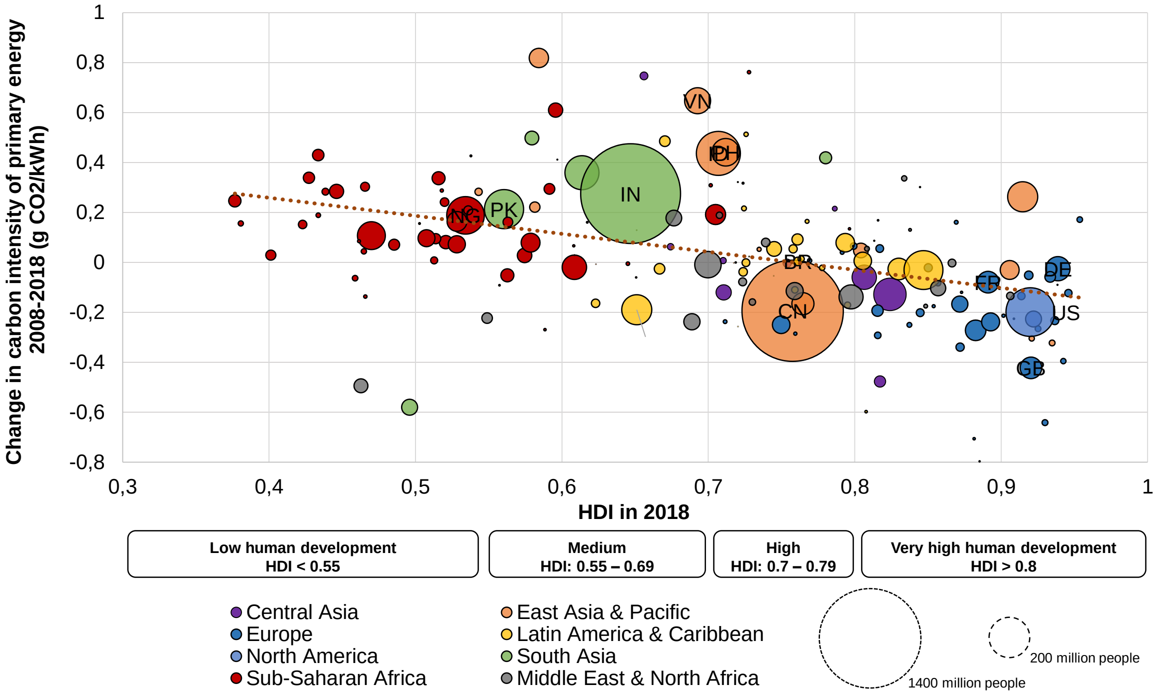
[1] Referring, in this context, to countries with a Human Development Index lower than 0.8 (see Figure 1 and section 4 for an overview of countries' categorization by human development level)

the cost structure of these projects characteristically entails comparably high upfront capital investments (Hirth et al. 2016; Steckel et al. 2018b, 2018a; UNEP 2020).

Figure 1: Change in carbon intensity of primary energy consumption between 2008 and 2018 vs. Human Development Index HDI

Own elaboration based on Enerdata 1 and UNDP17



To date, most of the installation of capital intensive renewable energies has taken place in highly developed countries. Eight of the ten countries with the highest capacity additions in solar PV in the timeframe 2010-2020 are highly developed western European countries, the United States, Japan, Australia and South Korea, as well as China (Enerdata 2021). Together, these countries comprised approx. about 90% of the 760 GW of global solar PV capacity additions in the observed timeframe. Total wind power capacity additions (465 GW) in the same timeframe show a similar picture, with seven out of ten countries with the highest capacity additions being highly developed countries of Europe (Germany, UK, France, Sweden, Spain) and North America (USA and Canada), and China, India and Brazil representing the remainder. Despite vast potentials in countries of the Global South, the integration or renewable energy to the energy system has just recently taken off (Enerdata 2021). Most outstanding examples are India and Vietnam, which added 37 GW and 17 GW of solar PV, respectively, in the same timeframe of 2010-2020 (Enerdata 2021). As for wind power, India (25 GW) and Brazil (16 GW) rank among the top countries with capacity additions.

Previous studies have analyzed the determinants of LCOEs for different power sector technologies (Egli et al. 2018; Ondraczek et al. 2015; Schmidt 2014; Waissbein et al. 2013), as well as the perspective of falling costs of renewable energies at global or country specific level (Creutzig et al. 2017; Pietzcker et al. 2014). However, an integrated perspective to the viability of capital intensive renewable energies in the power sector by country development level is not explicitly studied. Arguably, in absence of a global or effective national climate policy regime, the extent to which large investments in carbon neutral power technology are realized will strongly depend on their cost-competitiveness. In light of this, our study provides an in-depth analysis of the perspective of integration of solar PV to decarbonize the power sector by countries, classified by human development. We limit our study to solar PV for several reasons 1) due to its wide global availability,

2) the fact that it is the technology that has observed the largest cost reductions in recent years, 3) that it is widely claimed to already be cost competitive with fossil fuels, 4) the fact that further cost reductions are expected in years to come, 5) that it can be implemented at different scales, i.e. from stand-alone devices to residential or commercial systems to utility wide power plants, and is thereby a potential candidate for a large-scale integration (6) it can be easily combined with storage technologies such as batteries whose costs have also strongly fallen and are expected to further do so. For these reasons, solar PV is projected to play a pivotal role in the decarbonization of the global energy sector (IEA 2018; IEA 2021a, 2021b).

To provide a global picture of carbonization and decarbonization trends in the past decades and systematically analyze the state of RE integration across country development level, we first apply Kaya decomposition to country groups categorized by Human Development Index and analyze CO_2 emission drivers by development level. We then conduct extended Kaya decomposition to examine the role of renewable energies in carbon intensity changes (see methods section for detailed description). We examine financing data and solar PV potentials by development level and combine them to compute indicative LCOEs across countries by development level.

2 Results

Our empirical analysis of the drivers of CO_2 emissions by Human Development Index (HDI) is based on data on demographic development, economic growth, total primary energy supply and energy related CO_2 emissions. Data is retrieved from United Nations and Enerdata Global Stat, based on data of the International Energy Agency and World Bank. Our dataset includes data for 170 countries in the period 1990-2018.

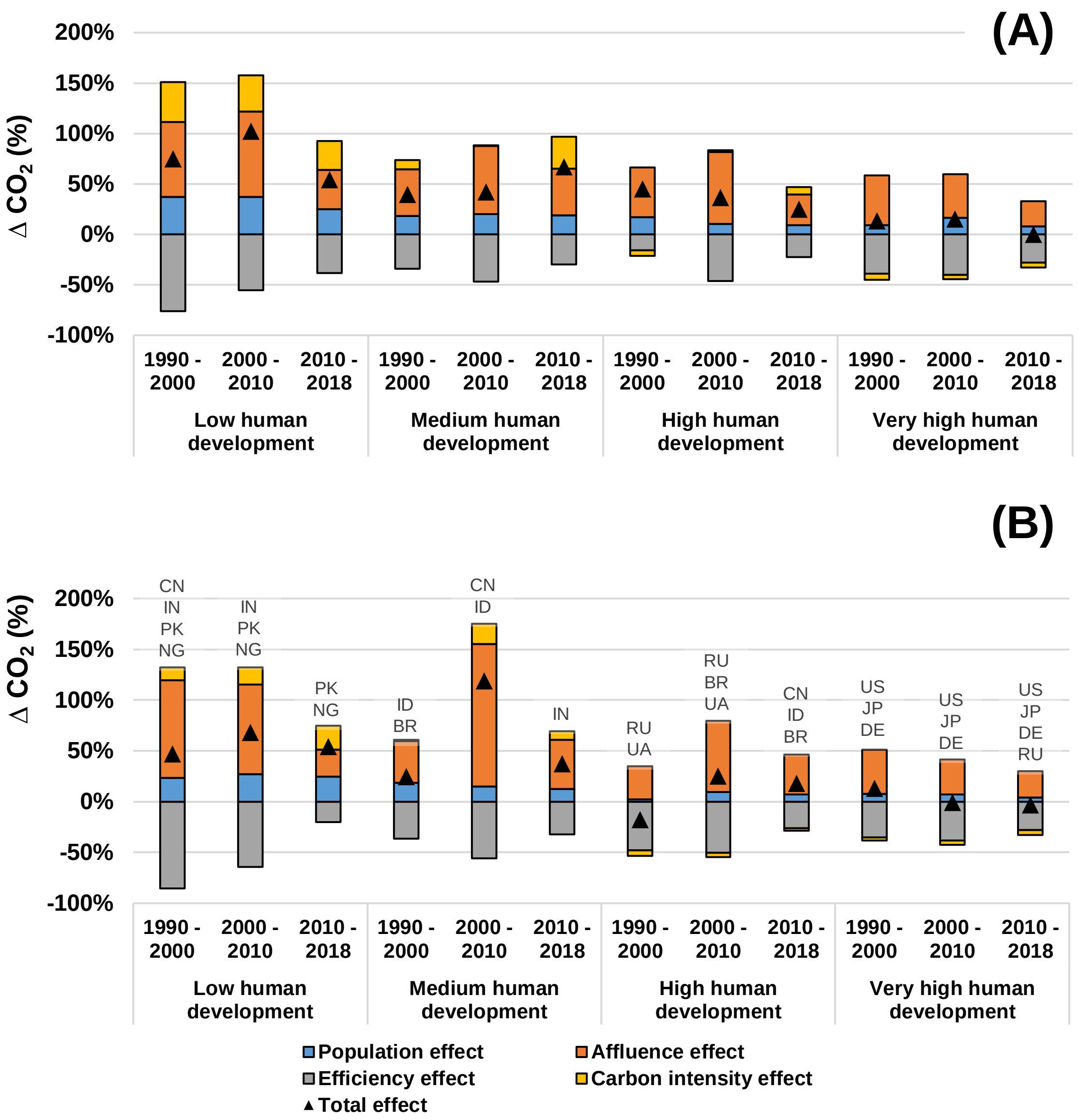
We further retrieve data on country-specific financing rates, more specifically, nominal commercial debt lending rates from the International Monetary Fund (IMF 2022). Data is available for 94 countries. We also retrieve data on country specific solar potential from the Global Solar Atlas (World Bank 2022). We match the financing data and solar potential data with the country specific HDI (UNDE 2019). We then systematically present the relationship between HDI and financing rates, and the juxtaposed data on renewable energy potentials and HDI. We compute indicative LCOE for countries in different world regions and development levels, and derive conclusions.

2.1 Drivers of CO_2 emissions by country development level

The Kaya decomposition allows decomposing the relative and absolute change of energy-related CO_2 emissions in a certain period into four effects. These effects are the population effect, the affluence effect (per capita GDP), the efficiency effect (energy intensity in terms of primary energy per GDP), and the carbon intensity effect (in terms of carbon emissions per primary energy, see Methods). The development of these effects was examined in three periods (1990-2000, 2000-2010, 2010-2018) and across the four development level groups (low, medium, high, very high) based on the average HDI of each country in the respective timeframe. To ensure the comparability of the effects in different development levels, the results are presented based on the relative change across the periods. We provide two sets of results on the Kaya drivers of CO_2 emissions, an *aggregated* and an *average* perspective. In the aggregated perspective, we decompose emission drivers for each development level group by firstly aggregating data over all countries in the respective group and then decomposing emissions. In this aggregated perspective, large economies such as USA, China, India, Russia, Indonesia, Pakistan or Nigeria have a dominant impact on their group results. In contrast, in the (arithmetic) average perspective, we decompose emissions for each country and then compute the arithmetic mean over all countries in the respective group to obtain the group results. Thus, in this average perspective, we give all countries the same weight. Table 3 in the methods section provides an overview on the share of the most influential countries in each human development group and for each Kaya factor. While neither approach is right or wrong, by contrasting them, we aim to account for the dominant impact of large economies on the results of their respective development level group. Figure 2 presents the development of each factor, as well as total emission change, for the average (A) as well as the aggregated (B) perspective for each development group in the considered time periods.

Figure 2: **Percentage changes in CO₂ emissions in each respective timeframe, decomposed by Kaya effects by development level groups in the (arithmetic) average perspective (A) and the aggregated perspective (B)**

Labels over the aggregated perspective show countries with a share higher than 25% in at least one of the group´s Kaya effects, while an overview of the shares of most influential countries in each group is provided in Table 3 in the methods section.



Both representations show how carbon emissions strictly grew for all periods in countries of low to medium human development. Growth in CO_2 emissions is, across all countries and development groups, most strongly driven by the affluence effect. For countries of low and medium human development, CO_2 emission growth was further driven by an increasing carbon intensity for all periods in their energy system, combined with a comparably higher population effect.

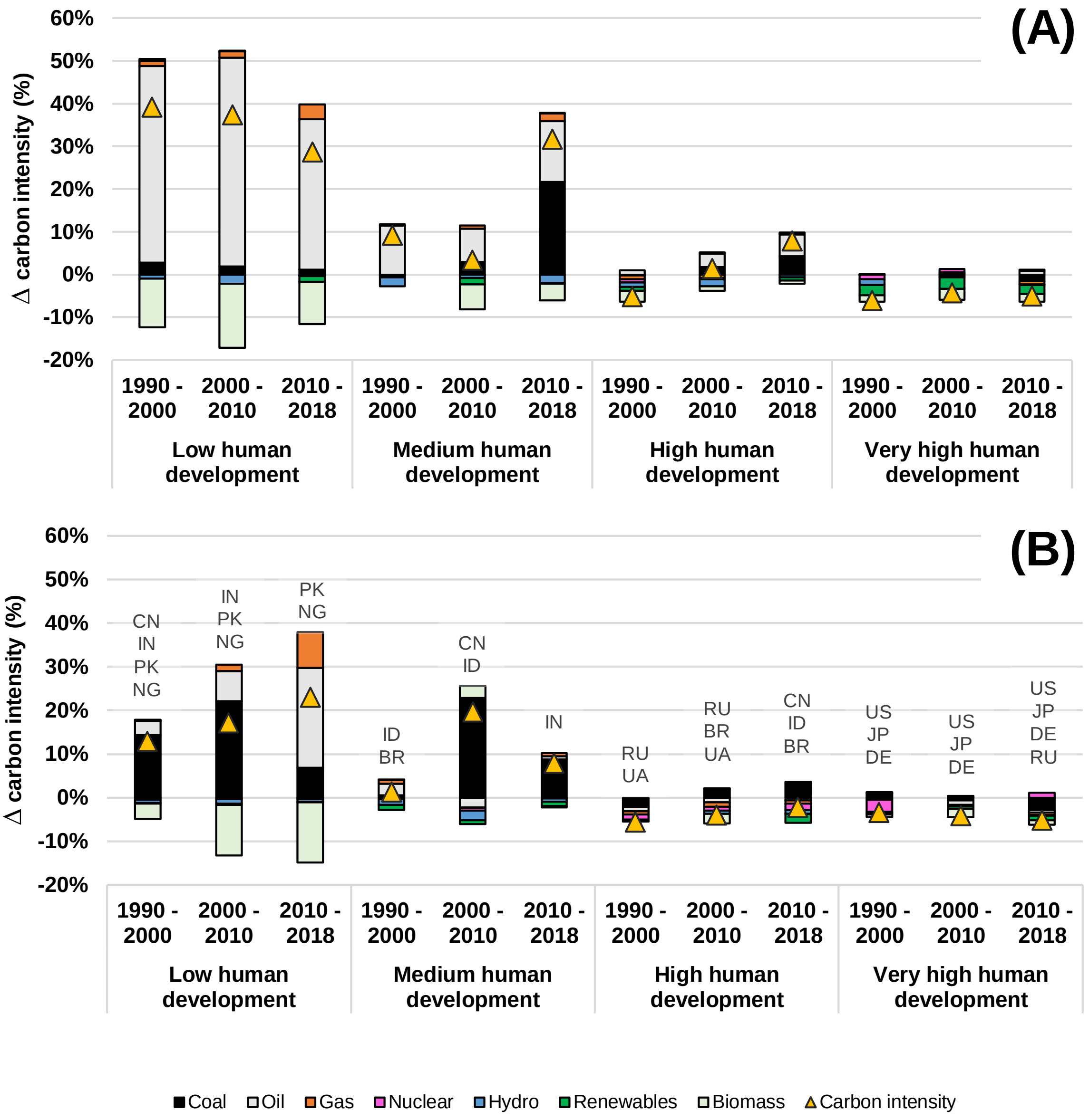
Countries of high and very high human development show a mixed picture, with a comparably smaller growth in total CO_2 emissions, resulting from a combination of a mostly slightly decreasing carbon intensity, and a comparably smaller population growth. The efficiency effect is negative across all countries and development groups, counteracting the affluence and population effects.

With exception of the group of countries of high human development in the period 1990-2000, strongly determined by the low population and economic growth of the former Soviet Union countries, only countries of very high human development have stabilized their emissions and only in the last two decades (Figure 2, B). A comparison between the aggregated and average perspective shows that the stabilization in emissions for highly developed countries between 2000 and 2010 is due to the effect of large countries in the group, e.g. the United States or Japan, as the effect is present in the aggregated perspective yet absent in the average perspective in the same timeframe. The group of countries of very high human development is mostly composed by Western European countries, the United States, Canada, and highly developed Asian countries, such as Japan or South Korea, among others.

To examine the role of renewable energies, referring to solar PV and wind power, on emission change by human development level, we decompose the (primary) carbon intensity effect into the effect of fuel carriers (Figure 3 and Table 1). An expansion of renewable energies over all time periods and in absence of a strong expansion of fossil fuels has only taken place in the group of very highly developed countries (Figure 3, A). However, the comparison between the average and the aggregated perspective shows that large countries of very high human development have decreased their carbon intensity rather by an increased use of nuclear energy (1990-2000) and the retirement of coal-fired power plants (2010-2018) than by a substantial increase in the use of renewable energies.

Figure 3: **Extended decomposition of carbon intensity effect into underlying energy carrier effects for each development level group in the average perspective (A) and the aggregated perspective (B)**

Labels over the aggregated perspective show the most influential countries in the respective human development group, while an overview of the shares of most influential countries in each group is provided in Table 3 in the methods section.



The increasing carbon intensity effect in the low human development group is mostly owed to increases in the consumption of fossil fuels, overcompensating the mitigating effects of the prevalent use of biomass[2]. On average, numerous countries of low human development strongly rely on expanded oil use, while coal and gas only play a minor (Figure 3, A). Some very large and rapidly expanding economies, such as India, China, Indonesia, Vietnam among others, have

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[2] Of note, biomass use might go along with deforestation and land use change, contributing to the release of land use, land use change and forestry related emissions. We limit our analysis to energy related emissions and account biomass use as a negatively contributing factor to carbon intensity change.

strongly relied on carbon intensive coal for the expansion of their power sector, a development identified by scholars as the *renaissance of coal* (Edenhofer et al. 2018; Steckel et al. 2015) (Figure 3, B).

Table 1: Kaya decomposition analysis of CO_2 emission drivers

(p= population, a= affluence, e=energy intensity and k=carbon intensity) by country development groups and extended Kaya decomposition of the carbon intensity effect by fossil carriers in the average and aggregated perspective.

Average perspective	**p**	**a**	**e**	**k**	*Coal*	*Oil*	*Gas*	*Nuclear*	*Hydro*	*RE*	*Biomass*	**Δ CO_2 (%)**
Low human development												
1990 - 2000	37.4%	74.2%	-76.2%	39.2%	2.9%	45.9%	1.2%	0.0%	-0.9%	0.4%	-11.4%	**74.6%**
2000 - 2010	34.6%	72.1%	-66.6%	37.3%	1.9%	48.8%	1.5%	0.0%	-2.1%	0.2%	-15.0%	**77.4%**
2010 - 2018	25.1%	38.5%	-38.2%	28.6%	1.2%	35.1%	3.4%	-0.1%	-0.3%	-1.2%	-9.9%	**54.0%**
Medium human development												
1990 - 2000	18.2%	46.2%	-34.2%	9.2%	-0.1%	11.5%	-0.2%	-0.4%	-2.0%	0.0%	0.3%	**39.4%**
2000 - 2010	25.7%	86.9%	-34.0%	3.3%	3.0%	7.8%	0.7%	0.0%	-0.8%	-1.4%	-5.9%	**81.8%**
2010 - 2018	18.7%	46.3%	-29.9%	31.6%	21.7%	14.3%	1.7%	0.0%	-1.9%	-0.2%	-3.8%	**66.7%**
High human development												
1990 - 2000	17.0%	49.3%	-16.1%	-5.2%	-0.2%	1.1%	-0.9%	-0.9%	-1.1%	-0.8%	-2.6%	**45.0%**
2000 - 2010	10.4%	71.4%	-46.6%	1.3%	1.7%	3.3%	-0.7%	-0.3%	-1.6%	0.2%	-1.1%	**36.6%**
2010 - 2018	9.3%	30.1%	-22.3%	7.8%	4.2%	5.2%	0.3%	0.0%	-0.6%	-0.8%	-0.8%	**24.8%**
Very high human development												
1990 - 2000	9.0%	49.6%	-39.1%	-6.2%	0.0%	0.0%	0.0%	-1.2%	-1.2%	-2.5%	-1.4%	**13.3%**
2000 - 2010	16.3%	43.5%	-40.4%	-4.3%	0.3%	-0.4%	0.3%	0.7%	-0.3%	-2.6%	-2.6%	**15.1%**
2010 - 2018	7.8%	25.0%	-27.8%	-5.1%	-1.5%	0.8%	-0.8%	0.4%	-0.1%	-2.1%	-1.7%	**-0.2%**
Aggregated perspective	**p**	**a**	**e**	**k**	*Coal*	*Oil*	*Gas*	*Nuclear*	*Hydro*	*RE*	*Biomass*	**Δ CO_2 (%)**
Low human development												
1990 - 2000	23.1%	96.4%	-85.3%	12.9%	14.3%	3.3%	0.3%	-0.5%	-0.7%	-0.1%	-3.6%	**47.1%**
2000 - 2010	27.3%	88.0%	-64.3%	17.2%	22.1%	6.9%	1.5%	-0.3%	-1.0%	-0.3%	-11.6%	**68.2%**
2010 - 2018	24.5%	26.9%	-20.2%	23.1%	6.9%	22.8%	8.2%	-0.4%	-0.6%	-0.2%	-13.7%	**54.3%**
Medium human development												
1990 - 2000	18.4%	41.1%	-36.4%	1.3%	0.6%	2.7%	0.8%	-0.3%	-1.3%	-1.2%	0.1%	**24.5%**
2000 - 2010	15.0%	140.0%	-55.8%	20.1%	22.8%	-2.2%	-0.2%	-0.7%	-2.1%	-0.9%	2.9%	**119.3%**
2010 - 2018	12.5%	48.6%	-32.0%	7.9%	8.7%	0.8%	0.6%	-0.2%	-0.7%	-1.0%	-0.4%	**37.1%**
High human development												
1990 - 2000	2.2%	33.0%	-48.1%	-5.0%	-2.0%	-1.1%	-0.8%	-1.2%	-0.2%	0.0%	-0.2%	**-17.9%**
2000 - 2010	9.7%	70.0%	-50.6%	-3.8%	2.0%	-1.0%	-1.1%	-0.8%	-0.8%	0.1%	-2.2%	**25.3%**
2010 - 2018	7.1%	39.1%	-26.4%	-2.0%	3.4%	-0.7%	-0.7%	-1.3%	-1.0%	-2.1%	0.3%	**17.8%**
Very high human development												
1990 - 2000	7.5%	43.6%	-35.0%	-2.9%	0.9%	0.3%	-0.5%	-2.8%	-0.3%	-0.2%	-0.7%	**13.1%**
2000 - 2010	6.8%	34.5%	-38.4%	-3.9%	-0.6%	-1.1%	0.3%	-0.2%	0.0%	-0.7%	-1.8%	**-1.0%**
2010 - 2018	4.3%	25.6%	-28.3%	-4.8%	-2.8%	-0.6%	-0.5%	1.1%	-0.1%	-1.1%	-1.0%	**-3.1%**

Overall, the results illustrate how predominantly only very high developed countries stabilized their carbon emissions and only in the last two decades. A substantial integration of renewable energies remains largely absent in countries of low and medium human development, while the comparably dominant use of coal, gas and oil has substantially increased the carbon intensity of energy supply.

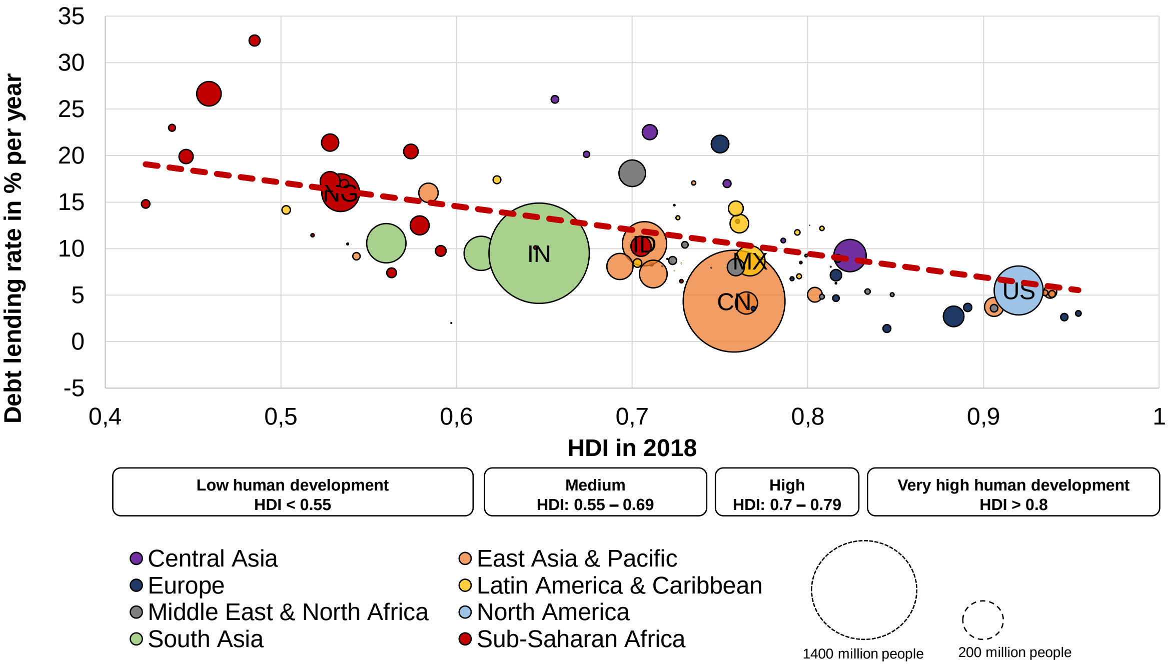
2.2 LCOE Determinants by country development level

High up-front investments and the almost insignificant variable costs make RE projects highly sensitive to the faced financing conditions. Based on the publicly available IMF nominal commercial debt lending rates in 2018 for 94 countries, we present the relationship between the level of human development and the country specific debt interest rates from commercial banks (Figure 4). Assuming a linear functional relationship, a HDI decline of 10 percentage points goes along with an increase in interest rates for commercial debt of 2.5 percentage points. Most countries with a

HDI lower than 0.7, e.g. countries in South Asia or Sub-Saharan Africa, are characterized by double-digit lending rates, reflecting comparably challenging conditions for the financing of capital intensive RE technologies. In contrast, most European countries, as well as the USA, China and East Asian countries feature moderate or low single-digit lending rates. Of note, these interest rates rather reflect the general country-specific risks – those present uniformly across all economic sectors – than project-specific risks, unique to power sector investments and specifically those using RE technologies. Nevertheless, there is no reason to assume that solar PV or other RE projects are systematically exempt from country specific risks. Decreasing interest rates with increasing level of human development are no coincidence. Investments in developing and emerging countries are commonly exposed to higher political risks (e.g., political instability or political crisis), macroeconomic risks (e.g., economic instability, inflation, currency volatility), legal risks (e.g. less reliable legal environment, higher level of corruption, lower state capacity) than industrialized countries, and thus respective country risk premiums in countries of lower human development can be expected to be higher (Waissbein et al. 2013).

Figure 4: Commercial debt lending rates as of January 2019 in % per year based on (IMF Data 2021) in relation to HDI

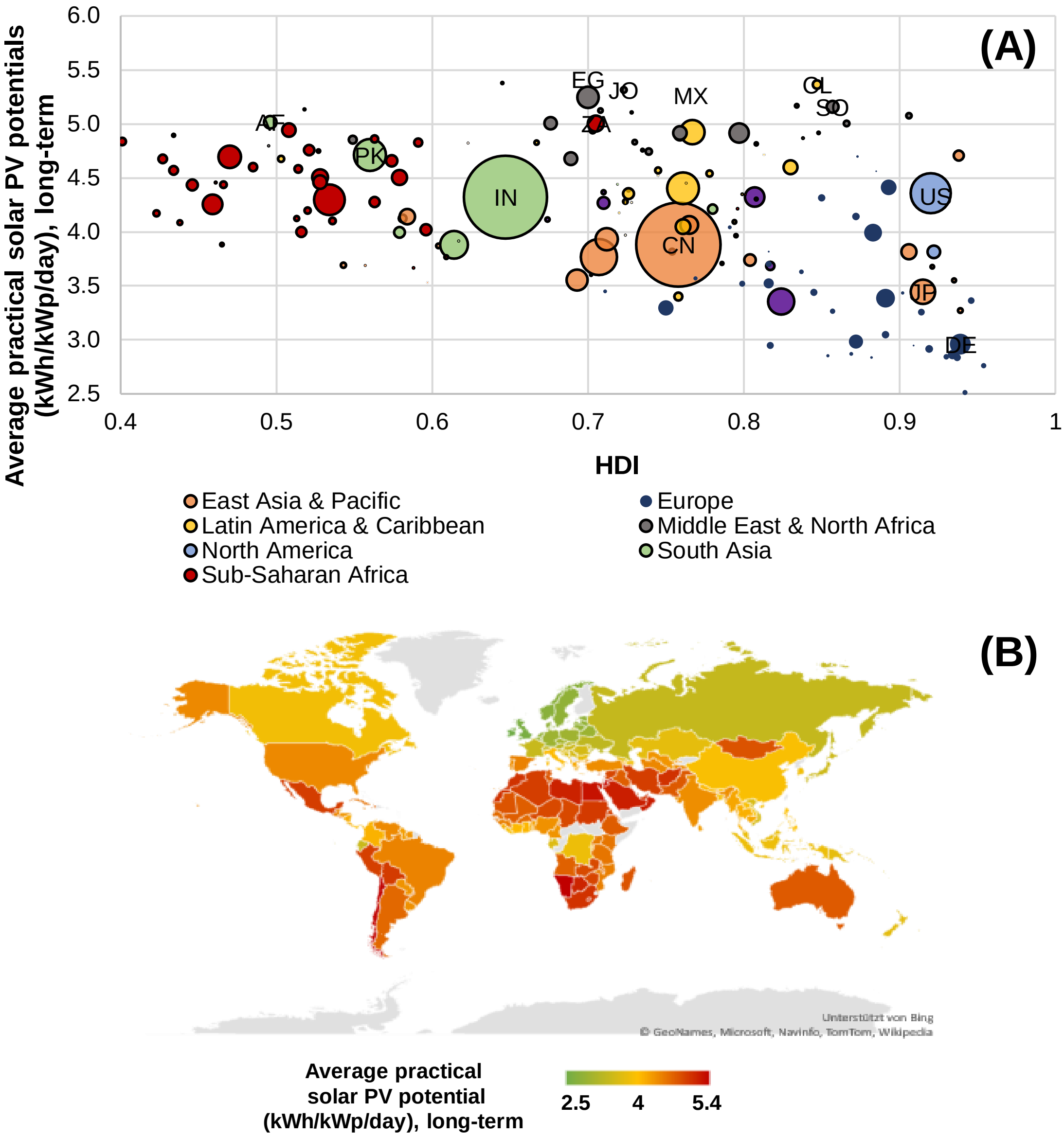
Size of the bubbles reflects the population of the respective country in 2018



Aside from the faced financing costs and the globally determined technology costs, the LCOE of a specific RE project are evidently determined by the available local renewable resources and the resulting electricity output of the project (see LCOE definition in methods). Solar PV potentials vary significantly depending on the location. The available resource quality is determined by the solar radiation, the seasonal variability of the radiation, and air temperature. These parameters allow the computation of the average practical PV potentials of a country, expressed as capacity factors in kWh/kWp/day (for an extended definition, see *World Bank 2020* (World Bank Group 2020)). We juxtapose the average practical solar PV potentials by countries with the HDI (Figure 5), finding that many countries of low human development are located in world regions with comparably very high potentials, while many very highly developed countries are located in Europe, with comparably worse potentials. Particularly countries in Sub-Saharan Africa and the Middle East are characterized by nearly twice as high average practical PV potentials than Central and Northern European countries, as for instance cloudy Germany, UK or the Netherlands. In addition, highly populated emerging economies such as India, Pakistan, Egypt, are also found to have very promising PV potentials.

Figure 5: **Average practical PV potential in kWh/kWp/day**

(A) as map, (B) in relation to HDI and population (bubble size) in 2018 based on Solar Global Atlas(World Bank Group 2020)



2.3 LCOEs by world regions

To which extent LCOE for solar PV in a given country are competitive with alternative energy sources is contingent on whether the combination of financing conditions and available practical potentials lead to competitive LCOE.

By combining the country specific commercial debt lending rates with the country specific solar PV potentials, we compute country specific, indicative LCOE. While LCOE are typically computed by using the weighted average cost of capital (WACC), comprising both cost of equity and debt, we regard the use of typical commercial debt lending rates only as indicative for a lower bound estimate of country specific capital costs. Costs for equity are typically higher than commercial debt, reflecting the higher risk of shareholders relative to commercial lenders in case of bankruptcy. Thus, in absence of a global dataset on country-specific equity costs, our indicative country specific LCOE can be interpreted as a lower bound for financing costs, informative in the comparison between countries rather than in its absolute height. Figure 6 graphically presents the LCOE as a function of country specific commercial nominal lending rates with the country specific practical solar PV potentials for all countries in which both data are available. More specifically, Figure 6 presents isoquants of LCOE depending on capacity factor (horizontal) and commercial debt interest rates (vertical) at the global average[3] total upfront technology expenditures of USD 1200 per kWp.

Notably, countries of very high human development (mostly European and East Asian countries) are characterized by both more favorable financing conditions (largely below 10% per year) and comparably low irradiation potentials (less than 4 kWh/kWp/day), and thus located in the left and lower part of the figure. Most countries have typical LCOE between the isoquants of 50 USD/MWh and 100 USD/MWh, i.e. in the lower range of fossil fuels LCOE (50-177 USD/MWh) in absence of carbon pricing(IRENA 2020a). Most countries of Latin America and South Asia, belonging to the group of countries of low to medium human development, have better solar irradiation potentials (3.7-4.9 kWh/kWp/day), yet face higher interest rates (5%-17%) than European countries, and hence their indicative LCOE are above most highly developed countries. Notably, the high lending rates present in countries of very low human development overcompensate the effect of higher solar PV potentials on LCOE. Countries in Sub Saharan Africa, home to most least-developed countries, have comparably inferior financing conditions (7%-33%), many with interest rates above 10%. Paired with comparably high solar irradiation potentials (3.9-5.2 kWh/kWp/day), LCOE range between 50 USD/MWh and 250 USD/MWh, showing a wide cost range, yet with many countries showing a substantial distance to the fossil fuel cost range. Finally, countries of the Middle East have excellent solar potentials (4.7-5.2 kWh/kWp/day) and financing rates mostly between 5-10%, resulting in LCOE in a comparable level to highly developed countries.

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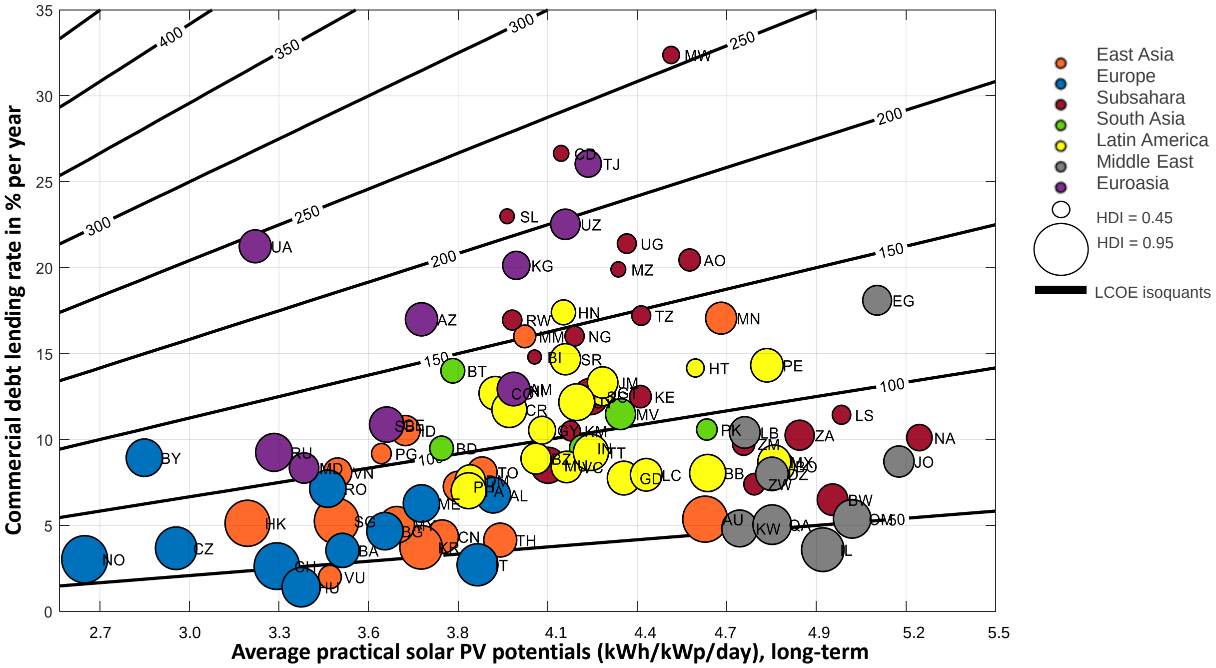
[3] While technology costs may vary across regions, the manufacturing of global solar PV cells production is highly concentrated in China and East Asian countries. For the sake of the analysis, we assume prices in the global market to be rather uniform across countries and world regions, highlighting the effect of financing rates and potentials on LCOE.

Figure 6: Isoquants of indicative solar PV LCOE depending on capacity factor (horizontal) and commercial debt lending rates (vertical)

At a technology cost level of 1200 USD/kWp, Scatter elements represent countries by world region, while the size of the elements represents the HDI in 2018. Own elaboration based on potentials from Global Solar Atlas 2020 and country specific nominal interest rates from the International Monetary Fund



3 Discussion and conclusion

Developing countries and emerging economies already emit over half of the global CO_2 emissions. Our Kaya analysis shows how despite the time window for the achievement of the goals of the Paris Agreement is closing, almost exclusively countries of very high human development have achieved a small reduction on energy related CO_2. This effect is attributable to the combination of an improving energy- and decreasing carbon intensity, in the context of a comparably lower population and economic growth. Most developing countries and emerging economies, characterized by a strong population and economic growth, still satisfy their growing energy demand by fossil fuels. The emission dynamics in countries other than very high human development level raises the question on how to decarbonize energy systems in developing and emerging economies.

Our study highlights that despite comparably outstanding solar PV potentials, prevalent high interest rates for many countries of lower human development still make a large scale implementation of capital intensive solar PV projects an unviable alternative, even in light of falling technology costs. Indeed, while technology costs for solar PV and other RE technologies have shown a massive decrease in recent years, risk-reducing stable and accountable regulatory and policy frameworks, coupled with guaranteed long-term offtake agreements to minimize the project-specific risks in the developing world, will be much needed for RE investments to materialize. Beyond our study, the presented findings on prohibitive financing rates in countries of low human development are also highly relevant for other capital intensive climate mitigation technologies, such as other RE technologies, e.g. wind or geothermal power, but also for nuclear energy, carbon capture and storage or utilization, direct air capture facilities, electrolyzers for green hydrogen production, batteries for storage of electricity, etc., in which high upfront capital expenditures and high interest rates make projects unviable. Arguably, carbon pricing can make renewable energy projects competitive with fossil fuels, while support schemes for renewables, such as feed-in tariffs or feed-in premiums, have shown to foster large-scale RE uptake. Yet, it remains unclear to which extent these instruments create regulatory certainty and thereby reduce the cost of equity and debt and thus the overall LCOE. Next to climate change mitigation, affordable electricity access plays a pivotal role in poverty reduction, most relevant in countries of lowest human development. Over 700 million people live in absolute poverty (at a 1.9 international USD per day poverty line) and without access to electricity (World Bank 2021). In this light, both from a climate mitigation, as well as from a poverty reduction perspective, climate policies in these countries should go beyond approaches of carbon pricing and or renewable support schemes, and decidedly be designed focusing on reducing risk premiums, providing regulatory certainty and assuring access to affordable finance. Options include backing RE projects by central or regional governments, guarantees from credible offtakers, pooling projects across different geographies, solar parks with a plug-and-play model, among many others.

Our study also has several limitations. In order to focus on country comparisons, it simplifies LCOE as a function of financing conditions and average solar PV potentials, using only commercial debt to approximate the cost of capital. In reality, the cost of capital is determined by the weighted average cost of capital, comprising cost of equity and debt. Also, financing costs are determined by the project-specific risks, and country-specific lending rates do not necessarily apply to specific RE projects. Indeed, recent projects results in countries with comparably high commercial debt rates, such as Argentina or Mexico have shown very low bids in their renewable energy procurement auctions, hinting to the possibility of low financing conditions despite overall higher country risks (Timilsina 2020). Also, the presented solar PV potentials do not reflect the exact distribution of potentials, possibly omitting making reference to the best potentials on the one hand, but also to a discrepancy between potentials' location and demand centers. Likewise, LCOE of variable renewables do not reflect total system costs, which include, inter-alia, grid expansion and flexibility options. Our results provided rather offer an indication of characteristic and indicative LCOEs, and the challenges associated with financing capital intensive RE projects in countries of lower human development, despite the existence of excellent renewable resources.

4 Methods

Human Development Index (HDI)

The HDI is an indicator that encompasses the dimensions of the standard of living, health, and education. Each dimension is represented through dimension indexes, composed by specific sub-indicators. The standard of living index is represented by the proxy gross national income per capita, the dimension of health by life expectancy at birth (in years), and education by the expected years of schooling and the mean years of schooling. To create standardized indexes ranging from 0 to 1, for each of the four sub-indicators minimum and maximum values are defined based on historical evidence (see Table 2).

Table 2: Minimum and maximum values of HDI sub-indicators (source: own elaboration based on (UNDP 2019, p. 2))

Dimension	Indicator	Minimum	Maximum
Standard of living	Gross national income per capita (2011 PPP $)	100	75,000
Education	Expected years of schooling (years)	0	18
	Mean years of schooling (years)	0	15
Health	Life expectancy (years)	20	85

With these values being set, for each of the indicators a dimension index is calculated as follows (UNDP 2019, p. 2):

$$Dimension\ index = \frac{actual\ value - minimum\ value}{maximum\ value - minimum\ value}$$

To account for the decreasing utility or capability from increasing income, the income dimension index is calculated based on the logarithm of the actual, minimum, and maximum value. The HDI is composed of the geometric mean of the single dimension indexes using for education the arithmetic mean of both sub-indexes. Based on the total result the UNDP in its Human Development Report groups countries according to the following intervals, here referred to as human development level groups: Very high human development (0.800 and above), high human development (0.700 – 0.799), medium human development (0.550 – 0.699), and low human development (below 0.550) (UNDP 2019, p. 3).

Kaya decomposition

The decomposition analysis is carried out to investigate the carbon emission dynamics and the impact of the underlying socio-economic drivers on energy related carbon emissions. The methodology of the decomposition of carbon emissions is founded on the Kaya identity, an adaption of the more general IPAT-identity, introduced by Kaya in 1990. This formula decomposes the total carbon emissions (F) into a product of population (P), per capita GDP (G), primary energy intensity (E), and carbon emissions (F):

$$F = P * \frac{G}{P} * \frac{E}{G} * \frac{F}{E} = P * a * e * c \tag{1}$$

The same fundamental relation can also be expressed as the multiplication of the population (P) with the relative indicators GDP per capita/affluence (a=G/P), primary energy intensity (e=E/G), and carbon intensity (c=F/E). This central identity forms the basis for many decomposition approaches for emission such as those performed by the IEA (IEA 2020). Nevertheless, there also relevant caveats such as the assumption of completeness of the four driving factors for explaining all emissions, as well as the supposed independence between the driving factors. In fact, in case of the latter assumption, there is large evidence for interaction between population and economic growth as well as economic growth and technological change (IPCC 2000).

For the actual decomposition of the change of any aggregate, e.g. also energy demand or energy intensity, into pre-defined driving factors there exist a multitude of different methodological approaches (Bhattacharyya 2019). Generally, these techniques can be distinguished into perfect decomposition methods which allow a complete decomposition without a residual, unlike conventional techniques that do not. Further, it can be differentiated between models that allow an additive decomposition of the change in the aggregate, i.e. the absolute change of the aggregate can be split and attributed additively to the underlying factors, and multiplicative models which disentangle the relative change of the ratio as a product of the ratios of all effects (Ang et al. 2003).

For the purpose of this study the Complete Laspeyres Index Method, originally developed by (Sun et al. 2000), was applied in its adapted form as used in (Steckel et al.). This method was selected because of its desirable feature of leaving no residual, its suitability for cross-country/regional decompositions, the possibility for an extended decomposition of the carbon intensity, and its understandability and the simplicity of its implementation (Zhang et al. 2001). The additive property of this method allows expressing the absolute change of carbon emissions from fuel combustion between period t and t' (ΔF) as the sum population effect P_f, affluence effect a_f, efficiency effect e_f and carbon intensity effect c_f:

$$F(t') - F(t) = \Delta F = P_f + a_f + e_f + c_f \tag{2}$$

The calculation of the contribution of each effect is conducted as shown exemplified in the following for the population effect P_f:

$$\begin{aligned} P_f = {} & \Delta P * a_t * e_t * c_t + \frac{1}{2} * (\Delta P) * [(\Delta a) * e_t * c_t + a_t * (\Delta e) * c_t + a_t * e_t * (\Delta c)] \quad + \frac{1}{3} * (\Delta P) \\ & * [(\Delta a) * (\Delta e) * c_t + (\Delta a) * e_t * (\Delta c) + a_t * (\Delta e) * (\Delta c)] \quad + \frac{1}{4} * (\Delta P) * (\Delta a) \\ & * (\Delta e) * (\Delta c) \end{aligned} \tag{3}$$

For a deeper analysis of the dynamics of carbon intensity, Steckel et al. proposed an extended decomposition of the carbon intensity effect c_f enabling a decomposition of the change in carbon intensity into the changes in the respective supply of energy carriers. The following formula describes the relationship between the carbon intensity and the energy supply of a specific energy carrier E_{jt}, with j indexing the different energy carriers, and c_{jt} being the energy carrier-specific carbon intensity between t and t':

$$c_{t'} = c_t * \frac{E_t}{E_{t'}} + \sum_j \left(\frac{c_{jt'} * E_{jt'} - c_{jt} * E_{jt}}{E_{t'}}\right) \tag{4}$$

This formula can be further manipulated based on the definition provided in (5):

$$E_t = E_{t'} - \sum_j (\Delta E_j) \tag{5}$$

$$c_{t'} = c_t * \frac{E_{t'} - \sum_j (\Delta E_j)}{E_{t'}} + \sum_j \left(\frac{c_{jt'} * E_{jt'} - k_{jt} * E_{jt}}{E_{t'}}\right) \quad (6)$$

This can be rearranged to express Δc based on the changes in energy carrier structure and their specific carbon intensities:

$$\Delta c = \frac{1}{E_{t'}} * \sum_j (c_{jt'} * E_{jt'} - c_{jt} * E_{jt} - \Delta E_j * c_t \quad (7)$$

To capture all effects and cover all residuals, the complete Laspeyres decomposition, foresees the following calculation of the final carbon intensity effect with R being the residual:

$$c_f = \Delta c * R \quad (8)$$

$$\begin{aligned} R = P_t * a_t * e_t + \frac{1}{2} * [(\Delta P) * a_t * e_t + (\Delta a) * P_t * e_t + (\Delta e) * P_t * a_t] + \frac{1}{3} \\ * [(\Delta P) * (\Delta a) * e_t + (\Delta P) * (\Delta e) * a_t + (\Delta e) * (\Delta a) * P_t] + \frac{1}{4} * (\Delta P) * (\Delta a) \\ * (\Delta e) \end{aligned} \quad (9)$$

The carbon intensity effect can then be computed by the multiplication of (7) and (9).

Both decompositions are carried out for each of the 179 countries in the study for the periods 1990-2000, 2000-2010, and 2010-2018[4]. The potential distortion arising from the fact that the last period is two years shorter than the previous ones due to the limited data availability is considered to be marginal and is thus neglected given the scope of this study. We carry out the decomposition analysis by groups of HDI in two different manners. Firstly, in an *aggregated perspective*, we decompose CO_2 emissions based on the aggregation of the respective Kaya drivers (population (P), GDP (G), primary energy (E), and carbon emissions (F)) of all countries in the considered development level group. In the second approach, the *average perspective*, we apply the Kaya decomposition analysis for each country and then compute the arithmetic mean of emission drivers all countries in the respective group. By giving all countries the same weight, we thereby aim to account for the dominant impact of large economies such as China, USA, India, Russia, Indonesia, Japan, Brazil, Nigeria, Pakistan, etc. on the results of their respective development level group. In other words, the average perspective gives large countries a comparably small weight. We consider both approaches valid yet providing different results and insights, and thus present both sets of results. Table 3 presents the share of the largest countries on the respective human development group. Of note, the composition of the group changes over time, as countries change their development level.

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[4] Depending on considered time period number of considered countries may vary marginally due to lacking data

Table 3: Share of largest countries within their respective Human Development Group

Country	Human Development Level			Population			GDP			Primary energy consumption			CO2 emissions from fuel combustion		
	1990-2000	2000-2010	2010-2018	2000	2010	2018	2000	2010	2018	2000	2010	2018	2000	2010	2018
China	Low	Medium	High	38%	62%	51%	49%	65%	52%	59%	76%	64%	72%	81%	70%
United States	Very high	Very high	Very high	33%	28%	22%	40%	35%	31%	49%	41%	34%	53%	44%	34%
India	Low	Low	Medium	32%	49%	64%	30%	60%	60%	23%	57%	59%	21%	79%	61%
Russia	High	High	Very high	30%	14%	10%	17%	17%	6%	39%	29%	11%	39%	29%	11%
Indonesia	Medium	Medium	High	17%	11%	10%	11%	11%	8%	11%	6%	5%	9%	4%	4%
Japan	Very high	Very high	Very high	15%	11%	9%	13%	10%	8%	11%	9%	6%	10%	9%	7%
Brazil	Medium	High	High	14%	19%	8%	18%	16%	8%	13%	11%	6%	10%	7%	3%
Pakistan	Low	Low	Low	4%	7%	18%	5%	8%	26%	3%	7%	20%	2%	7%	41%
Nigeria	n.a.	Low	Low	n.a	6%	16%	n.a	9%	26%	n.a	10%	29%	n.a	3%	21%

Database

The Kaya decomposition is founded on the data of up to 179 countries retrieved from the Enerdata platform. This platform provides merged and aggregated energy and emission data from the most relevant multilateral institutions such as the World Bank, IEA, OECD etc. The base year for all static examinations is 2018 due to the availability of complete and consistent data. For the same reason, the interval between 1990 and 2018 is considered for all dynamic retrospective analyses. The compiled data and statistics of 179 countries are classified according to the HDI of 2018.

Data availability

The data used in this study is only partially publicly available. While the data for the HDI can be accessed freely via the UNDP the emission and energy data as well as the economic data were retrieved from the restricted Enerdata platform. Enerdata gathers and merges data from the most relevant international institutions such as IEA, World Bank and OECD.

LCOE

The LCOE are a common metric, that despite known caveats[5], is used to calculate and compare the lifecycle generation costs of electricity of different electricity generation technologies and projects. It represents the ratio between the discounted lifetime costs of a project (investment costs, fuel costs, operation and maintenance, taxes, decommissioning cost, etc.) and the discounted electricity production over the project's lifetime (largely depending on natural resources at location and efficiency of technology). For a project with the technology i and the expected lifetime N the LCOE can be calculated as follows

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[5] There are certain caveats related to the comparative use of LCOE as they do not price in the system costs that are associated with the variability and grid integration of intermittent RE ((Ueckerdt et al. 2013)). Further, as they only cover generation costs, they neglect other important factors that need to be considered when comparing RE and fossil fuel technologies such as fuel price certainty, greenhouse gas abatement or energy security. In addition, the value of LCOE depends ultimately highly on the made assumptions on project and financing costs which may not be easy to determine correctly depending on the country ((Kammen et al. 2004)).

$$LCOE_i = \frac{costs\ over\ lifetime}{electricity\ produced\ over\ lifetime} = \frac{\sum_{t=1}^{N} \frac{C_{i,t}}{(1+r)^t}}{\sum_{t=1}^{N} \frac{G_{i,t}}{(1+r)^t}} = \frac{\sum_{t=1}^{N} \frac{I_{i,t} + M_{i,t} + F_{i,t}}{(1+r)^t}}{\sum_{t=1}^{N} \frac{G_{i,t}}{(1+r)^t}}$$

with $C_{i,t}$ being the costs[6] that arise in year t, $G_{i,t}$ the electricity production in year t, and r being the discount rate or weighted cost of capital between commercial debt and equity (WACC). Of note, in order to compute the indicate LCOE in this paper, we base our estimate on commercial debt only, as coherent data on the cost of equity for multiple countries is rather scarce.

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[6] In this illustration of the formula, the costs are reduced, as provided by(IRENA 2020b), to $I_{i,t}$ being the investment expenditures, $M_{i,t}$ the operations and maintenance expenditures and $F_{i,t}$ being the fuel expenditures respectively in year t.

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