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# Emerging emitters and global carbon mitigation efforts

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***Abstract***

International efforts to avoid dangerous climate change have historically focused on reducing energy-related $CO_2$ emissions from countries with the largest economies, including the EU and U.S., and/or the largest populations, such as, China and India. However, in recent years, emissions have surged among a different, much less-examined group of countries, raising the issue of how to address a next generation of high-emitting economies that need strong growth to reduce relatively high levels of poverty. They are also among the countries most at risk from the adverse impacts of climate change. Compounding the paucity of analyses of these emerging emitters, the long-term effects of the COVID-19 pandemic on economic activity and energy systems remain unclear. Here, we analyze the trends and drivers of emissions in each of the 59 developing countries whose emissions over 2010-2018 grew faster than the global average (excluding China and India), and then project their emissions under a range of pandemic recovery scenarios. Although future emissions diverge considerably depending on responses to COVID-19 and subsequent recovery pathways, we find that emissions from these countries nonetheless reach a range of 5.1-7.1 Gt $CO_2$ by 2040 in all our scenarios—substantially in excess of emissions from these regions in published scenarios that limit global warming to 2°C. Our results highlight the critical importance of ramping up mitigation efforts in countries that to this point have played a limited role in contributing the stock of atmospheric CO2 while also ensuring the sustained economic growth that will be necessary to eliminate extreme poverty and drive the extensive adaptation to climate change that will be required.

Keywords: $CO_2$ emissions, developing countries, COVID-19, post-COVID

### *Introduction*

Fossil fuel carbon dioxide ($CO_2$) emissions are the largest contributor to global warming. Going back to the 1990s and before, analyses of fossil emissions and energy-emissions models (IAMs) have focused on a handful of regions that include industrialized economies where emissions have been high (US, EU), and rapidly-industrializing countries such as China and India (Raupach et al. 2007; Fernández González, Landajo, and Presno 2014; Hubacek, Guan, and Barua 2007; Cantore and Padilla 2010). To the extent other countries are included, they are typically heavily aggregated, often literally into a "Rest Of World (ROW)" group, or "other developing countries" in the non-Annex I countries' list of UNFCCC (Winkler, Brouns, and Kartha 2006). Yet, since 2010, most of the growth in global emissions has been among these non-annex I, "ROW" countries. Over 2010-2018, all the countries with an emissions growth rate higher than the world average are developing economies, including countries currently in the lists of the least developed countries (LDCs) and/or landlocked developing countries (LLDCs) (IEA 2018a; United Nations 2020).

In contrast to large emitters, such as the United States, China and India, these developing countries individually have small emissions, but collectively the emissions are comparable with those of the top emitters and have a large potential to dominate global emissions in the future. These countries face multiple daunting challenges. Many of these emerging emitters face high costs in adapting to climate change while having the weakest adaptation capacity. At the same time, they need to sustain economic growth to generate jobs and lift people out of poverty. It is this growth that is accelerating the rise of their global $CO_2$ emissions and leads to the challenge of implementation of their intended nationally determined contributions (INDCs) toward climate change mitigation. A key issue is the increasing demand for oil and rising coal-related $CO_2$ emissions that may cause a lock-in of emission-intensive energy use patterns among Asian (Steckel, Edenhofer, and Jakob 2015) and African countries (IEA 2019a, Steckel et al. 2020, Lucas et al. 2015).

Following the COVID-19 pandemic outbreak, countries have applied various lockdown measures to avoid the rapid spread of the virus. As these lockdown strategies limit production and consumption activity, they are having a significant impact on energy consumption and $CO_2$ emissions (Le Quéré et al. 2020; Liu et al., n.d.). For example, the world's energy demand in the first quarter of 2020 declined by 3.8% relative to Q1 of 2019 (IEA 2020), and global $CO_2$ emissions were over 5% lower in Q1 2020 than in Q1 2019 (IEA 2020). The severity of the pandemic and the strictness of the lockdown measures vary among the emerging emitting developing countries. For example, Peru has experienced severe outbreaks with over 835,000 cases and over 33,000 deaths as of October 2020 (World Health Organization 2020), although with a prolonged lockdown. Vietnam applied strict lockdown measures early in the outbreak and largely succeeded in controlling the spread of COVID, with 1,100 cases by October 2020 (World Health Organization 2020).

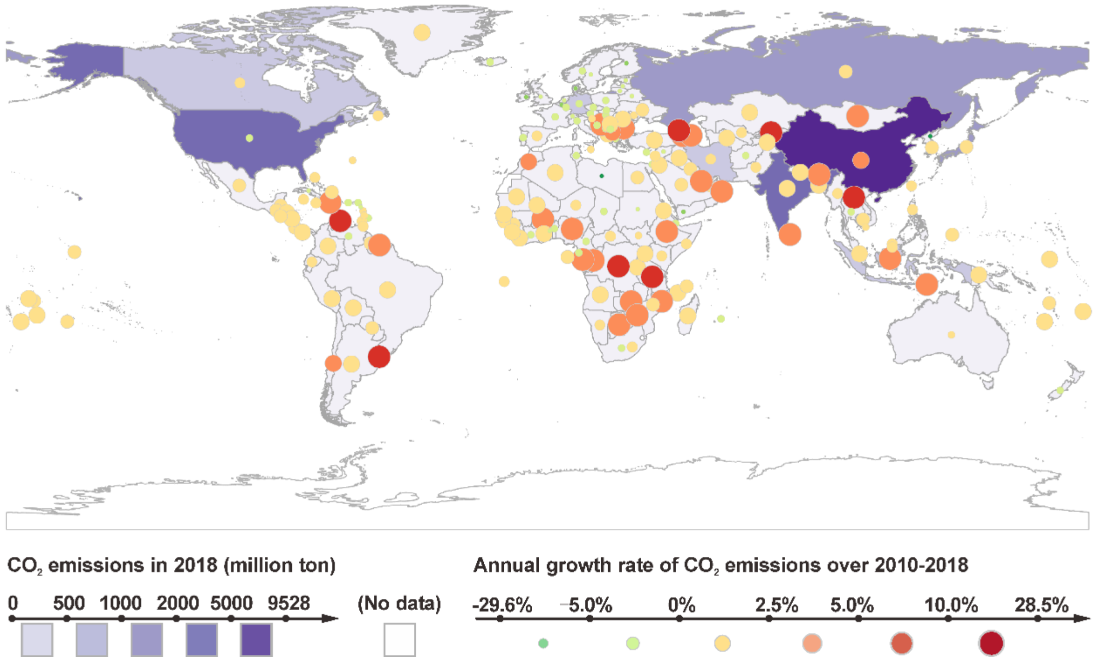
Since COVID is projected to re-emerge and have impacts for nearly four years (Kissler et al. 2020), it might reshape the emission pattern of the emerging emitters and substantially influence their future emissions. Therefore, understanding the driving forces behind previously growing emissions, the impact of COVID and likely future trajectories of $CO_2$ emissions of these developing countries is essential in the context of measures to achieve global emissions reduction. Although, even prior to COVID, emissions of some major economies were declining (US, EU) (Le Quéré et al. 2019) or had at least flattened (Guan et al. 2018), few studies have focused outside of those main regions, on countries where growth rates are high but emissions remain relatively low for now. Here, we comprehensively assess the situation of these emerging emitters, develop country-specific emissions scenarios that capture the impact of COVID and finally discuss potential measures for global emission reduction.

In this study, we use index decomposition to analyze the drivers of emissions of 59 fast growing developing countries. We then develop country-specific emission scenarios for a range of future energy and development trajectories using an Adaptive Regional Input-Output (ARIO) model. These capture region-specific COVID effects combined with more aggregate shared socioeconomic pathways (SSPs) generated by large Integrated Assessment Models and assumed application of low-carbon technologies in the emerging emitters.

***Emerging emitters from the developing world***

Figure 1 shows countries with $CO_2$ emissions growing faster than the world national average over 2010-2018 based on $CO_2$ fuel combustion emissions data from the International Energy Agency (IEA). China, India, and 59 other countries (see Annex 1 for the full list) had above average growth in $CO_2$ emissions. Located in Asia, Africa, and Latin America, these 59 developing countries discharged $CO_2$ emissions of between 0.7 Mt (Eritrea) and 542.9 Mt (Indonesia), individually much smaller emissions than the emission giants in North America and Europe. However, the 59 emerging emitters as a group accounted for growth of $CO_2$ emissions from 2.7 Gt in 2010 to 3.8 Gt in 2018. These countries combined now emit 65% more than India, which has the 3$^{rd}$ largest emissions at 2.3 Gt. Specifically, the 1.1 Gt of increased emissions from these countries contributed to almost 40% of the world emissions growth over this period, signaling a new generation of emerging emitters.

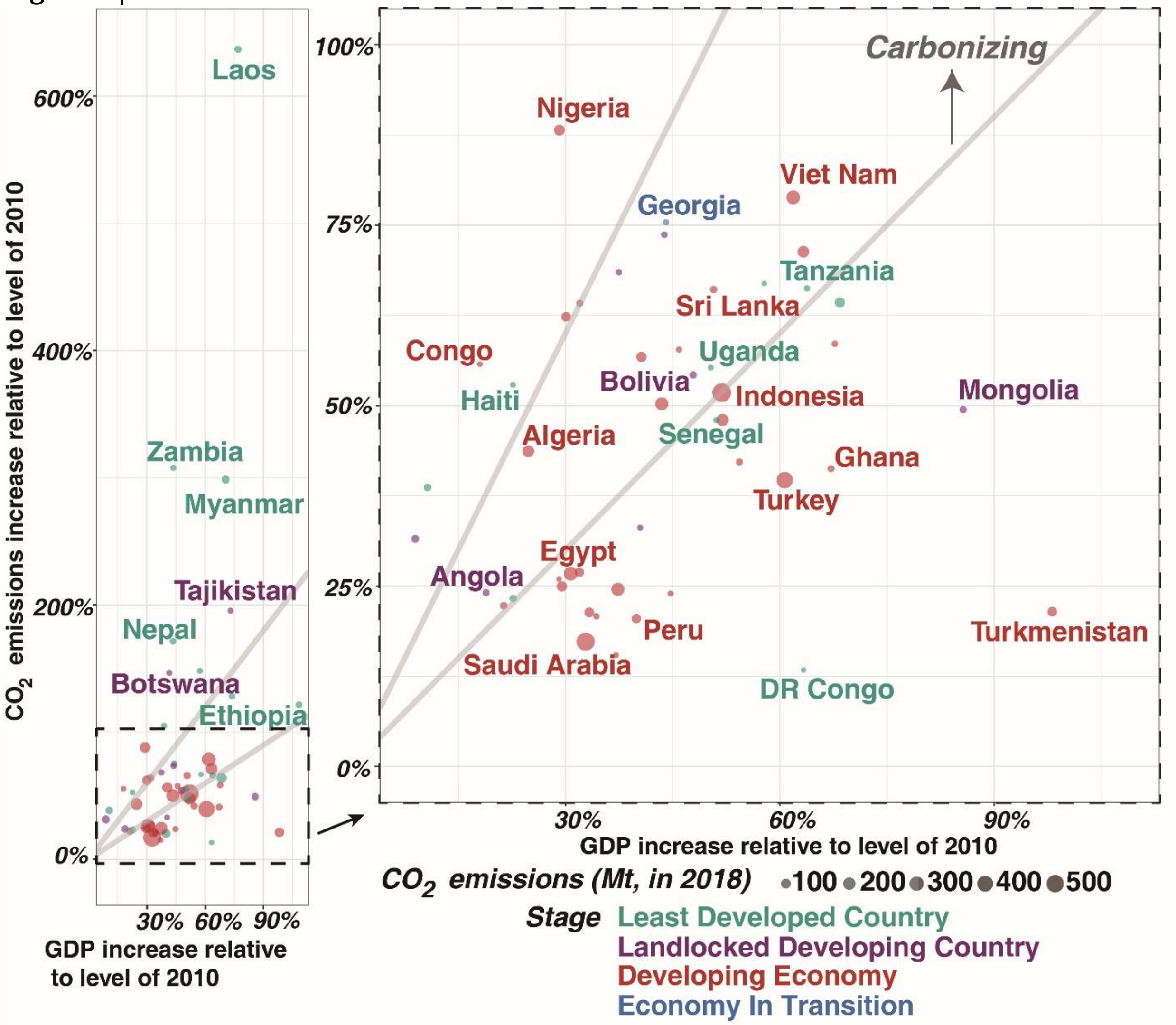
**Figure 1 | Map of countries with fast-growing $CO_2$ emissions.**




Note: The depth of purple reflects the volume of emissions in 2018, and the size and the color of the bubbles represent the annual growth rate of emissions (2.5% is the global average), green for declining, yellow for slow-growing, and red for fast-growing.

The average annual emission growth rate of the 59 countries was 6.2%, much higher than the global average of 2.5%. The average annual growth rate of GDP of the 59 countries' GDP was 4.6%. Over half (34 out of 59) of this group of developing countries have experienced emission growth faster than GDP growth over the past decade and 12 have seen emission grow at twice the rate of GDP growth. These countries are in diverse stages of development ranging from LDCs, such as Ethiopia and Uganda, to economies in transition (EIT)(United Nations 2020), including Georgia. For most LDCs and LLDCs the increase in emissions appears to be strongly coupled with GDP growth (mapped as bubbles above the lines of slopes of 1 and 2 in Figure 2, which represent a 1 to 1 and two to one ratio of emissions growth to GDP growth respectively). These countries include Laos, Zambia, Myanmar, Ethiopia, Georgia, Uganda, and Vietnam. There are another 25 countries for which $CO_2$ emissions have grown more slowly than GDP, including Mongolia, Ghana, and Peru. We now move to discuss how the diverse natural and economic situation of these countries has shaped different patterns and drivers of $CO_2$ emission growth.

**Figure 2 | Relative increase of $CO_2$ emissions and GDP in 2018 over 2010**




**Notes:** Each bubble represents a country, plotted by GDP increase in 2018 relative to the level of 2010 on the horizontal and $CO_2$ emissions increase on the vertical. The bubbles of countries with below 100% emission increase (within the black dotted box) in the left part are zoomed in on the right part. The size of the bubbles represents the amount of $CO_2$ emissions in 2018. The colors represent the developing stages of the countries *(United Nations 2020)*, red for developing economies (DE), cyan for economies in transition (EIT), green for least developed countries (LDC), and purple for landlocked developing countries (LLDC). The two grey lines with slopes of 1 (lower) and 2 (upper) mean the $CO_2$ emission growth rate is the same as or twice the rate of the GDP growth. The figure includes 57 countries (South Sudan and Eritrea lack GDP data).

***Emerging emitters carbonizing together, but in diverse ways.***

To understand the driving forces behind these fast-growing emissions we decompose emissions growth (C) over 2010 to 2018 into contributions from six factors: $C_P$ from population (P) growth; $C_G$ from economic growth measured by GDP (G) per capita; $C_{IS}$ from industrial structure (IS), as reflected by changes in the share of primary industry, secondary industry, and tertiary industry in GDP; $C_{EI}$ from energy intensity (EI) defined as energy consumption (E) per unit of GDP; $C_{ES}$ from energy structure (ES), the share of energy consumption of coal, oil, natural gas, and other energy sources; and $C_{CI}$ from $CO_2$ emissions intensity (CI) which is the emissions per unit of energy consumption, as follows:

$$C = \sum_{ij} P \times \frac{G}{P} \times \frac{G_i}{G} \times \frac{E_i}{G_i} \times \frac{E_{ij}}{E_i} \times \frac{C_{ij}}{E_{ij}} = \sum_{ij} P \times G \times IS_i \times EI_i \times ES_{ij} \times CI_{ij}$$

Where, *i* refers to the *i*th industry in primary industry, secondary industry, and tertiary industry; *j* refers to the *j*th energy type in coal, oil, natural gas, and other types. The change in C from time 0 to time T can be divided into six parts using the logarithmic mean Divisia index (LMDI) method as follows:

$$\Delta C = C^T - C^0 = \Delta C_P + \Delta C_G + \Delta C_{IS} + \Delta C_{EI} + \Delta C_{ES} + \Delta C_{CI}$$

Where:

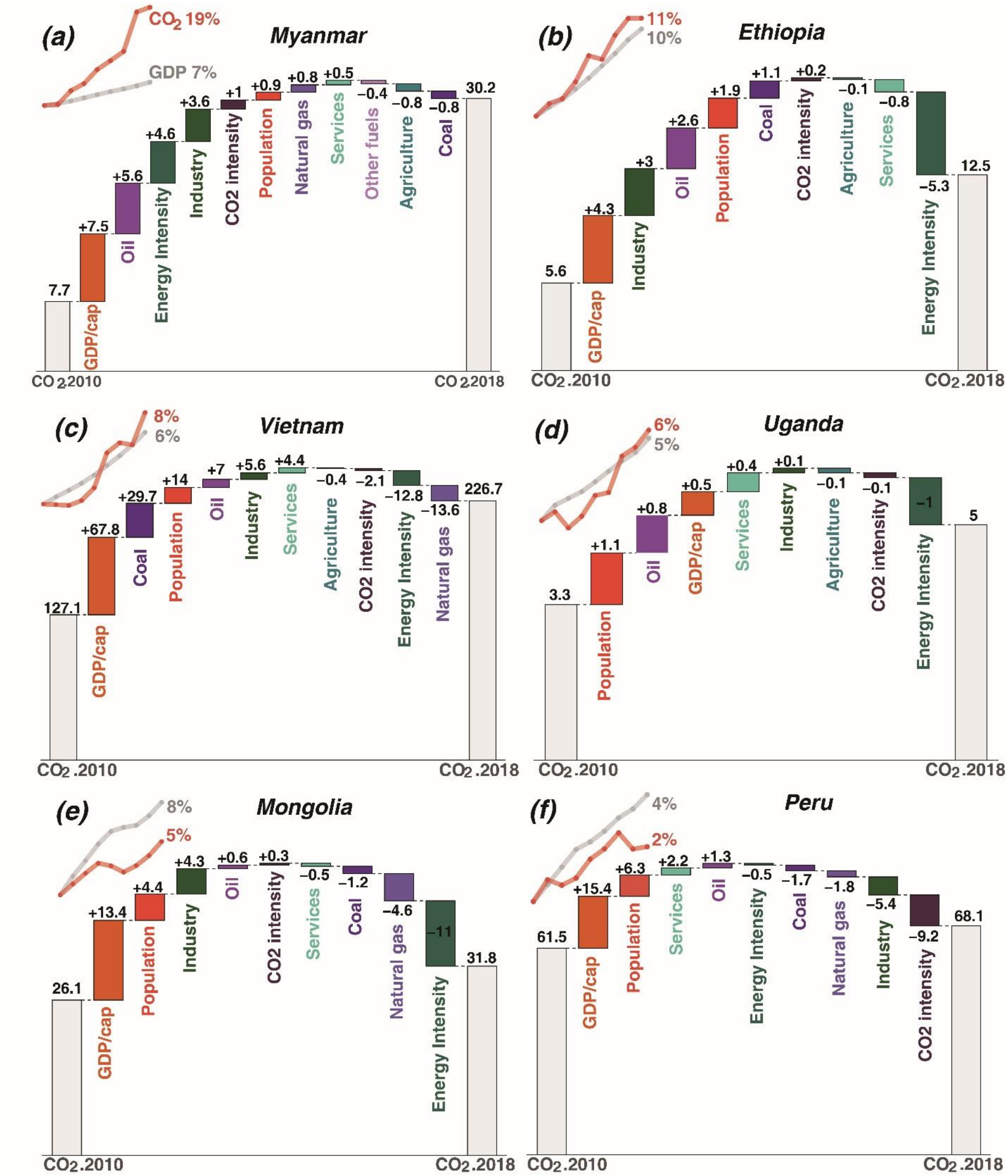
$$\Delta C_X = \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \times \ln\left(\frac{X_{ij}^T}{X_{ij}^0}\right)$$

Where, $X_{ij}$ refers to the driving factors, i.e. $P$, $G$, $IS_i$, $EI_i$, $ES_{ij}$, and $CI_{ij}$. We select Myanmar, Ethiopia, Vietnam, Uganda, Mongolia, and Peru as case countries to reveal the different drivers of emission growth. The results are shown in Figure 3 and are summarized below for each country:

**Myanmar** (Figure 3a): Following implementation of political and economic reforms that started in 2011, Myanmar has seen strong economic growth. From 2011 to 2018, Myanmar's GDP grew on average by around 7% each year and reached 71.2 billion dollars in 2018. This has led to a substantial decline in poverty, with the available data showing a fall in the headcount ratio at the national poverty line from 48.2% in 2005 to 24.8% in 2017. However, along with this economic development, $CO_2$ emissions increased by up to 300%. Compared with 2010, Myanmar released 22.5 Mt $CO_2$ more in 2018, with per capita GDP, oil consumption, and energy intensity as the top three contributors. GDP growth has been the main driving force of emission increments. Next, the energy structure of Myanmar has become oil-oriented, especially in construction, power generation, manufacturing, and household sectors. Further, shifts in the structure of industry towards manufacturing, a key factor behind Myanmar's success in poverty reduction, have also contributed to increasing $CO_2$ emissions.

While economic development has progressed in Myanmar, substantial potential remains for sustained economic growth. On the one hand, this will contribute further to growing $CO_2$ emissions, but on the other hand, it is essential to continue to take people out of poverty, including the more than three-quarters of a million people still in extreme poverty. At the same time, Myanmar is ranked 160 out of 181 countries on the ND-Gain index which measures a country's vulnerability to climate change together with its capacity to improve resilience.  Myanmar is also second on the Germanwatch list of countries most impacted by climate change over the past 20 years.

**Figure 3 | Drivers of Emissions Growth in Case Study Countries**




Notes: The relative increase of GDP and $CO_2$ emissions from 2010 to 2018 are shown in the grey and red lines (left top of each sub-figure), and the annual growth rates are noted beside the lines.

**Ethiopia** (Figure 3b): Over 2010-2018, Ethiopia, one of the poorest countries in the world, enjoyed an economic boom with an average annual growth rate of 10% (84.4 billion dollars in 2018) accompanied by $CO_2$ emissions rising by 11% on average each year. From 2010, Ethiopia implemented its Growth and Transformation Plan (GTP), which encouraged large-scale foreign investment in agriculture, industry and infrastructure towards a goal of achieving rapid industrialization. The extraction of minerals (gold, salt, precious stones, fuels, etc.), infrastructure development, increasing manufacturing industry and growing GDP per capita were the largest drivers of emissions growth (7.3 Mt increment). The expanded use of oil in transport and the higher use of coal in manufacture contributed 3.7 Mt emissions. Population growth of 2.7% per annum was also an important contributor. On the other hand, a decline in energy intensity as a result of increasing electrification in commerce and households, led to a 5.3 Mt emission reduction over the period. This demonstrates the role that new technologies and shifts away from carbon intensive sources of energy can play in offsetting increases in emissions that inevitably result from strong economic growth in poor countries. Ethiopia is ranked 157 on the ND-Gain index and so is highly vulnerable to the effects of climate change.

**Vietnam** (Figure 3c): Vietnam experienced rapid growth of both GDP and $CO_2$ emissions with annual growth rates of 6% and 8%, respectively. In 2018, Viet Nam's GDP reached 245.2 billion dollars and $CO_2$ emissions reached 226.7 Mt. During this period of economic development in Vietnam, increasing GDP per capita was the main driver of emissions growth (67.8 Mt, 68.1% of the total increment). With fast-growing production and exports of textiles, real estate, transport, and electrical equipment parts, Vietnam achieved rapid economic growth, in which industry and services contributed a 10 Mt emissions increment, and the related energy consumption was increasingly fueled by coal (in power supply) and oil (in textile and electrical parts production) that led to 36.7 Mt incremental emissions. Population growth also contributed 14 Mt to emissions growth. Hence, Vietnam is one of the fastest growing locations for manufacturing industry in the world with a carbonized energy structure and large population, and has considerable potential to increase $CO_2$ emissions in the near future. This economic growth, however, has taken more than 28 million people out of extreme poverty.[1] Nevertheless, almost 2 million people remain below the international poverty line. Vietnam is also vulnerable to climate change being ranked 98 on the ND-Gain index and 6th on the Germanwatch Long-term Climate Risk Index of damage over the past 20 years.

**Uganda** (Figure 3d): Uganda experienced an average 5% annual growth rate in GDP between 2010-2018. Carbon emissions also increased slightly more than GDP with an annual average growth rate of 6%, increasing to 5 Mt in 2018. Increasing population and oil consumption were the main impetus behind the

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[1] Defined by the international poverty line of $1.9 per day in 2011 PPP.

growth of emissions in Uganda, contributing 37.0% (1.1Mt) and 27.6% (0.8Mt) to the $CO_2$ emission increment, respectively. Uganda saw a 3.6% annual average population growth rate over 2010-2018, and its net population increase was 10.29 million. Over the period, oil consumption increased at an annual growth rate of 7.1%, which also contributed substantially to the increase of $CO_2$ emissions. The increasing contribution of services to GDP and, in particular transport services, also added to the growth of $CO_2$ emissions. On the other hand, investments in renewable energy led to a lower energy intensity that reduced the growth of emissions by 1 Mt over the period.

Uganda has yet to achieve the sustained inclusive growth necessary to drive poverty reduction. In 2009, 14 million people lived below the international poverty line, amounting to 44.5% of the population. By 2016, the number of extreme poor has increased to 16.5 million, 41.5% of the population. Uganda is ranked 166 on the ND-Gain index and is therefore highly vulnerable to the effects of climate change together with very limited capacity for adaptation. In terms of the impact of climate related events over the past 20 years, Uganda is ranked 66 by Germanwatch.

**Mongolia** (Figure 3e): Over 2010-2018, Mongolia experienced rapid economic growth with an average annual growth rate of 8%, and its GDP reached 13.1 billion dollars mainly driven by exports (metals and fuels to China). Meanwhile, $CO_2$ emissions of Mongolia saw a rising trend but slower than GDP growth with an average annual increase of 5%. GDP per capita, population, and industry are the main drivers of Mongolia's emissions growth. The mining industry has been the engine of economic growth: in 2014, mining accounted for about 30% of Mongolia's GDP, and is crucial in explaining $CO_2$ emission growth. In 2018, Mongolia's coal production reached a record high of over 50 million tons and coal exports also reached a new peak of 36.3 million tons. This contributed to additional emissions of 4.3 Mt. Mongolia's population growth has also been a  cause of increasing carbon emissions resulting in rising household consumption and reflecting adverse natural conditions, the cold climate and traditional carbon intensive means of heating. It is worth noting, however, that changes in energy intensity led to substantially lower carbon emissions (-11Mt) than would have otherwise occurred, due for example, to the resource efficiency achieved from large district heating systems connecte to supply from combined heat and power plants. These systems have become integral to the energy strategy and supply nearly 40 % of the urban heat demand.[2]

Mongolia is still highly dependent on coal as an energy source and Ulaanbaatar is one of the world's most polluted cities in terms of air quality.[3] It is also vulnerable to climate change with the average temperature

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[2] https://www.climateinvestmentfunds.org/sites/cif_enc/files/srep_ip_mongolia_final_14_dec_2015-latest.pdf
[3] https://www.nationalgeographic.com/environment/2019/03/mongolia-air-pollution/

having increased by more than 2ºC since 1940, more than double the global average. It is ranked 67 on the ND-Gain index. The government is seeking to increase the share of renewables in the energy mix, with a range of options including wind, solar, hydro and geothermal. The objective is to achieve a share of renewable energy in national energy capacity of 30% by 2030.

**Peru** (Figure 3f): From 2010 to 2018, Peru's GDP grew on average by 4.3% per year, nearly twice the rate of carbon emissions growth (2.4%). The growth in emissions was primarily driven by increases in GDP per capita and by the increase in population growth rate from 2010 to 2018 (0.7% in 2010, to 1.5% in 2018). The absolute increase in the Peruvian population, was, in part, due to the young population structure, but was also the result of higher immigration, especially from Venezuela. By 2018, more than three million immigrants have been officially accepted by the Peruvian government. Both industry and changes in $CO_2$ intensity contributed to substantial reductions in emissions over the period, amounting to over 14 Mt, offsetting to a large degree the increases driven by population growth and increases in GDP per capita.

***Future emissions: COVID19 delay and potential mitigation***

Economic development will continue to be a strong driver of emissions growth in these developing countries and essential to eliminate extreme poverty. Nevertheless, as the experiences of some of the countries discussed above has shown, structural changes in these economies towards less carbon intensive activities, such as, shifting away from coal to other less carbon intensive sources of energy, and improvements in the energy intensity of GDP can significantly dampen the growth in emissions from these emerging emitters. An additional factor impacting the trajectory of emissions from these and all other countries is the COVID-19 pandemic and economic slowdowns resulting from countries applying lockdown strategies to limit the spread of the virus. We now move to model the impact of COVID-19 scenarios on the emissions growth of these developing countries and how this may impact on overall emissions by 2040 and on achieving the objective of limiting global warming to 2°C .

We use the projections from GAINS[4] and an ARIO model (see Annex 2 for description of the modelling approach) to explore a scenario for the impact of COVID and then, after 2024, supposing that COVID is under control and countries return to their normal development path, we show the impact of different Shared Socioeconomic Pathways (SSPs)[5], that countries can follow. The four COVID assumptions covering the

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[4] GAINS (Greenhouse Gas - Air Pollution Interactions and Synergies) model of IIASA (2020)

[5] The SSPs have been defined by the climate change research community to facilitate analysis of a changing climate. The different pathways capture plausible global developments that would lead to different challenges in the future for mitigation and adaptation to climate change see for example. We adjusted the SSP data and the NPS data from GAINS model by considering the impact of COVID on their original trajectory and harmonizing the post-COVID results to the COVID model's results (see Annex 3 on data harmonization). The CO2 emissions of countries under SSP1 and SSP5 scenarios are calculated based on the results of AIM/CGE model of IIASA SSP database. The CO2 emissions data from AIM/CGE model are an aggregation at the five region level: the OECD countries and EU member states

period 2020-2024 are: 1) the baseline assumption, where there is no COVID and countries develop under the present policy ambitions; 2) the default COVID lockdown assumption, where there are eight instances of lockdown (over 2020-2023 (Kissler et al. 2020)) but with declining lockdown strictness (medium adaptation rate to the impact of COVID, see Annex 2 for full details of the lockdown scearios) and technology improves at 75% of the rate in the baseline scenario as a result of the impact of COVID; 3) the mildest COVID lockdown assumption, where there are two lockdowns over 2020-2022, with declining lockdown strictness, (fast adaptation rate to the COVID impact), and technology improves as in the baseline scenario; and 4) the strictest COVID lockdown assumption, where there are two lockdowns each year over 2020-2024 with the same strictness as the first lockdown (no adaptation to the impact of COVID) and technology improves at half the speed of the baseline scenario.

To investigate the short-term (next five years) changes in emissions brought about by the sudden shock of COVID-19, we assume that production efficiency and economic structures are unlikely to change significantly within such a short time. The relationship between emissions and GDP (the emission intensity) will not be altered. Therefore, we simply estimate the emissions of countries based on their sectoral emission intensities and economic outputs:

$$Emissions_{ir}(t) = intensity_{ir}(t) \times output_{ir}(t)$$

where subscript $i$ and $r$ represent sector and country/region, respectively. The superscript $t$ stands for year and $output_{ir}(t)$ is obtained from the ARIO economic impact model. For $intensity_{ir}(t)$ we use the sectoral emission intensity in 2014. A similar method has been used to estimate the recent emission decline in Chinese provinces (Han et al. 2021).

The scenarios for the post-2024 period include the NPS (no policy scenario) baseline assumption, where there was no COVID and countries develop under previous trajectories, the most sustainable pathway, SSP1, and that with the slowest adaptation away from fossil fuels, SSP5. In addition, we show emissions under a scenario with adoption of low-carbon technologies (LCT)[6] from 2030 including carbon capture and storage,

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and candidates (OECD), countries from the reforming economies of Eastern Europe and the Former Soviet Union (REF), Asian countries except the Middle East, Japan and Former Soviet Union states (ASIA), countries of the Middle East and Africa (MAF), and countries of Latin America and the Caribbean (LAM). Therefore, we assumed the countries reach the regional average emission intensity (emission per unit GDP); and based on that emission intensity and the country-level GDP forecast, the region-level emissions are allocated to country level.

[6] Low-carbon technologies (LCT) applied from 2025 (linearly increasing in application and fully applied by 2040), including carbon capture and storage (CCS), renewable energy for the production of newly-demanded electricity, and electric vehicles replacing the newly-increased oil fueled automobiles from 2030. More specifically, countries are categorized into two groups, thermal-powered countries and non-thermal-powered countries, according to whether the percentage of thermal-powered emissions over total emissions is greater than 50%. For the thermal-powered countries, the low-carbon technology for the power sector is set as CCS and for the non-thermal-powered countries the low-carbon technology is set as renewable energy for power generation. Both are applied to newly-demanded electricity, linearly increasing in coverage from 0 in 2025 to 100% in 2040.

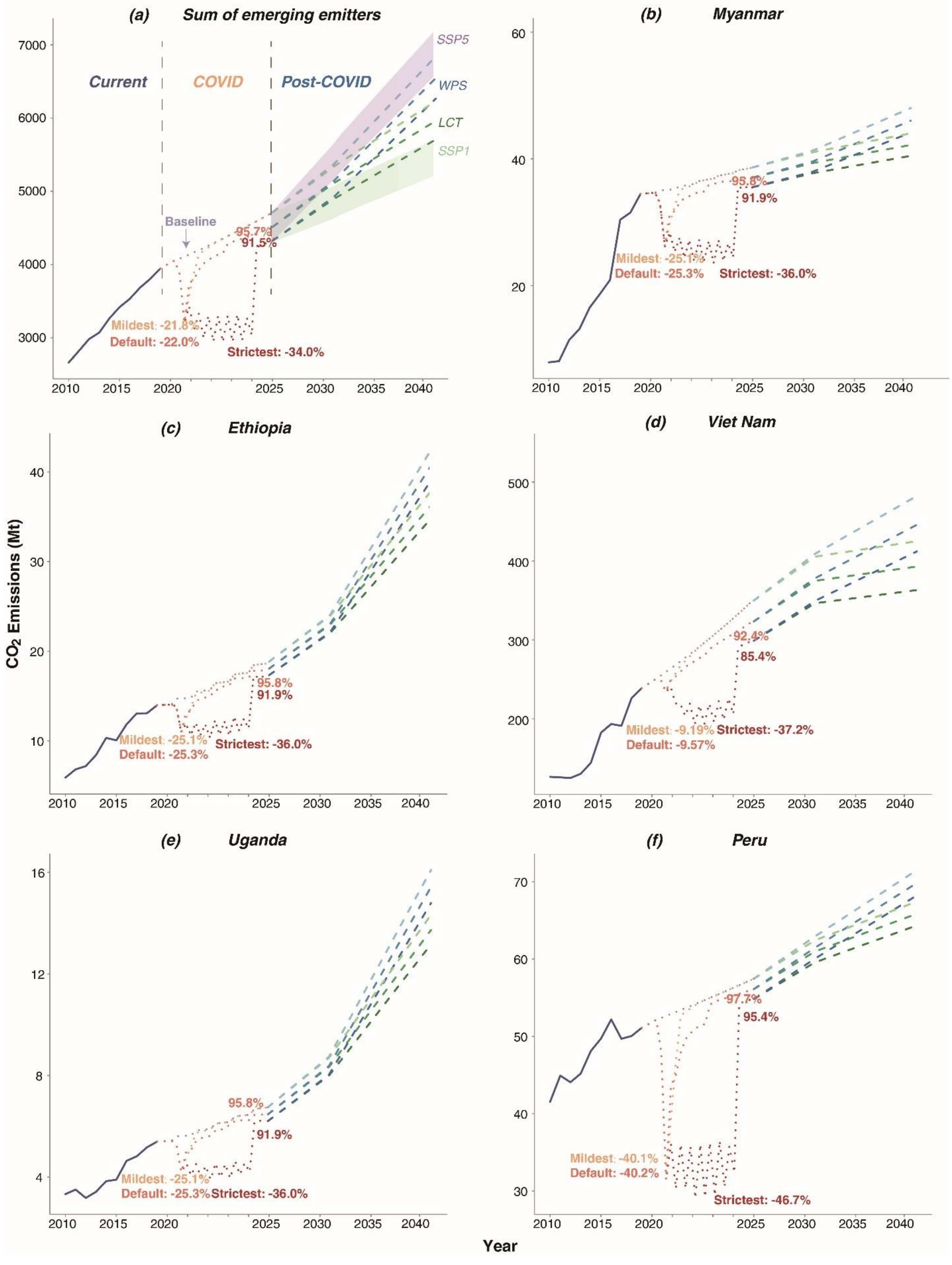
renewable energy for power generation, and with electric vehicles replacing oil fueled automobiles, and a weak policy scenario (WPS) where no low-carbon technologies are applied (i.e. the SSP2 scenario from the GAINS model, a middle of the road scenario in terms of mitigation and adaptation).

As shown in Figure 4a, COVID causes a visible decline to the sum of all of the emerging emitting countries' emissions. Compared to the baseline assumption without COVID, the emissions under the default COVID lockdown assumption drop by nearly 22% at the first lockdown and take until 2024 to recover to 92% of the baseline level. Under the mildest COVID lockdown scenario emissions drop by nearly 22% after the first lockdown and take two years to recover to the baseline level. On the other hand, emissions under the strictest COVID lockdown assumption undergo eight periods of decline and rise between 2020 to 2024, reaching a trough of 66% of the baseline level in 2023 but then surge to nearly 92% of the baseline level in 2024.

The $CO_2$ emissions of these emerging emitting countries reach a range of 5.2-7.1 Gt by 2040, the limits of which are the emissions under SSP1 after the strictest lockdown and the emissions under SSP5 after the mildest lockdown period, respectively.  After the COVID setbacks, the alternative SSPs under each scenario lead to disparate growth of emissions over 2025-2040. For example, the trajectory of future emissions under the baseline scenario and the mildest COVID lockdown are nearly identical, while under the default COVID lockdown scenario a given level of emissions is achieved with a 2 year delay and under the strictest COVID lockdown scenario with a 4 years delay. For the SSP1 scenario, the given level of emissions under the baseline and the mildest COVID lockdown is achieved 4 years and 8 years ahead of that of the default and the strictest COVID lockdown, respectively. For the SSP5 scenario, those gaps are 1 years and 3 years.

If large scale adoption of low-carbon technologies were applied from 2025, including CCS (carbon capture and storage) and renewable energy for power generation and electric vehicles in place of oil-fueled automobiles, the aggregated emissions of these countries could be reduced by 611 Mt $CO_2$, 9% of the 2040 emissions of 6.7 Gt under the baseline scenario**.** We also modelled a more-extensive scenario for the application of low carbon technologies with carbon capture and storage and renewable energy applied for all the production of newly-demanded electricity from 2025, and electric vehicles replacing all the newly-increased oil fueled automobiles from 2030. In this case, the aggregated emissions of these emerging emitting countries would be 5.9 Gt, which is 811 Mt (12%) lower than the baseline scenario. Even with the rapid application of low-carbon technologies, the emission growth rate is higher than that under SSP1. This suggests that while new technologies can help to reduce the emissions of these countries, alone they are insufficient to enable them to achieve a "sustainable pathway".

**Figure 4 | Future $CO_2$ emissions of case study countries and the sum of the 59 emerging emitters**



Within this overall trend for the emerging emitters there are important differences among countries over the COVID and post-COVID periods. Taking a deeper focus on each of the case countries, the future emissions under the four scenarios of COVID lockdown and the corresponding five SSPs of Myanmar, Ethiopia, Vietnam, Uganda, and Peru are depicted in Figure 3 (b-f):

**Myanmar** (Figure 4b) is projected to experience slower growth from 2020 to 2024 in the absence of COVID impact while emissions under the default lockdown assumption drop by about 25% and recover to 96% of the baseline level by 2024. After 2024, the emissions of Myanmar under the SSP5 scenario surge to 77 Mt after the mildest lockdown. Myanmar has seen a rapid increase in infections since the end of August 2020, which may lead to a future that approximates the default lockdown assumption or even closer to the strictest lockdown assumption. However, if Myanmar continues following the fossil-fuel pathway (SSP5) after the COVID setbacks, emissions under even the strictest lockdown quickly reach that under the baseline with a delay of only one more year. Choosing a more sustainable pathway using low-carbon technologies in the future can reduce emissions by nearly 3 Mt in 2040.

**Ethiopia** (Figure 4c) is projected to experience moderate emissions growth from 2020 to 2024 without COVID, while under the default lockdown assumption emissions drop by about 25% and then recover to 96% of the baseline level in 2024. To date, Ethiopia has applied a partial lockdown strategy and has seen an outbreak of infections since July 2020. By October 2020, there were over 78 thousand cases, which indicates a high probability of further lockdown. That may lead to a pathway close to the default lockdown assumption. As Ethiopia has an industrializing economy with rising coal and oil use, development after the COVID pandemic will drive a sharp increase in $CO_2$ emissions under the no-policy scenario (NPS) to reach 40 Mt in 2040, which will be only one year later than the baseline scenario under the no-COVID assumption.

**Vietnam** (Figure 4d) in the absence of COVID would have been expected to maintain rapid emissions growth from 2020 to 2024. Under the default COVID lockdown assumption emissions drop by about 10% before recovering to 95% of the baseline level by 2024. Vietnam implemented strict early lockdown measures, which appear to have led to some success in control of the spread of COVID. By October 2020, Viet Nam had just over 1,000 confirmed cases for a population of 97 million and started to return to its pre-COVID development pathway. Therefore, $CO_2$ emissions from Vietnam will likely follow the "mildest-lockdown" situation with little difference from the baseline scenario. Subsequently, with high dependence on fossil fuels including coal and oil, emissions in 2040 are likely to reach 482 Mt under NPS, which would be almost double the emissions of 2018. However, with radical low-carbon technologies, Vietnam could achieve a 12% (57 Mt) reduction in emissions with carbon capture and storage in power plants and with electric vehicles replacing oil-fueled automobiles. That would lead to the approximate SSP1 scenario where the emissions growth rate flattens.

**Uganda** (Figure 4e) is also projected to experience slower growth from 2020 to 2024 even without the impact of COVID. Emissions under the default lockdown assumption fall by about 25% and recover to 96% of the baseline level by the end of the COVD period. There has been some spread of COVID since August 2020, following the loosening of the strict lockdown in July 2020. Nevertheless, the situation is much better than the African average, and the effectiveness of the initial lockdown strategy, means that Uganda may achieve a mild-lockdown pathway, at least no worse than the default lockdown scenario. In this situation and if the country continues increasing consumption of oil without applying low-carbon technologies, the post-COVID emissions will be around 15.4 Mt $CO_2$ in 2040, compared to the 13.7 Mt emissions with LCT.

**Peru** (Figure 4f) is projected to experience a steady increase in growth from 2020 to 2024 in the absence of COVID. However, emissions under the default lockdown assumption fall considerably by about 40% although they recover to 98% of the baseline level by 2024; Despite applying strict lockdown measures since March 2020, Peru has been fighting one of the worst COVID outbreaks with over 820 thousand confirmed cases and more than 32 thousand deaths. By October 2020, the spread has yet to be controlled, and if the trend continues, Peru will probably maintain its strict lockdown strategies and its future $CO_2$ emissions may decline substantially. In such circumstance, Peru's emissions will reach 68 Mt in 2040 under NPS, which is 4 years behind that of the baseline and mildest-lockdown assumption. With low-carbon technologies emissions could be reduced by 5.7% in 2040.

***Discussions and Conclusion***

Emerging emitters among developing countries have collectively contributed extremely little to the overall stock of $CO_2$ in the atmosphere. However, they have come to the forefront of the growth of $CO_2$ emissions over the past decade and will likely increasingly be so. Strong and sustained economic growth, crucial for poverty reduction, increases in population and heavy carbon energy consumption will drive significant emissions growth. Taking energy structure as an example, over the period 2010-2018, among the 34 countries that use coal in our sample of developing countries, 23 countries show a rising share of coal consumption in the energy mix and 29 countries increased their absolute consumption of coal. The impact of COVID is hitting developing countries hard and putting back progress on poverty reduction. The World Bank predicts that the COVID-19 pandemic could result in between 71 and 100 million people being pushed into extreme poverty[19]. There will, therefore, be a need to quickly revive growth in these economies, and their current dependence on traditional fossil fuels is likely to result in significant carbon emissions.

These countries are confronting the massive challenges of achieving inclusive economic development, contributing to climate change mitigation and adapting to rising global temperatures, changing precipitation and more extreme weather events. Indeed, these emerging emitters are the most vulnerable and least prepared to adapt to climate change. For these countries, climate change will undermine their ability to drive poverty reduction as it will constrain productivity growth, especially in agriculture, and requires scarce resources to be redirected towards adaptation. Costinot et al (2016), for example, compute that the impact of climate change on agricultural productivity alone will result in a decline in welfare equivalent to almost 4% of GDP in Uganda and over 6.5% of GDP in Vietnam. This assumes that trade and production patterns adjust to dampen the impact. If adjustment is constrained then losses could amount to more than 7.5% of GDP in Uganda and over 11 per cent in Vietnam.

These countries actions relating to emissions reduction will significantly influence the global effort to mitigate climate change. There is a large degree of diversity across these countries in terms of the size of national absolute $CO_2$ emissions, the relationship between GDP growth and increases in $CO_2$ emissions, the drivers of the emissions growth, the response to the COVID impact, and the impact of alternative post-COVID pathways. This requires country specific assessments and responses rather than common strategies defined for all the countries. Many of these countries are also already at the forefront of mitigation efforts in terms of enhancing the ambition of their Nationally Determined Contributions under the Paris Agreement[20]. In the post-COVID era, the outcomes from different pathways could lead to a difference of over 1 Gt in emissions from these countries.

Hence, to limit global warming well below 2 °C, the world needs to reduce emissions by 25% less than 2018 levels and emerging emitters have a significant role to play. This would be facilitated by measures in emerging emitters to adopt lower-carbon development pathways, including progress on accelerating changes to industrial structure, energy transformation and adoption of new production technologies. For example, in countries where industry drives emissions growth, efforts could focus on accelerating structural transformation, which in turn is essential for economic diversification and job creation; countries with increasing energy consumption as major drivers of emissions growth can explore ways to lower their emission intensity, through both technologies that improve energy efficiency and shifts towards low carbon sources of energy, such as, clean oil, gas, and renewable energy.

A global adoption of a “low carbon lifestyle” would lessen the carbon intensity of production in developing countries. Low-carbon technologies are a crucial means to limit the surging emissions. In our scenario analyses, adoption of low-carbon technologies can have a considerable influence on future emission reduction: with early application of CCS and renewable energy in the power sector and electric vehicles replacing the oil-fueled automobiles, the emerging emitters could reduce emissions by 600 Mt $CO_2$ by 2040. The challenge for the global community is to facilitate these economic transformations in ways that support sustained growth and poverty reduction. This can be achieved by improving access to the finance and knowledge necessary to support adoption of new technologies and the shift towards lower carbon intensity of growth. More advanced countries could assist developing countries by sharing energy-saving technologies and knowledge about renewable energy. Climate clubs have been identified as one solution to deliver coordinated climate mitigation (Nordhaus 2015; Paroussos et al. 2019), facilitating, for example, the technology diffusion that would lower the cost of mitigation in developing economies. More generally, simultaneously addressing the challenges of ending extreme poverty, achieving inclusive growth throughout the world and meeting climate goals will require cooperative solutions that integrate both the development needs and emission realities of developing countries.

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***Annex 1: The 59 countries with fast-growing $CO_2$ emissions***

| Country | Stage | Country | Stage |
|---|---|---|---|
| Lao People's Dem. Rep. | LDC, LLDC, DE | Kenya | DE |
| Myanmar | LDC, DE | Uganda | LDC, LLDC, DE |
| Zambia | LDC, LLDC, DE | Qatar | DE |
| Mozambique | LDC, DE | Pakistan | DE |
| Tajikistan | LLDC, EIT | Turkey | DE |
| Nepal | LDC, LLDC, DE | Indonesia | DE |
| Botswana | LLDC, DE | Mongolia | LLDC |
| Cambodia | LDC | Algeria | DE |
| Ethiopia | LDC, LLDC, DE | Jordan | DE |
| Sri Lanka | DE | Iraq | DE |
| Georgia | EIT | Ghana | DE |
| Cote d'Ivoire | DE | Eritrea | LDC, DE |
| Tanzania | LDC, DE | Azerbaijan | LLDC, EIT |
| Philippines | DE | Namibia | DE |
| Dem. Rep. Congo | LDC, DE | Armenia | LLDC, EIT |
| Mali | LDC, LLDC, DE | Colombia | DE |
| Haiti | LDC, DE | Sudan | LDC, DE |
| Bolivia | LLDC, DE | United Arab Emirates | DE |
| Paraguay | LLDC, DE | Saudi Arabia | DE |
| Nigeria | DE | Chile | DE |
| Rep. Congo | DE | Honduras | DE |
| Niger | LDC, LLDC, DE | Morocco | DE |
| Bangladesh | LDC, DE | Cameroon | DE |
| Kyrgyzstan | LLDC, EIT | Angola | LDC, DE |
| Oman | DE | Turkmenistan | LLDC, EIT |
| Guatemala | DE | Nicaragua | DE |
| Vietnam | DE | Peru | DE |
| Senegal | LDC, DE | South Sudan | LDC, LLDC, |
| Benin | LDC, DE | Egypt | DE |
| Lebanon | DE | | |

*Note for the stages: LDC for least developed countries, LLDC for landlocked developing countries, DE for developing economies, EIT for economies in transition.*

# Annex 2: The Economic Impacts Model

We extend the ARIO model to a multiregional economic impact model which has the ability to simulate the propagation of the shocks in multiple regions (Hallegatte 2008). After calibrating the model with the latest GTAP database (Aguiar et al. 2019), we assess the dynamic impact of COVID-19 control measures on the global economy throughout production supply chains by considering available production imbalances and consumer behaviour changes (Guan et al. 2020).

In the model, there are two types of agents, producers and households. In an economy, each sector can be regarded as a producer, in which labour and capital are the two main inputs for producing products. Meanwhile, economic sectors are also consumers that require intermediate products from other sectors.

There are various functional forms for industrial production, such as Leontief, Cobb-Douglas (C-D) and the Constant Elasticity of Substitution (CES) function. The Leontief production function does not allow for substitution between inputs and is more suitable for this study, as the COVID pandemic shock occured without any warning and economic agents cannot make timely adjustments. According to the Leontief function, the output from sector $i$ in region $r$ ($x_{i,r}$) can be expressed as:.

$$x_{i,r} = min\left(\text{for all } p, \frac{z_{i,r}^{p}}{a_{i,r}^{p}}; \frac{va_{i,r}}{b_{i,r}}\right) \qquad \text{Equation 1}$$

where $p$ denotes type of intermediate products; $z_{i,r}^{p}$ refers the intermediate product $p$ used in sector $i$; $va_{i,r}$ refers the primary inputs for the sector $i$, including labour ($L$) and capital ($K$). $a_{i,r}^{p}$ and $b_{i,r}$ are the input coefficients of intermediate products $p$ and primary inputs of sector $i$, which can be calculated in Equation 2. All the economic transactions and industrial interdependence are expressed in monetary values.

$$a_{i,r}^{p} = \frac{\bar{z}_{i,r}^{p}}{\bar{x}_{i,r}}, b_{i,r} = \frac{\overline{va}_{i,r}}{\bar{x}_{i,r}} \qquad \text{Equation 2}$$

Before COVID-19 occurred, total output satisfies both intermediate demands and final demands from consumers. However, such economic balances are broken by the pandemic and constrain supply chains. From the view of the producer, restriction of labour input caused by control measures decreases production capacity and outputs.

Labour constraints after a disaster may impose severe knock-on effects on the rest of the economy(Guan et al. 2020). This makes labour constraints a key factor to consider in disaster impact analysis. For example, in the case of a pandemic, these constraints can arise from employees' inability to work as a result of illness or death, or from the inability to go to work and the requirement to work at home (if possible). In this model, the proportion of surviving productive capacity from the constrained labour productive capacity ($x_i^L$) after a shock is defined as:

$$x_i^L(t) = \left(1 - \gamma_i^L(t)\right) * \bar{x}_i$$

Where $\gamma_i^L(t)$ is the proportion of labour that is unavailable at each period $t$ during the lockdown containment period. $(1 - \gamma_i^L(t))$ contains the available proportion of employment at period $t$.

$$\gamma_i^L(t) = (\bar{L}_i - L_i(t))/\bar{L}_i$$

The proportion of the available productive capacity of labour is thus a function of the losses from the sectoral labour forces and its pre-disaster employment level. Following the assumption of the fixed proportion of production functions, the productive capacity of labour in each region after a disaster ($x_i^L$) will represent a linear proportion of the available labour capacity at each time step. Take COVID-19 as an example, during an outbreak of an infectious disease, authorities often adopt social distancing and other measures to reduce the risk of infection. This imposes an exogenous negative shock on the economic network.

The shortage of intermediate products will further affect the production capacity of downstream sectors and reduce their outputs due to the forward linkage effect. If we consider the limitations of primary and intermediate inputs, the maximum production capacity of sector $i$ in period $t$ ($x_{i,r}^{max}(t)$) can be calculated as Equation 3.

$$x_{i,r}^{max}(t) = min\left(x_i^L(t); \text{for all } i, r, x_{i,r}^p(t)\right) \qquad \text{Equation 3}$$

$x_{i,r}^L(t)$, $x_{i,r}^p(t)$ are the maximum outputs when considering the labour constraints and intermediate input scarcity, respectively.

From the view of demand, 1) direct contact business activities become less when keeping social distancing; 2) alternative consuming activities impact on the output of producers through changing demand of consumers (i.e. backward effect). Hence, the total order demand for the sector $i$ in period $t$ ($TD_{i,r}(t)$) equals to the sum of intermediate demand and household demand (Equation 4).

$$TD_{i,r}(t) = \sum_{j,s} FD_{i,r}^{j,s}(t) + \sum_s HD_{i,r}^s(t) \qquad \text{Equation 4}$$

where $FD_{i,r}^{j,s}(t)$ refers the order demand that sector $j$ in region $s$ required from supplier $i$ in region $r$; $HD_{i,r}^s(t)$ is the order demand that household in region $s$ required from supplier $i$ in region $r$.

For a more realistic representation of the real production process, we assume that each sector holds some inventory of intermediate goods. In each time step, sectors use intermediate products from their inventories for production, and purchase intermediate products from their supplying sectors in order to restore their inventories( Hallegatte 2014). The amount of intermediate product $p$ hold by sector $j$ in region $s$ in period $t$ is denoted as $S_{j,s}^p(t)$, and we assume the inventory of intermediate product $p$ required by sector $j$ in region $s$ is $S_{j,s}^{p,*}(t)$, which could fulfil its consumption for $n_{j,s}^p$ days.

$$S_{j,s}^{p,*}(t) = n_{j,s}^p * a_{j,s}^p * x_{j,s}^{max}(t) \qquad \text{Equation 5}$$

Then the order issued by sector $j$ to its supplying sector $i$ is

$$FD_{i,r}^{j,s}(t) = \begin{cases} \left(S_{j,s}^{p,*}(t) - S_{j,s}^p(t)\right) * \frac{\overline{FD}_{i,r}^{j,s} * x_{i,r}^{max}(t)}{\sum_{j\to p}\left(\overline{FD}_{i,r}^{j,s} * x_{i,r}^{max}(t)\right)}, & \text{if } S_{j,s}^{p,*}(t) > S_{j,s}^p(t); \\ 0 & \text{if } S_{j,s}^{p,*}(t) \le S_{j,s}^p(t). \end{cases} \qquad \text{Equation 6}$$

$HD_{i,r}^s(t)$ is measured by the household demand and the supply capacity of their suppliers. In this study, the demand of final products $q$ by household in region $s$, $HDT_s^q(t)$, is given exogenously at each time step. Then, the order issued by household $s$ to its supplier $i$ is

$$HD_{i,r}^s(t) = HDT_s^q(t) * \frac{\overline{HD}_{i,r}^s * x_{i,r}^{max}(t)}{\sum_{i\to q}\left(\overline{HD}_{i,r}^s * x_{i,r}^{max}(t)\right)} \qquad \text{Equation 7}$$

Taking both forward effects and backward effects into consideration simultaneously, the actual output of the producer $i$ in period $t$ ($x_{i,r}^a(t)$) is

$$x_{i,r}^a(t) = min\left(x_{i,r}^{max}(t), TD_{i,r}(t)\right) \qquad \text{Equation 8}$$

The actual production will be allocated to downstream economic sectors and households according to their orders. If the output is not enough to meet all orders, it will be split according to the order proportion(Hallegatte 2008; Li et al. 2013).

If we assume the growth rate for each producer ($g$) remains the same within the entire process, then the actual output of the producer $i$ in time $t$ after adjusting the economic growth ($xx_{i,r}^{a}(t)$) can be calculated in Equation 9.

$$xx_{i,r}^{a}(t) = \left(1 + g_{i,r}\right) * xx_{i,r}^{a}(t-1) * \left(\frac{x_{i,r}^{a}(t)}{x_{i,r}^{a}(t-1)}\right) \qquad \text{Equation 9}$$

The scenarios of lockdown are defined in terms of length and strictness.

Lockdown periods (T): Kissler et al. 2020b projected the dynamic spread of the pandemic over the coming years and defined intermittent social distancing scenarios to ensure that critical care capacities are not exceeded. With reference to their results, we define three scenarios for "lockdown periods" and "recovery periods" (see Table A1). Scenario $T$ incorporates the intermittent social distancing scenario defined by Kissler et al. 2020b, under Scenario $T_{+}$ each lockdown period requires 10% more time, while under Scenario $T_{-}$ the lockdown period is 10% shorter.

*Table A1*.1 *Scenarios of lockdown periods*

| Period | Scenario $T$ | Scenario $T_{+}$ | Scenario $T_{-}$ |
|---|---|---|---|
| Lockdown period 1 | 18/03/20 – 07/07/20 | 11/03/20 – 14/07/20 | 25/03/20 – 30/06/20 |
| Recovery period 1 | 08/07/20 – 11/08/20 | 15/07/20 – 17/08/20 | 01/07/20 – 04/08/20 |
| Lockdown period 2 | 02/09/20 – 17/11/20 | 26/08/20 – 24/11/20 | 09/09/20 – 10/11/20 |
| Recovery period 2 | 18/11/20 – 15/12/20 | 25/11/20 – 22/12/20 | 11/11/20 – 08/12/20 |
| Lockdown period 3 | 05/01/21 – 02/03/21 | 30/12/20 – 09/03/21 | 13/01/21 – 23/02/21 |
| Recovery period 3 | 03/03/21 – 23/03/21 | 10/03/21 – 30/03/21 | 24/02/21 – 16/03/21 |
| Lockdown period 4 | 21/04/21 – 22/06/21 | 14/04/21 – 29/06/21 | 28/04/21 – 15/06/21 |
| Recovery period 4 | 23/06/21 – 13/07/21 | 30/06/21 – 20/07/21 | 16/06/21 – 06/07/21 |
| Lockdown period 5 | 04/08/21 – 21/09/21 | 28/07/21 – 28/09/21 | 11/08/21 – 14/09/21 |
| Recovery period 5 | 22/09/21 – 12/10/21 | 29/09/21 – 19/10/21 | 15/09/21 – 05/10/21 |
| Lockdown period 6 | 10/11/21 – 21/12/21 | 03/11/21 – 28/12/21 | 17/11/21 – 14/12/21 |
| Recovery period 6 | 22/12/21 – 04/01/22 | 29/12/21 – 11/01/22 | 15/12/21 – 28/12/21 |
| Lockdown period 7 | 16/02/22 – 29/03/22 | 09/02/22 – 05/04/22 | 23/02/22 – 22/03/22 |
| Recovery period 7 | 30/03/22 – 12/04/22 | 06/04/22 – 19/04/22 | 23/03/22 – 05/04/22 |
| Lockdown period 8 | 18/05/22 – 28/06/22 | 11/05/22 – 05/07/22 | 25/05/22 – 21/06/22 |
| Recovery period 8 | 29/06/22 – 05/07/22 | 06/07/22 – 12/07/22 | 22/06/22 – 28/06/22 |

*Note: The scenarios of lockdown and recovery periods are designed for countries other than China. In our model, China has two months' lockdown period starting from 22nd January and then recovery period afterwards.*

Strictness of the future lockdown periods (S2): Considering the learning effects and potential herd immunity, countries might achieve the same control of pandemic spread with weaker strictness in the future periods of lockdown. Therefore, we design three scenarios of the strictness of lockdown in different periods, see

Table .

*Table A2.2 Scenarios of lockdown strictness*

| Period | Scenario $S2$ | Scenario $S2_{+}$ | Scenario $S2_{-}$ |
|---|---|---|---|
| Lockdown period 1 | 100% | 100% | 100% |
| Lockdown period 2 | 50% | 60% | 40% |
| Lockdown period 3 | 30% | 40% | 20% |
| Lockdown period 4 | 20% | 30% | 10% |
| Lockdown period 5 | 20% | 30% | 10% |
| Lockdown period 6 | 20% | 30% | 10% |
| Lockdown period 7 | 20% | 30% | 10% |
| Lockdown period 8 | 20% | 30% | 10% |

*Note: The numbers in the table refer to the percentage of the strictness of lockdown periods to the first lockdown period.*

Based on the basic settings of the scenarios, we take three representative scenarios: (1) the mildest lockdown scenario, which means that there are only two lockdowns within the lockdown period 1 and 2, and the technology level improves as in the baseline scenario; (2) the strictest lockdown scenario of eight lockdowns with the same duration and strictness of the first period and where technology improves at half the speed of the baseline scenario; and (3) the default lockdown scenario, where lockdown strictness is defined by Scenario S2 in Table A2.2 and technology improves at 75% of the speed of the baseline scenario.

## Annex 3: Data sources and adjustments.

*Historical data on emissions and economic characteristics*: Data on $CO_2$ emissions from fuel combustion and energy consumption over 2010-2018 are from the International Energy Agency (IEA 2018b; 2018c) and cover of over 140 countries by energy type and economic sector. The population and the GDP data, and the information on industrial structure, the percentage of agriculture, forestry, and fishing, industry and services in value added are from the World Bank (World Bank 2020). The emission intensities are collected from the GAINS (Greenhouse Gas - Air Pollution Interactions and Synergies) model of IIASA (International Institute for Applied Systems Analysis 2020) and World Energy Model 2019 of IEA (IEA 2019b).

*Data for COVID models*: The global multi-regional input-output (MRIO) table used in the model is compiled from the latest GTAP database (version 10)(Aguiar et al. 2019). The GTAP database presents values of transactions of intermediate products between 65 sectors, the output of each sector, and final consumption of commodities in 141 countries/regions. It also provides global bilateral trade links among the sectors and countries/regions. The growth rates of sectoral GDP ($g_{i,r}$) are collected from the International Institute for Applied System Analysis (IIASA)(International Institute for Applied Systems Analysis 2020).

The no-COVID assumption data including sectoral value added, sectoral post-COVID energy mix and $CO_2$ emissions are from the No Policies Scenario (NPS) projections of GAINS. The data on $CO_2$ emissions, population and GDP under SSPs are from the SSP Database (version 2.0) (Riahi et al. 2017; KC and Lutz 2017; Cuaresma 2017; Jiang and O'Neill 2017; Leimbach et al. 2017; Dellink et al. 2017). The energy mix data and the corresponding $CO_2$ emissions by sector and region are from the No Policies Scenario (NPS) projections of GAINS model.

*Data harmonization*: There are gaps between data from the different sources. In this work, we took the IEA $CO_2$ emissions as the standard by which to harmonize the $CO_2$ emissions data from the COVID model, the SSP-scale-down results and the results from the designed WPS and LCT scenarios. Specifically, the COVID model's results are adjusted by the ratio to IEA extrapolated results in 2020, and the SSP results, the WPS results, and the LCT results are then adjusted by the ratio to COVID model's results in 2024.