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The statistical projection of global GHG emissions from a consumption perspective

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Abstract

Projections of future emissions based on current trends are vital to assess the performance of mitigation efforts and to devise mitigation strategies. However, previous studies are uncertain how the persistence and convergence of mitigation efforts may impact future trajectories from the consumption perspective. Here we assume regional convergence over time after finding strong supporting historical evidence and develop a Markov Chain Monte Carlo (MCMC) Bayesian analysis of historical and projected consumption-based emissions during 1995–2050 via a modified Kaya identity. We find global emissions of 21–94 GtCO₂eq yr⁻¹ by 2050, slightly higher than SSP1-2.6 and encompassing SSP3-7.0, resulting in 1.4–2.9 °C of warming above pre-industrial levels mid-way through the century. The median projection shows a 2028 peak of 42 GtCO₂eq yr⁻¹ and an annual average decrease of 0.25 GtCO₂eq thereafter. Future emission decreases result from the interplay between a rapid reduction driven by decreasing consumption-based emission intensities, especially in clothing and transport, and the change of final demand structure (−1.53 GtCO₂eq yr⁻¹) against increases from economic and population growth (−1.33 GtCO₂eq yr⁻¹). This highlights the importance in continually updating projections and considering models that reflect convergence and consumption structure changes, in order to better inform climate policy.

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1. Introduction

Future emissions trajectories are dependent on a complex set of dynamics, including social and technical lock-ins, policy feedbacks, and cultural or technological developments (Geels et al., 2017). Investigating these trajectories often involves two predominant modelling approaches: scenario analysis, in which parameters can be normatively altered to match future storylines, including technologies and socio-political trends (Tavoni et al., 2015; Schaeffer et al., 2020; Hultman et al., 2020); and statistical projections based on the continuation of current trends (Raffery et al., 2017, Liu and Raffery, 2021). The scenario analysis can explicitly account for idealized/real-world climate policies, such as carbon taxes, across multiple scenarios of interest (Iyer et al., 2015; Krey et al., 2019; Fragkos et al., 2021). However, the scenario analysis (e.g., Integrated Assessment Models or SSP scenarios) are not predictions (Marquardt et al., 2021), as they aim to inform what could happen if certain assumed, normative conditions prevail in the future (Swart et al., 2004; van Vuuren et al., 2011; Schwalm et al., 2020). Conversely, a statistical projection is a probabilistic statement that something will happen in the future based on what is known today. This is because statistical projections have the potential to reflect the emissions impact of the persistence of historical macro-scale socio-economic trends by extrapolating historical trends in mitigation efforts into the future (Raffery et al., 2017; Liu and Raffery, 2021). Statistical projections also hold the potential for characterizing future emission uncertainty based on these trends in multiple factors (Girod et al., 2013; Friedlingstein et al., 2014).

As such, statistical modelling cannot identify potential emission reduction pathways by assessing the impacts or feasibility of prescribed policies. But it can reflect how the persistence in current macro-economic dynamics to reduce emissions, including any ongoing acceleration of these efforts, impacts future emissions. This is in contrast with other future storylines consistent with specific socio-economic assumptions since they require the modeler to explicitly acknowledge which mitigation efforts continue or change. Importantly, a statistical projection should not be confused with a no-policy baseline, also sometimes
term Business-As-Usual (BAU) (IPCC, 2014; Hausfather and Peters, 2020) (a term which has fallen out of favor due to its opacity), since such a scenario holds all technologies, policies, and many other drivers of emissions constant at historical values. Here, our statistical model assumes a strengthening of climate mitigation efforts into the future (based on the rate of change in previous efforts) and so could arguably be useful as a baseline against which more aggressive efforts could be assessed. Furthermore, statistical projections can offer a complementary method for assessing the emission trajectories over time, estimating uncertainties in such trajectories, and highlight the importance of further acceleration in mitigation efforts. The decomposition analysis we did can also show how emissions might drop through factors within and outside policy control. For example, short-run population change is largely outside policy control for many countries, whereas decarbonization through consumption-based emissions intensity reduction is within policy control, which can be realized by technological improvement in the supply chain.

The estimation of future emissions trajectories is typically based on production-based emissions accounts (Grubler et al., 2018; Tong et al., 2019; Rogelj et al., 2018) and so omit developments in consumption patterns that may alter total emissions via developing consumption patterns, including the ratio between household consumption and investment (Guan et al., 2014). By moving to consumption-based emissions, we can investigate the persistence of trends in the volume of GHG embodied in the final consumption of goods and services, and to abstract the specifics from those emissions occur along supply chains. This is not just important for the composition of products that people buy (for example shifts from physical goods to services, which may influence emissions) but also for the ways in which economies transition between consumption-based and infrastructure-led growth over time. The result is an improved insight into the evolution of consumption behavior within nations and the comparison between them (Davis and Caldeira, 2010; Chen et al., 2018). Especially, when the demand for drastic changes in consumption is well reflected in the 2030 Agenda for sustainable development through indicating one of its seventeen sustainable development goals (SDG 12), our model variables offer the opportunity to establish future strategies regarding emissions factors. This allows for the definition of future public policies to achieve sustainable development goals. Broadly, as GDP rises, we see a final demand adjustment from high to low-carbon products as economies restructure both nationally and in the global production system (Yu et al., 2018; Luderer et al., 2018). There have been several studies dealing with the historical impact of consumption structure on emissions using decomposition analysis (Arto and Dietzenbacher, 2014; Lan et al., 2016). These studies find that such analyses are especially important for analyzing the emissions of emerging nations. Overall, the projection of consumption-based emissions may provide a more nuanced understanding of endogenous reductions in carbon emissions and could provide a reference from which to formulate low-carbon policy (Scherer et al., 2019; Harris et al., 2020).

In this study we use Bayesian statistical approaches and a modified Kaya identity to explore how global emissions may evolve in the coming decades if currently observed rates of change in the driving forces in the global economy persist. Additionally, we investigate the trends in consumption-based emissions from 7 product categories (food, clothing, housing, household appliances, transport, services, and construction) and 3 final demand categories (household, investment, and government). The 7 product categories reflect the composition of product consumption, and the 3 final demand categories reflect the structure of final demand. We also project the evolution of global temperature using a standard linear response and we omit specific carbon-cycle feedbacks (see Methods). Previous studies on the decomposition of consumption-based emissions investigated the influence of factors on emissions changes based on multiregional input-output models (see details in Table S1). Six driving forces of GHG emissions were identified (emission intensities, consumption structure, final demand structure, final-demand-to-GDP ratio, GDP per capita, and population). Thus, we allocate total emissions into six blocks, each corresponding to one driving force. To project emissions, we extrapolate the historical evolution of emission intensities, consumption structure final demand structure and final-demand-to-GDP ratio, and use exogenous projections of GDP and population from the OECD (2019) and United Nations et al. (2019), considering the specific socio-economic and technical context for 38 individual countries and 2 world regions (see Table S2). Historical data for the drivers of consumption are from the global multi-regional input-output model EXIOBASE from 1995 to 2015. We observe the historical data for convergence between nations and find that consumption-based emissions intensities converge to the best performer with time (Fig.S1-S2). Moreover, consumption and final demand structure converge for nations at different levels of economic development, dependent on GDP per capita (Fig.S3-S6). We characterize this convergence and use it to project the key emission drivers to 2050. Note that, to avoid unreasonably fast growth of emissions intensity, we posit a regional convergence in emissions intensity, which can be viewed as a catch-up effect, with worst-performing regions improving in relative terms based on their historical paths when compared with best performers. This can occur through technological diffusion along the global supply chain (Ciscar and Soria, 2000), especially when we

### Nomenclature

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>SDG</td>
<td>Sustainable Development Goal</td>
</tr>
<tr>
<td>MRIO</td>
<td>Multi-regional input-output</td>
</tr>
<tr>
<td>LMDI</td>
<td>Logarithmic Mean Divisia Index</td>
</tr>
<tr>
<td>MCMI</td>
<td>Markov Chain Monte Carlo</td>
</tr>
<tr>
<td>Z</td>
<td>Intermediate flow matrix</td>
</tr>
<tr>
<td>Y</td>
<td>Final demand matrix</td>
</tr>
<tr>
<td>V</td>
<td>Primary input flow matrix</td>
</tr>
<tr>
<td>X</td>
<td>Total output</td>
</tr>
<tr>
<td>B</td>
<td>Direct emission coefficients</td>
</tr>
<tr>
<td>P</td>
<td>Population</td>
</tr>
<tr>
<td>E</td>
<td>The GHG emissions associated with the consumption</td>
</tr>
<tr>
<td>S</td>
<td>Consumption-based emission intensity</td>
</tr>
<tr>
<td>G</td>
<td>Final demand structure</td>
</tr>
<tr>
<td>O</td>
<td>The ratio of final demand to GDP</td>
</tr>
<tr>
<td>C</td>
<td>GDP per capita</td>
</tr>
<tr>
<td>N</td>
<td>Normal distribution</td>
</tr>
<tr>
<td>TN</td>
<td>Truncated normal distribution</td>
</tr>
<tr>
<td>LN</td>
<td>Lognormal distribution</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>RoW</td>
<td>Rest of World</td>
</tr>
<tr>
<td>IEA</td>
<td>International Energy Agency</td>
</tr>
<tr>
<td>BAU</td>
<td>Business-As-Usual</td>
</tr>
<tr>
<td>R</td>
<td>The direct emissions from activity sectors</td>
</tr>
<tr>
<td>H</td>
<td>The emissions from final demand components</td>
</tr>
<tr>
<td>curr</td>
<td>Current price</td>
</tr>
<tr>
<td>Const</td>
<td>Constant price</td>
</tr>
<tr>
<td>def</td>
<td>Previous year’s price deflator</td>
</tr>
<tr>
<td>U</td>
<td>Bridge matrix</td>
</tr>
<tr>
<td>PYP</td>
<td>Previous year’s price</td>
</tr>
<tr>
<td>Dvoid</td>
<td>The original WIOD deflator</td>
</tr>
<tr>
<td>Dah</td>
<td>The deflator in the ad-hoc classification</td>
</tr>
<tr>
<td>D</td>
<td>The deflator for every EXIOBASE region which also exists in the WIOD region classification</td>
</tr>
<tr>
<td>M</td>
<td>Production-based emission intensity</td>
</tr>
<tr>
<td>L</td>
<td>Leontief inverse matrix</td>
</tr>
<tr>
<td>A</td>
<td>Technical coefficients matrix</td>
</tr>
</tbody>
</table>
define the consumption-based emission intensity as all emissions that occur along the supply chain to consume one unit of product. Previous papers also have tested the existence of regional convergence of consumption-based emission intensity (Camarero et al., 2013, Kounetas, 2018, Bolea et al., 2020). Finally, we provide overall uncertainties for these projections, identifying specific probability distributions for each of the drivers.

2. Methods

In this paper we are interested in quantifying the historical evolution of GHG emissions in different countries that result from the consumption of different product categories in different final demand categories, as well as to estimate future emissions and identify drivers of change. Therefore, we need to consider different regions, indexed with \( r \) and \( s \), different types of product (or industry), indexed with \( i \) and \( j \), different types of final demand category (households, investment, government), indexed with \( k \). In the paper we also consider different years, so when relevant variable \( t \) will be specified. The relevant source data consists in a set of, for each year: interregional transactions, \( Z_{ij}^r \) (flows from sector \( i \) in region \( r \) to sector \( j \) in region \( s \)); final demand flows, \( Y_{rk}^i \) (flows from sector \( i \) in region \( r \) to final demand category \( k \) in region \( s \)); primary inputs, \( V_{jr}^i \) (primary input payments of sector \( j \) in region \( r \)); total output, \( X_{jr}^i \) (sum of all flows leaving sector \( i \) in region \( r \)); direct emissions coefficients, \( B_{ir}^j \) (GHG emitted by sector \( j \) in region \( r \)); population, \( P_r \) (number of inhabitants in region \( r \)). Emission projections are obtained using a hierarchical Bayesian model and drivers of change are calculated using the LMDI decomposition.

2.1. Kaya identity

The Kaya identity (Kaya, 1990) considered in this study has as main goals the isolation of emission intensity associated with the consumption of different products from other factors such as composition, total consumption growth, and population. For a given country and year, total emissions are the sum of the product of the emission intensity associated with the consumption of a product, the share of that product in the total expenditure of a given final demand category, the share of that final demand category in total final demand, the ratio from total final demand to GDP, GDP per capita and population. To obtain the total consumption of the country it is necessary to sum over all products and all final demand categories. The result is the GHG emissions associated with the consumption of region \( r \) (\( E_r \)). Mathematically:

\[
E_r = \frac{q}{k} \sum_{i} \sum_{j} F_{ijk} \times v_{ik} \times v_{jr} \times v_{fr} \times P_r
\]

(1)

Summation is performed over \( m = 40 \) regions (either specific countries or aggregates thereof), over \( n = 3 \) final demand components and over \( q = 7 \) product categories. \( v_{ik} \) is the consumption for product \( i \) of consumption component \( k \) in region \( r \); \( v_{jr} \) is the consumption of consumption component \( k \) in region \( r ); \( v_{fr} \) is the total GDP in region \( r \). The first factor, \( F_{ijk} \), is the emission intensity for consumption of product \( i \) in final demand category \( k \) in region \( r \). The second factor, \( v_{ik} \), is the share of product \( i \) in the total expenditure of final demand component \( k \) in region \( r \) and is referred to as consumption structure. The third factor, \( v_{jr} \), is the fraction of final demand component \( k \) over total final demand in region \( r \), and is referred to as final demand structure. The fourth factor, \( v_{fr} \), is the ratio of final demand to GDP in region \( r \). The fifth factor, \( C_r \), is the GDP per capita in region \( r \). The sixth factor, \( P_r \), is the total population in region \( r \).

The time range considered in this study is 1995–2050 and the year up to which historical data is available differs between factors. Table S5 indicates those years and data sources, with subsequent years projection intervals being estimated. The final demand components considered are households, government, and investment; the product categories are listed in Table S3; countries and world regions are listed in Table S2. The MRIO model and the calculation of consumption-based emission intensity are elaborated in SI Appendix, Section 1 and 3. Moreover, since the LMDI method delivers an exact decomposition and fulfills some useful properties like the circular test under the condition of data homogeneity, we use it decompose the historical and future changes in GHG emissions into a set of above mentioned factors. The LMDI decomposition (Ang, 2004, 2005) are elaborated in SI Appendix, Section 4.

2.2. Projections

We have so far described how all historical terms in the Kaya identity have been calculated (with population being read directly from source data). We now describe how projections were made for each factor. We employ Bayesian hierarchical models (Kevin, 2012; Gelman et al., 2013) to obtain projection intervals of each factor of the Kaya identity through a sampling of Markov Chain Monte Carlo (MCMC) chains. That means there is a set of expressions that determine how a variable change based on information of the same or other variables in the preceding year and possibly other variables in the same year, with all or at least some of those variables being stochastic, meaning that at every year the variable is sampled from a probability distribution. The model is hierarchical meaning that the parameters of those probability distributions are themselves taken from another probability distribution. Each factor has different properties so below we clarify them separately, and a table with variables and their ranges of calibration is supplied in Table S5.

2.2.1. Projection of consumption-based emission intensity

We found that in most regions, emission intensities have peaked and have begun to decline after 2010 (Fig.S1). The differences in emission intensity of most regions and the best performers (those with the lowest emission intensities of a product) have been narrowing. That is, most regions have been converging to the performance of the best performers (Fig.S2). In finding the best performer we identified a country that saw the lowest emission intensity for each product category (for example Switzerland for the emission intensity of food) and projected the evolution of that product/country pair, \( F_{t,ijk} \), following the historical decrease rate as a function of GDP per capita, reflecting its historical improvement in performance. The best performers in each product and final demand category are listed in Table S7. Note that there is no negligible consumption of some product categories within different final demand categories (e.g., construction for households and food for investment). These empty categories were not projected neither in terms of emission intensity nor in terms of consumption structure but simply set to zero. In the case of government, since its consumption volume and associated emissions are minor, all product categories are bundled together for the purpose of modelling the projection. The emission intensity of that same product category in all other countries is modelled as a first-order auto-regressive model, converging to the intensity of the best performer at its own historical rate. The projected consumption-based emission intensity factor (\( F_{t,ijk} \)) is:

\[
\ln F_{t,ijk} = \alpha_{ijk} + \beta_{ijk} \ln C_r + \epsilon_{ijk}^T
\]

\[
\ln F_{t,ijk} - \ln F_{t-1,ijk} = \delta_{ijk}(\ln F_{t-1,ijk} - \ln F_{t-1,ijk}) + \epsilon_{ijk}^T
\]

where \( N \) is a normal distribution; \( TN \) is a truncated normal distribution by bounding the random variable from 0 to 1. These parameters were
First, we project the target level for each product category in a final demand structure, and GDP structure, with consumption structure that when we talk about supply chains of a region, we mean the supply chain delivery the final consumption of that region. Previous studies have discussed the convergence of emission intensity using the Phillips and Sul (2007) method (Camarero et al., 2013; Cialani and Mortazavi, 2021; Nazlioglu et al., 2021), and highlighted the contribution of globalization and supply-chain specialization. This leads to the assumption that product-specific emission intensities of different regions are converging.

### 2.2.2. Projection of final demand structure

We found GDP per capita has a large effect on the evolution of consumption structure and GDP structure, with consumption structure converging as a function of economic growth (Fig.33–35), in accordance with the findings of Lyons et al. (2009) and Fernández-Amador et al. (2019). For both variables we use a two-step procedure to model projections of consumption structure which, in contrast to the projection of emission intensities, does not use a particular region as a benchmark. First, we project the target level for each product category in a final demand category (e.g., household consumption) using a logarithmic linear relationship between each variable and GDP per capita based on panel data, which can be viewed as a panel-data frontier. Then, to reflect regional convergence, we assume that each region will approach the panel-data frontiers as a function of economic growth but not as a function of time, using a first-order autoregressive model. This means that a probability distribution for each variable is determined by region-specific parameters that reflect local characteristics, and the panel-data frontier. Consumption structure, or consumption share factor \( S_{t,i,k} \), is modelled as:

\[
\ln S_{t,i,k} = \alpha_{i,k} + \beta_{i,k} \ln C_{t,r} + \epsilon_{i,k}^{(5)}
\]

This would not reflect the specific change in the consumption intensity across all regions and select the best performer region as projection reference, such that all regions follow a general emission intensity decrease trend through converging to the best performer. This does not mean substitution between products for this part of the modelling. The choice of benchmark can have an impact on the model. We could, in principle, have chosen a panel of regions for the benchmark, but that would imply that for some regions, convergence would lead to an increase in future emissions intensities since countries with higher emission intensities would be mixed in with countries with lower emission intensities. This would not reflect the important historical trends of declining emission intensities across the world as described above. Thus we assume that there is a convergence trend in the emissions intensity across all regions and select the best performer region as projection reference, such that all regions follow a general emission intensity decrease trend through converging to the best performer. This does not mean we are stating that all countries will continue doing so in the future emissions intensities since countries with higher emission intensities would be mixed in with countries with lower emission intensities. This would not reflect the important historical trends of declining emission intensities across the world as described above. Thus we assume that there is a convergence trend in the emissions intensity across all regions.

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### 2.2.3. Projection of final demand structure

Since the projection of final demand structure during 2015–2023 can be obtained from the World Bank, we model the final demand structure of all regions from 2023 onward. The projection of final demand structure follows the same logic of consumption structure but is more involved as different nations seem to display different historical patterns. Final demand structure is affected by economic development, with China in particular having witnessed a rapid change, with the investment share first increasing and then decreasing in the past two decades (Fig S6). This is because during the period 1995–2015, China experienced a strong economic growth. Considering that economy will continue at an accelerated pace in major developing countries (i.e., India, Indonesia, and the ROW) (OECD, 2019), which can lead to significant increases in investment referring to the projection of World Bank, we assume that developing countries will undergoing a similar economic transition with China. Thus, we divide the 40 regions considered in this study into two groups. One group consists of the ROW, Indonesia and India, and the members of this group follow the non-monotonic pattern of China’s historical evolution during 1995–2023, converging to a frontier derived from China’s experience between final demand share and GDP per capita during 1995–2023. Final
demand share component \((G^*_t, k)\) for the ROW, Indonesia and India, is modelled as:

\[
G^*_t, k = \alpha_k + \beta_k \ln C_t + \phi_k \ln (C^*_t)^2 + \epsilon_k^{(G)}
\]

These parameters were calibrated by applying MCMC sampling during the historical period with the following prior distributions:

\[
\begin{align*}
\alpha_k^{(G)} &\sim \text{uniform}(-1.5, 1) \\
\beta_k^{(G)} &\sim \text{uniform}(-3, 1) \\
\phi_k^{(G)} &\sim \text{uniform}(-1, 1) \\
\epsilon_k^{(G)} &\sim N\left(0, \sigma_G^{(G)}\right) \\
\sigma_G^{(G)} &\sim LN(-20, 50) \text{(lognormal)} \\
\end{align*}
\]

(7)

During 1995–2015, the investment shares in other 37 regions did not show significant shifts because their economic growth is relatively stable. Moreover, we observe a decline in the China's investment share with the implementation of China’s consumption-driven growth strategy (Fig. S6). Thus, for other 37 regions (including China), we use a method similar with the one used for consumption structure, to define the model for final demand structure. This requires the 37 regions to converge to a frontier obtained from panel data of 36 regions (excluding China), in terms of a linear relationship between final demand share and GDP per capita log scale during 1995–2023. Note that the 36 regions converge to the frontier based on the experience of 1995–2023, while China converges to the frontier based on the experience of 2010–2023, as China’s tipping point occurred in 2010. GDP share component \((G^*_t)\) for 37 regions is modelled as:

\[
G^*_t, k = \alpha_k + \beta_k \ln C_t + \epsilon_k^{(G)}
\]

(9)

These parameters were calibrated by applying MCMC sampling during the historical period with the following prior distributions:

\[
\begin{align*}
\alpha_k^{(G)} &\sim \text{uniform}(-1.6) \\
\beta_k^{(G)} &\sim \text{uniform}(-1, 1) \\
\epsilon_k^{(G)} &\sim N\left(0, \sigma_G^{(G)}\right) \\
\sigma_G^{(G)} &\sim LN(-20, 50) \text{(lognormal)} \\
\end{align*}
\]

(10)

2.2.4. Projection of final-demand-to-GDP ratio

We find that the range of final-demand-to-GDP ratios is relatively large (reaching 40%–180%) in the early years of the time-series (Fig. S14). In later years that range narrows (60%–120% after 2004). We explain this pattern by the compounding of errors. The errors originate in inconsistencies between data sources and aggregation: GDP data in current prices and national-level GDP PYP (previous year’s price) deflators are from the World Bank; while final demand data in current prices are from EXIOBASE and product-specific PYP deflators are from WIOD. Furthermore, EXIOBASE distinguishes 200 products in 49 regions while WIOD only 31 products in 40 regions (see SI Appendix, Section 2). The errors compound since by the nature of the deflation operation the farther we move from the baseline year (2010) the more multiplications are involved. Note however that this factor (the ratio of final-demand-to-GDP) has only a minor impact on emissions. Changes in this factor during the historical period of 1995–2015 have only contributed to a variation of −0.3% yr−1 of total emissions. We find that for most regions the change of final-demand-to-GDP ratio during the recent five years (2000–2015) is close to zero (Fig. S14). Thus, we use the final-demand-to-GDP ratio in 2015 as the expectation value. This means that future average yearly change is assumed to be zero. To involve uncertainty, we use historical observed variances in 2010–2015 to calibrate remaining model parameters. Therefore, we build a linear model to project the ratio \((O_t)\) as:

\[
O_t = O_0 + O_1 t + \epsilon_t^{(G)}
\]

(11)

Since we assume that future average yearly change is zero, the expected value of \(a\) is zero (that is the parameter \(\mu^{(G)} = 0\)). The other parameters in the model are calibrated using the 2010–2015 data with prior distribution as:

\[
\begin{align*}
\alpha_t^{(G)} &\sim N(\mu_t^{(G)}, \sigma_{\alpha}^{(G)}) \\
\beta_t^{(G)} &\sim LN(-5, 20) \text{(lognormal)} \\
\epsilon_t^{(G)} &\sim N(0, \sigma_{\epsilon}^{(G)}) \\
\sigma_{\epsilon}^{(G)} &\sim LN(-3, 20) \text{(lognormal)}
\end{align*}
\]

(12)

2.2.5. Projection of GDP per capita

The OECD provides the expected values of the projection of GDP per capita for the whole projection period (2021–2050), from which average yearly change can be obtained. To incorporate uncertainty, we use the historically observed variances in 1960–2020 to calibrate remaining model parameters. However, for some nations (e.g., Poland and Russia), the available data for GDP from the World Bank are more limited (from 1990 to 2020). The specific period range for historically observed GDP in each region can be seen in the Table S8. That is, the projected GDP per capita factor \((C_t)\) is:

\[
\ln C_t = \alpha + \ln C_{t-1} + \epsilon_t^{(C)}
\]

(13)

with parameter \(\mu_t^{(C)} = \frac{gd_{Pmax}}{gd_{Pmin}}\) for \(t_{min} < t \leq t_{max}\) and \(gd_{Pmax} - gd_{Pmin} = 1\), where \(gd_{Pmax}\) and \(gd_{Pmin}\) are sequential annual expectation projections from OECD. The other parameters are obtained by applying MCMC sampling with the same model in the historical period using as priors:

\[
\begin{align*}
\alpha_t^{(C)} &\sim N(\mu_t^{(C)}, \sigma_{\alpha}^{(C)}) \\
\beta_t^{(C)} &\sim LN(-3, 20) \text{(lognormal)} \\
\epsilon_t^{(C)} &\sim N(0, \sigma_{\epsilon}^{(C)}) \\
\sigma_{\epsilon}^{(C)} &\sim \text{uniform}(0, 80)
\end{align*}
\]

(14)

2.2.6. Projection of population

The UN database provides the expectation and annual-year projections intervals of population in the period 2020–2050. Thus, we use a model that is similar to the projection of GDP per capita and we have
checked a posteriori that the projection interval does not differ much from the UN predictions. The largest difference between our calculation and UN projection interval occurs in the EU. The upper bound of our estimation is 8.4 % higher than the upper bound of UN projection interval (see details in Fig. S15). In particular, the projection of population factor \( p_t \) is:

\[
\ln p_{t+1} - \ln p_t = \alpha + \varepsilon_t(P)
\]

with parameter \( \mu_{p_t} = \frac{pop_{t+1}}{pop_{t+1} - pop_{t+1}} \) for \( t < t \leq t_{max} \) and \( t_{max} - t_{min} = 1 \), where \( pop_{t+1} \) and \( pop_{t+1} \) are sequential annual expectation projections from the UN. The other parameters are obtained by applying MCMC sampling with the same model in the historical period using as priors:

\[
\begin{align*}
\alpha &\sim N(\mu_\alpha, \sigma_\alpha^2) \\
\sigma_\alpha &\sim \text{lognormal}(\mu_\sigma, \sigma_\sigma) \\
\varepsilon_t &\sim N(0, \sigma_\varepsilon^2) \\
\sigma_\varepsilon &\sim \text{uniform}(0, 80000)
\end{align*}
\]

2.3. Model estimation

Our model is run by the JAGS package in the R programming language. We use seven MCMC chains and simulated 10,000 iterations for each chain. 300 iterations are viewed as a burn-in period. The prior distributions of all blocks of parameters are listed in Eqs. (3), (5), (8), (10), (12), (14) and (16), and within each block every parameter has the same prior (e.g., the prior for every country \( \alpha_i \) is the same). Every prior has one of three probability distributions: lognormal, normal or uniform. Some of the uniform priors have parameters (the ranges) that are constrained by the model. The specific procedure we used is to start with a particular arbitrary selection of parameters, and then to vary them until a certain condition is met. We hope that the posterior distribution falls into the 95 % interval of prior distribution, such that the lower and upper bounds of posterior distribution are far from the bounds of prior distribution. The range of log-normal distributions is \((0, +\infty)\) and we use them for priors of variances, since variances should be positive but have no upper bound (see Raftery et al., 2017 for a similar choice). Truncated normal distributions with range \((0, 1)\) are used for priors of the parameter in the first-order auto-regressive model. This implies that most countries converge to the frontier, albeit each one at its own historical rate, \( \beta_i(T) \) in Eq. (3) has a uniform distribution with range \((-30, 0)\) because emissions intensities of the best performers should reach peak and then decline, such that the slope coefficient of the model in the Eq. (3) should be negative. In the case of all other priors, such as \( \alpha_i(T) \) in Eq. (3) are free, normal distribution are chosen so that the posterior probability distribution would be narrower than the prior and, when applicable, further away from the bounds. We interpret this as meaning that the prior is uninformative and that there is learning during the calibration procedure. We provide the numerical details on how we checked if they are informative in an Excel file called “distribution”. Moreover, we use data for 1995–2010 to project the emissions during 2011–2015 for a check of the robustness of model (Fig. S7). A good fitting with historical emissions reflects that our settings are reasonable.

2.4. Data sources

Consumption-based emissions report emissions induced by final consumption (households, government and investment) in a region by estimating the embodied emissions in global supply chains. We use the MIRIO tables from EXIOBASE (Stadler, 2018; Wood, 2015) to estimate consumption-based emissions and emission intensities during 1995–2015. The application of MIRIO tables is the standard approach for consumption-based emission calculation as described in Minx (2009). EXIOBASE provides data covering the period of 1995–2011 and has been extended to 2015. The emission accounts for 1995–2011 is based on Eurostat’s guidelines and energy data from the IEA’s energy balances (Wood et al., 2019). The updated emissions to 2015 are constrained to aggregate level data from the EDGAR dataset (Janssens-Maenhout, 2017). In order to keep consistency of economic data, we use the most recent economic datasets to constrain the total GDP for each region (The World Bank, 2020).

The emission intensity provides the kgCO2eq emitted through the consumption of one Euro. We convert emission intensity data during 1995–2015 into real inflation-adjusted data by selecting the base year 2010 and using the price deflator from WIOD (Dietzenbacher et al., 2013) and UN. Since WIOD does not provide price deflators for 200 products, we applied the same WIOD deflator to multiple EXIOBASE products. The currency ratio data are from UN. The calculation of deflators is elaborated in SI Appendix, Section 2. For clarity of analysis and exposition, we further aggregate 200 products into 7 product categories (i.e., food, clothing, housing, household appliances, transport, services and construction), in alignment with the classification of Hertwich and Peters (2009). The product classification can be found in Table S3.

The evolution of consumption and final demand structure during 1995–2015 is obtained from the MIRIO tables mentioned above. The evolution of final demand structure during 2015–2023 is obtained from short-term projections from the World Bank. For all regions, GDP per capita for 1960–2020 and population data from 1995 to 2050 are taken from the World Bank and UN respectively. Total final consumption data from 1995 to 2015 are from EXIOBASE. OECD provides the growth rate of GDP per capita during 2021–2050. OECD’s GDP projection does not cover Bulgaria, Cyprus, Croatia, Malta and Romania, but we find the GDP share of these countries in the total EU’s GDP was around 2 % during 1995–2018. We therefore incorporate the five nations into a region called RoW EU28 and make use GDP data of 25 EU’s member countries from OECD to estimate future GDP in EU.

Considering the poor quality of the data for several regions, our projections mainly focus on 40 regions’ GHG emissions. Bulgaria, Cyprus, Croatia, Malta and Romania are incorporated into a region called RoW EU28. Taiwan, the rest of Europe, the rest of Asia and Pacific, the rest of Middle East, and the rest of Africa are allocated to a region called the ROW. Merging these data results in 40 regions including 39 countries plus the ROW. For clarity of presentation, we further aggregate the 28 European Union (EU)’s member countries into a single region called EU, ending up with 17 regions. Table S2 shows the nations included in the EU and the ROW.

We compare emissions to SSP scenarios (IIASA, 2020). We follow the approach of Raftery et al. (2017) and use the temperature response to cumulative CO2eq emissions from IPCC (2014) to estimate the temperature change in 2050 relative to 2010. The transient climate response to cumulative carbon emissions (TCRE) is 2.4 °C/TtC.

3. Results

3.1. Emissions to 2050

To examine the robustness of model, we first perform an out-of-sample validation by comparing actual emissions for 2011–2015 with the prediction result that is from modelling only using data during 1995–2010. We find that the actual emissions during 2011–2015 lie within the 66 % intervals for prediction, and the predicted median value of emissions in 2015 is only 10 % higher than the historical data (see Fig. S7). Moreover, the uncertainties by MCMC do not continue to increase appreciably to 2050. Since the uncertainties grow quite quickly and then stabilize, or at least grow slowly up to 2050, our model
assumes that the general trend patterns during 1995–2015 persist into the future and we argue are well calibrated.

Based on the prediction of future emissions (Fig. 1a), we find a wide range of plausible emissions by 2050 of between 21 and 94 GtCO₂eq yr⁻¹ (describing a 95% interval). The lower bound at 21 GtCO₂eq yr⁻¹ sees emissions close to SSP1-2.6 by 2050, but significantly higher than SSP-1.9 (5 GtCO₂eq yr⁻¹). The upper bound at 94 GtCO₂eq yr⁻¹ is between SSP3-7.0 (72 GtCO₂eq yr⁻¹) and SSP5-8.5 (97 GtCO₂eq yr⁻¹). In the median projection, GHG emissions peak in 2028 at 50 GtCO₂eq yr⁻¹ and drop to 42 GtCO₂eq yr⁻¹ by 2050. This median result is lower than SSP2-4.5 at 53 GtCO₂eq yr⁻¹ in 2050 but higher than SSP4-3.4 at 28 GtCO₂eq yr⁻¹. The 66% probability interval suggests a global emissions peak between 2024 and 2032. The range of emissions leads to a temperature increase between 0.5 and 2.0 °C from a 2010 baseline (Fig. 1b). However, since the 2010 global mean temperature was already +0.9 °C relative to 1861–1880, our median projection of global temperature in 2050 is 2.1 °C compared to pre-industrial levels. According to the median projection, in 2050 total annual emissions are 10.6% lower than in 2015 (47 GtCO₂eq yr⁻¹), and according to all projections the peak of emissions occurs before 2050. Remaining emissions in the second half of the century would almost certainly push temperatures over 2 °C in the second half of the century for the median trajectory (in the absence of significant increases in natural or technological carbon sequestration (Anderson and Peters, 2016)). However, there is a low, but non-negligible chance of a +1.4 °C increase by 2050 implying some very limited space to realize a 2 °C target if efforts are significantly accelerated.

3.2. Shifting national emissions

The median projection sees significant changes in the proportion of emissions across and within different nations over time. Between 1995 and 2041 China is the largest emitting region, accounting for just over 28.1% of the global total in 2039 (see Fig. 2a which reports the median case). But with the fast growth in smaller emerging economies (e.g., Vietnam and Kenya, see Table S2), China’s share decreases to 25.2% by 2050, and in 2042 is overtaken by the nations in the Rest of World (indicated by ROW in the Fig. 2a), at 27.3% of global emissions, increasing to 28.3% by 2050 (the Rest of World region includes nations such as Iran, Chile and Malaysia). India’s share grows to 12.2% by 2050, exceeding the shares of the US (9.9%) and EU (8.4%) and. The median projection suggests that China’s absolute emissions begin declining after 2026 (Fig.S8), peaking at 15.1 GtCO₂eq yr⁻¹ (meeting its emission target to peak before 2030 (NDRC, 2019)). Meanwhile, EU and US emissions show a persistent decrease, down to 3.3 GtCO₂eq yr⁻¹ and 3.9 GtCO₂eq yr⁻¹ in 2050, respectively. The ROW and Indian emissions peak after 2030, in 2036 (at 12.9 GtCO₂eq yr⁻¹) and 2040 (at 5.0 GtCO₂eq yr⁻¹), respectively.

These trends can be partially explained by changes in consumption patterns. Due to the liberalization of capital movements, emissions from investment activities such as infrastructure development increased dramatically during 2000–2010 (Fig. 2b). But during 2010–2015, affected by the aftermath of the Great Recession, global shifts away from investment towards consumption activities start to moderate this effect. Extrapolating the average historical trend statistically, we see an increase in the share of investment-led emissions during 2015–2020 (from 30.9% to 32.8%, at +1.1% yr⁻¹). After 2020, the share of investment-led emissions in global emissions increases slowly at +0.3% yr⁻¹, accounting for 36.2% of the global emissions by 2050. This reflects a global slowing in investment-based expenditure. The remaining regions of the world still seeing large investments for rapid urbanization and industrialization are in emerging regions such as Brazil, Mexico, India and ROW. The shares of investment-led emissions in Brazil, Mexico, India and ROW are below 30% in 2020, increasing to 40.1%, 45.2%, 40.5%, 34.2% by 2050, respectively. However, these investment shares are likely to then reduce, following as similar trend observed in China and South Korea today (Fig.S9).

Since the structural shift from household consumption to investment might slow down, we see a shift from housing and construction towards services (Fig. 2c). During 1995–2015, housing was a major driver of global emissions at 18.9% of the total in 2015 but decreases to 18.1% by 2050. Construction accounted for 15.9% of the total in 2015, reaching a peak at 19.1% in 2026, and decreases to 17.8% in 2050. Services as a share of global emissions sees an increase from 21.4% in 2015 to 25.2% by 2050 due to a persistent shift from housing and construction to services in Brazil, Mexico, Turkey and India (Fig.S10). The proportion of services emissions in Brazil, Mexico, Turkey and India increase to 29.5%, 34.8%, 36.5% and 22.4% of their total 2050 emissions, from 17.7%, 18.4%, 25.5% and 13.1% in 2015, respectively.

3.3. Drivers of emissions

Overall, global emissions grew at an average rate of 2.1% yr⁻¹ between 1995 and 2015 (Fig. 3), almost doubling over the period. On
average, increasing GDP per capita contributed 3.2 % yr\(^{-1}\) and population 0.9 % yr\(^{-1}\) of this growth. Conversely, emission intensities improved, resulting in an average 1.6 % yr\(^{-1}\) decrease in emissions. Of the top five emitters, China and India saw the strongest GDP per capita growth, which contributed to emission increases of 8.4 % yr\(^{-1}\) and 5.1 % yr\(^{-1}\), respectively (Fig.S11). Population growth drove the largest emissions increase in the ROW (1.9 % yr\(^{-1}\)) and India (1.5 % yr\(^{-1}\)). Although final demand structure had a negligible negative impact on global emissions, it drove a +0.1 % yr\(^{-1}\) increase in China’s emissions due to large infrastructure and housing investments.

Towards 2050 continuing economic growth and population growth drives emissions at +2.5 % yr\(^{-1}\) and +0.5 % yr\(^{-1}\) from 2015, respectively. However, we find steeper reductions due to further improvements in consumption-based emission intensities (−3.4 % yr\(^{-1}\)) and a changing final demand structure (−0.1 % yr\(^{-1}\)) on average. On net, annual emissions plateau and then decrease 0.3 % yr\(^{-1}\) by 2050. These trends are in general agreement with other analytical approaches for future emissions (Marcucci and Fraggkos, 2015; Le Quéré et al., 2019). The radical acceleration of historical rates of decarbonization is mainly due to strong estimates of the convergence rate to the best performers of consumption-based emission intensity. This is not surprising because of two points. First, the emission intensities from product-specific consumption reflect the emissions along the world’s supply chain, and they can create convergence by technology diffusion (Phillips and Sul, 2007, 2009, Bhattacharya et al., 2007). Moreover, future climate mitigation efforts indeed will be strengthened as climate change is a global issue. This allows countries with high current reduction rates to continue declining fast in the short to medium term. Further, we find a rapid shift in emissions after 2028 and make a structural decomposition between 2028 and 2050 to identify driving forces (Fig. S12). We find a rapidly improving emission intensity is the main reason for the decline in the emissions, resulting in decreasing emissions of −5.0 yr\(^{-1}\). At the same time economic and population growth slows rapidly in several larger nations at +3.7 yr\(^{-1}\) and +0.7 yr\(^{-1}\), respectively. These accelerating trends superpose resulting in a faster reduction around 2028.

In China, slower economic growth and a rapid decrease of consumption-based emission intensities result in an annual net decrease of −0.5 % yr\(^{-1}\) on average, which contributed to emission changes of +3.1 % yr\(^{-1}\) and −3.7 % yr\(^{-1}\), respectively (Fig.S11). A persistent structural transition in China’s final demand structure from investment- to consumption-driven drives an additional emission decrease of −0.2 % yr\(^{-1}\) in total over the 2015–2050 period. The emissions’ growth rate of India and the ROW slows down to 1.2 % yr\(^{-1}\) and 0.6 % yr\(^{-1}\) on average between 2015 and 2050, respectively. During the whole projected period, the ROW and India see fast economic growth which drives increasing emissions of +4.1 yr\(^{-1}\) and +2.7 % yr\(^{-1}\), respectively. EU emissions continue to decrease, at −1.6 % yr\(^{-1}\), mainly driven by persistent improvements in consumption-based
crease over the same period at 1.6 % yr$^{-1}$. An increase in emissions of 1995 and 2015 (see Fig. 4). Conversely, construction saw a large increase in emission intensity, which lead to emissions reductions of $-1.9$ % yr$^{-1}$ over the period, resulting in an annual average reduction of $-1.9$ % yr$^{-1}$.

3.4. Trends in consumption-based emission intensities

As emission intensities are a critical driver for reducing emissions, we further investigate the trends of different products. We see broad decreases in the emissions intensities of the food sector ($-1.0$ % yr$^{-1}$), housing ($-0.8$ % yr$^{-1}$) and services ($-1.0$ % yr$^{-1}$) between 1995 and 2015 (see Fig. 4). Conversely, construction saw a large increase over the same period at 1.6 % yr$^{-1}$, resulting in a slower annual decrease of emission intensities of, on average, $-0.4$ % yr$^{-1}$. The increase in the emission intensity of construction was predominately due to construction in some middle-income nations (e.g., Brazil, Mexico and South Africa) where intensities grew on average more than $+4.5$ % yr$^{-1}$ (Fig. S13). Looking towards 2050 we see a faster decrease of global emission intensities, declining by an average of $-3.1$ % yr$^{-1}$. As construction practices diffuse from developed to emerging nations, we see a rapid decline in construction emission intensities in Brazil, Mexico and South Africa, where intensities decrease on average more than $-5.0$ % yr$^{-1}$ (Fig. S13). This results in a shift in the global emission intensity of construction from increase to decrease ($-3.5$ % yr$^{-1}$) between 2015 and 2050. The decrease in the emission intensity of housing is also significant ($-3.5$ % yr$^{-1}$) that is driven mainly by the continuing decarbonization of electricity and heating (see products classification in Table S3). However, the decreases in the emissions intensities of housing and construction are slower than the reduction in the emissions intensities of clothing ($-7.9$ % yr$^{-1}$) and transport ($-5.0$ % yr$^{-1}$). This reflects the challenge in decarbonizing construction processes (e.g., steel and cement use) (Davis et al., 2018) compared with other production processes.

4. Discussions

4.1. Comparisons with other studies

Our estimated global emissions peak, at 50 GtCO$_2$eq yr$^{-1}$ in 2028 (current emission reductions due to a global pandemic notwithstanding), is both earlier and of a lower magnitude than other similar studies (Fig. 1a). For example, similar to our findings, Liu and Raftery (2021) find that there has been an acceleration in decarbonisation efforts in recent years. While our assessment is in terms of CO$_2$eq we can compare with Liu and Raftery (2021) by isolating the CO$_2$ emissions only. We find an even lower emissions to 2050 of 24GtCO$_2$ compared to Liu and Raftery (2021)’s 38GtCO$_2$. This results in a 0.18 °C lower temperature by 2050 driven by CO$_2$ emissions (and not further GHG emissions). We propose that this is due to a faster convergence of emission intensities of products due to modelling products across international supply chains in contrast to the production-based analysis of Liu and Raftery (2021). This assumption is based on the concept of emissions convergence that reflects the fact that consumption-based emissions intensities are likely to converge over time (Cialani and Mortazavi, 2021). Le Quéré et al. (2019) analyzed the historical drivers of emissions in a peak-and decline group of 18 developed economies, concluding that emissions intensity reductions were a major driving force in lowering emissions across these countries. Our convergence aims to answer the question whether the persistent efforts to reduce emission intensities observed in this group of developed countries continues and expands to other countries as technological diffusion with the globalization development. Our peak estimate in the median case is lower than others in the literature but the 66 % range overlaps with other estimates. For example, the sustainable development scenario from IEA shows that global emissions decline persistently by 45 % between 2010 and 2030 (WEO, 2020). If current national pledges are met under a Pledges and Targets scenario (Climate Action Tracker, 2020) global emissions are estimated to peak in 2030 (towards the end of our 66 % probability window). Further, we employ the MCMC method to project global emissions by considering the uncertainties of drivers such that the projection ranges of emissions can be obtained. Thus, our result shows that global emissions will peak in 2024–2032 at a 66 % confidence level. While this suggests an earlier peak in emissions efforts will have to accelerate to meet 1.5° low- and high- overshoot trajectories (IPCC, 2018).

Our median projection is substantially lower than SSP2-4.5 and the range in uncertainty does not encompass SSP5-8.5. However, it is important to note that strong positive climate feedbacks could still push the earth system to a substantially warmer outcome even under more
modest emission scenarios (Hausfather and Betts, 2022). We also compare our results with other near-term scenarios in the literature (Table S4), and find that in 2030, the median projection (at 50 GtCO2eq yr\(^{-1}\)) is similar with the Conditional NDCs scenario (UNEP, 2019) (at 50 GtCO2eq yr\(^{-1}\)). By 2040, this median projection is in line with the Stated Policy scenario (IEA, 2020) (at 48 GtCO2eq yr\(^{-1}\)). In 2050, the median projection is 2.3% lower than the Pledges and Targets scenario (Climate Action Tracker, 2020), and the lower bound (at 21 GtCO2eq yr\(^{-1}\)) is close to the median value of the 2°C Consistent scenario (at 19 GtCO2eq yr\(^{-1}\)). Overall, when longer the time horizon of the projection, the closer our median results are in line with published lower emissions scenarios.

IAM model-based studies suggest that across scenarios, the most important factors driving future emissions are per capita energy demand and income (Marangoni et al., 2017; Grubler et al., 2018). We complement these findings by showing that, from a consumption perspective, projected emissions are strongly influenced by emission intensities (which encompass energy demand) and per capita GDP (which is analogous to income) (Fig. 3). Other studies projecting emissions on the basis of current infrastructure commitments have used bottom-up accounting models for some specific energy sectors and have coupled these projections with reduced-complexity climate models to assess future emissions (Tong et al., 2019). Our assessment is based on a decomposition of the Kaya identity, a top-down model, which allows us to gain insight into all sectors and assess emissions at a broader economic level. Earlier studies using a decomposition analysis of historical consumption-based emissions found that investment effects on emissions in developing countries (mostly in China, and also in Mexico, India and Indonesia) are larger than those in developed countries (Liu et al., 2019), but that this influence has weakened in China in recent years, due to the reduction in government subsidies (Mi et al., 2017; Meng et al., 2019; Wang et al., 2020). Based on these past trends, we show that, over the coming decades, although China and others (e.g., Australia and Russia) see declining infrastructure expenditure, the persistence of historical trends in the evolution of consumption pattern (a gradual increase in the shares of construction and investment) contributes to emission increases in major emerging nations (e.g., Brazil, Mexico and India) in a significant way (Fig. 2). This is because that we assume that these nations would follow China’s investment-driven growth pattern (using China as the reference region in the model setting), which could drive a slow increase in the demand for global infrastructure expansion.

Previous studies suggest that, assuming current technologies, emissions resulting from the new infrastructure will account for 35–60% of the remaining carbon budget by 2050 based on a 2°C target (Müller et al., 2013). This is similar to our finding that the contribution of investment for median emissions in 2050 will be 36.2%, although we found that the emission intensity of every aggregate product category is expected to decrease during 2015–2050, including construction, the sole product category with an increasing carbon intensity during 1995–2015 (Fig. 4). Therefore, further technological improvements in building construction have important ramifications for future emissions (Churkina et al., 2020). However, note that we do not take into account in our analysis potentially rapid changes in social behavior which may lead to rapid changes in mitigation rates (Otto et al., 2020). Nor do we take into account several important factors like the potential for positive climate feedbacks or the impact on global GDP as climate damages mount (Woodard et al., 2019).

4.2. Effectiveness of the statistical projection

It is important to stress that our projection is not a no-policy or Business-As-Usual (BAU) scenario. A no-policy/BAU scenario excludes all relevant climate policies after the starting point of the projection (Fei and Qiang, 2012). Nor is it a normative scenario for meeting specific targets. Rather, we provide a probabilistic interpretation of future emissions if current trends with regard to changes in final demand structure, consumption structure, and changes in emission intensities persist into the future. This means that we do not keep drivers at the same historical level by setting parameters for each factor, while considering specific mitigation efforts over the past 20 years. Rather, we extrapolate macro-scale patterns that result from currently implemented policies based on a specific version of the Kaya equation. This captures how emission intensities have decreased and consumption patterns have shifted over past 20 years and projects the persistence of these trends into the future. Such a projection based on historical trends may be useful in assessing the performance of on-going mitigation efforts. These analyses should be continually updated over time since we can already detect an acceleration in decarbonization trends between 2010 and 2015 which has had non-negligible impacts on the global emissions trajectory.

4.3. Limitations

Our analysis faces several data challenges. First, price deflators across specific products are not provided by EXIOBASE. Thus, we have to use price deflators from WIOD, which may impact the accuracy of historical data. We account for the uncertainty through building a joint Bayesian hierarchical statistical model, which allows observed data/model parameters to be random variables drawn from specific distributions, and our results provide a predictive distribution of emissions, not specific values. We also have extended the time series for two variables for which data are available, GDP (from the World Bank) and population (United Nations) to 1960–2020. However, our projection for emission intensities and consumption structure are extrapolated from the historical period of 1995–2015 due to limited data. Our projections do not consider any additional data for emission intensities and consumption structure in the recent four years (2016–2020). The deep uncertainty from recent impact of working from home and the COVID pandemic on consumption structure shifts could be included in the future estimates. Meanwhile, due to data availability, we have to put all the nations that are not included in EXIOBASE in a “rest of world” (ROW) category. These countries are mostly low- and middle-income nations, some of them quite large (e.g., Nigeria and Pakistan) and diverse. In the future we would like there to be access to time-series of the relevant data for such nations, so that future work could differentiate the projected emissions of these nations. Moreover, our analysis includes emissions of greenhouse gases other than carbon dioxide, such as methane, nitrous oxide and ozone. However, in terms of emission sources it excludes Land Use Change (LUC) emissions as they are not included in our emissions database and so cannot be connected to economic activity and consumption. Their exclusion may underestimate future emissions as LUC are not negligible (they accounted 11% of total emissions in 2010 (IPCC, 2014)) and there are large uncertainties surrounding their future trajectory.

In addition, some environmental economists have used regression models to analyze emissions and consumption. In our paper, we used relatively simple econometric models (e.g., first order auto-regressive models), a simple conceptual model (that is the Kaya identity) and a relatively sophisticated Bayesian hierarchical model. We believe that our work has merit since 1) the simple econometric models are based on the observation of historical data and related literature on regional convergence (the model is parsimonious), 2) we substantially improve the extrapolated patterns by using a substantial volume of calibration data, 3) by the nature of Bayesian modelling, we are able to provide probability interval of future emissions. However, this topic is worthy of further investigation using both simpler and more complex econometric and/or conceptual models.

Finally, as we use MCMCs to project emission trajectories we find there is a large uncertainty in future emissions. The uncertainties arise from the historical variations in the drivers we model. The uncertainties themselves may be interesting to policy makers for assessing the
current inertia of emissions for today’s policies. Moreover, we can obtain a probability distribution for projected climate change. This is useful as it describes the emissions changes at 95% or 66% intervals under the current inertia we may follow, which helps us evaluate how often some event (e.g., emission peak) will occur after many repeated trials. Additionally, we may be able to achieve the upper and lower bound of future emissions and find that based on 95% interval, SSP1-2.6 and SSP5-8.0 scenarios are difficult to be realized (Fig. 1a).

5. Conclusions

Here we assume regional convergence over time after finding strong supporting historical evidence and develop a Markov Chain Monte Carlo (MCMC) Bayesian analysis of historical and projected consumption-based emissions during 1995–2050 via a modified Kaya identity. We find global emissions of 21–94 GtCO2eq yr−1 by 2050, slightly higher than SSP1-2.6 and encompassing SSP3-7.0, resulting in 1.4–2.9 °C of warming above pre-industrial levels mid-way through the century. The median projection shows a 2028 peak of 42 GtCO2eq yr−1 and an annual average decrease of 0.25 GtCO2eq thereafter. Future emission decreases result from the interplay between a rapid reduction driven by decreasing consumption-based emission intensities, especially in clothing and transport, and the change of final demand structure (−1.53 GtCO2eq yr−1) against increases from economic and population growth (+1.33 GtCO2eq yr−1).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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