Structural change scenarios within the SSP framework

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Abstract

Shared socio-economic pathway (SSP) scenarios represent a consistent set of socio-economic assumptions and a major input of Integrated Assessment Models on climate change. This study added a driver that is missing so far in the SSP framework - the evolution of the sectoral structure of economies. A newly constructed set of structural change scenarios is presented. These structural change scenarios represent a well-known characteristic that accompanies the process of economic growth and development - the reallocation of economic activity between the three major sectors agriculture, manufacturing and services. While we construct scenarios for the sectoral shares of labor, value-added and energy based on historical data and an econometric approach, which comes with some limitation, these scenarios are linked to the SSP GDP scenarios and hence implicitly capture properties of the narratives underlying them. We find that the pattern and speed of structural change differ under different SSPs. Moreover, while the scenarios for developing countries reproduce structural change patterns (e.g., hump-shape of manufacturing labor share), observed for developed countries in the past, the projected transformation, in particular the reduction of labor shares in the agricultural sector, represents a tremendous challenge.

keywords: socio-economic scenarios, economic structural change, SSP scenario framework, fixed effects regression

1 Introduction

Major socio-economic drivers of long-term dynamics in models assessing climate change, particularly Integrated Assessment Models (IAMs), are taken into account by scenario as-

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sumptions. Population and GDP projections associated with the Shared socio-economic Pathway (SSP) scenarios (cf. KC and Lutz (2017), Crespo Cuaresma (2017), Dellink et al. (2017), Leimbach et al. (2017)) represent such drivers. The scenario method is a common research tool to improve the understanding of complex interactions of natural systems and human activities. While scenarios, in general, provide "plausible descriptions of how the future might unfold" (Moss et al. (2010)), the recently introduced SSP scenario framework (O'Neill et al. (2014); van Vuuren et al. (2014); Riahi et al. (2017)) was developed to facilitate analyses on the impacts of climate change, as well as their mitigation and adaptation. In a recent review of scenario and SSP-based literature, O'Neill et al. (2020) find that the SSPs have been widely adopted. They also identify needs and opportunities for improvement of the SSP framework. While the SSP scenarios represent a consistent and harmonized set of socio-economic assumptions, an important driver, among others, is missing so far – the evolution of the sectoral structure of economies.

Existing mitigation scenarios have been criticized for failing to take the role of structural change in altering energy use patterns into account. This failure results in transformation scenarios that could potentially underestimate the demand for energy and the policy cost of mitigation (Steckel et al. (2013)). Overall, the decoupling between economic growth and energy use in IAM scenarios are seen by some as unrealistic (Nieto et al. (2020), Scrieciu et al. (2013), Spangenberg and Polotzek (2019)), in particular for developing regions (Steckel et al. (2013)). Historically, a sharp increase in energy consumption is observed in the economic development process during the transformation from an agriculture-based economy towards a manufacturing-based economy. Transformation towards a service- and knowledge-based economy changes the pattern of energy demand (the quantity and the composition) again. Leapfrogging may help developing countries skip the energy–intensive stage of economic development. While few studies indicate this possibility (e.g., Marcotullio and Schulz (2007)), there is no agreement that this is a general pattern.

Climate change research by the IAM community and the IAV (impact, adaptation, and vulnerability) community has adopted different approaches to develop and use socio-economic scenarios (Absar and Preston (2015), Talebian et al. (2021), Reimann et al. (2021)). The IAV community has a stronger focus on particular regions and sectors. The existing SSP scenarios on GDP, widely used in IAMs, are often too coarse-grained. This study attempts to bridge between the scenario demands of the IAM and IAV community. Furthermore, it aims to extend the input provided by the SSP scenario framework and therefore joins studies that do the same but with a different focus. Rao et al. (2019) for example, add an extended inequality dimension to the SSP scenarios, and Andrijevic et al. (2020) introduce the government dimension, which plays a key role in future adaptive capacities.

Our contribution is a set of structural change scenarios that fit the five SSP scenarios on future GDP and population. These structural change scenarios represent a well-known characteristic that accompanies the process of economic growth and development - the reallocation of economic activity between the three major sectors agriculture, manufacturing, and services. Based on an econometric approach, we project sectoral shares of labor, value-added, and energy on a country level as well as on an aggregated 12-world-region level. Thereby, we extend the SSP scenario set by a component that can be used to generate energy demand scenarios and as an input to analyses that address the impact of climate change and climate change mitigation at a sectoral level.

The structural change scenarios do not represent predictions. While we recognize that in some studies the outcome of an econometric approach is called prediction, we want to emphasize that we use the notion of projection. In line with what Moss et al. (2010) have formulated, "the goal of working with scenarios is not to predict the future, but to better understand uncertainties in order to reach decisions that are robust under a wide range of possible futures." This understanding or concept also applies when we use the notion of projection synonymously with scenarios. At the same time, we also want to make clear that the projection method of this study differs from the SSP scenario methodology that follows an exploratory approach (O'Neill et al. (2017), Riahi et al. (2017)). In such an approach, scenarios are constructed that capture non-deterministic complexity and are robust to future uncertainty.

In this study, we use historical data and an econometric approach to quantify the structural change scenarios. This is a quite narrow, and sometimes rejected, usage of the scenario method, because it assumes that historic patterns will be reproduced in the future. While this a limitation, it should be noted that the underlying method does not include any type of time trend extrapolation. Furthermore, the applied approach does not completely ignore other elements that form scenarios, like for instance narratives. The constructed scenarios are linked to the SSP GDP scenarios and can be perceived as a downscaling of these. Hence, they implicitly inherit properties of the narratives those scenarios are based on, for example the different speed of regional convergence of economic development. Nevertheless, the way we capture uncertainty as a core element in scenario building is limited. Essentially, we adopt the uncertainty that is already captured within the existing SSP GDP scenarios, but do not add another layer of sector-specific uncertainty. Hence, the presented scenarios have to be conceived only as a first attempt at considering the change in economic structure within the SSP scenarios.

Given the historical patterns of economic structural change, and recognizing the methodological limitations in assuming that these will persist, we run an extended exercise of exploring possible paths of future structural change. We come up with scenarios that show different speed of structural change across the SSPs, near term peaks in the share of labor and value added in the manufacturing sector in a number of emerging and developing economies and a fast reduction of labor in the agricultural sector of developing economies. The latter can be expected as a major challenge given the quite high level of immobility of labor in those countries.

The remainder of the paper is organized as follows. The next section describes empirical facts on structural change and energy use. Section (3) introduces the regression model based method that we developed to construct structural change scenarios. We show that the model is able to reproduce historical patterns of structural change. The computed structural change scenarios are discussed in Section (4). Differences in projected structural change across different SSPs are highlighted. Section (5) concludes.

2 Empirics of structural change

Structural change has been thoroughly discussed in the economic literature (Kuznets (1957), Baumol (1967), Maddison (1980), Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008), Buera and Kaboski (2009), Herrendorf et al. (2014)). A majority of studies describe the process of structural change as the evolution of labor shares of the broad sectors agriculture, manufacturing, and services. As income grows, the share of labor in agriculture declines, and the share of labor in services increases. The share of labor in manufacturing increases at lower income levels, and it decreases at higher levels. Another commonly used measure of structural change in the literature is the sectoral share of value-added (see Herrendorf et al. (2014)), which shows a similar pattern as the labor shares. The facts on the sectoral energy use, which are also relevant for this study, are less known. One might expect a similar pattern again as with the labor shares, but the pattern is significantly different, as shown below.

Structural change has a strong impact on labor and energy productivity. The literature that decomposes the impact of sectoral reallocation on labor productivity is vast. An important reference is McMillan and Rodrik (2011), which decomposes the labor productivity changes coming from the sectoral reallocation of labor and the productivity inside the sector. Their findings suggest that periods of rapid economic growth were associated with migration from low productive sector, such as agriculture, to more productive ones, like manufacturing. Following similar methods, Diao et al. (2019) study the recent growth experience in developing economies, Ferreira and Da Silva (2015) focus on the case of Latin America, and Diao et al. (2018) on Sub-Saharan Africa. Similarly, the energy literature applies econometric methods to decompose the changes of energy intensity. In a study for the United States and thirty-five sectors, Sue Wing (2008) finds that intra-industry efficiency improvements were the main contributor to the decline of energy intensity after 1980.

Structural change and energy use interact with each other. At the level of aggregated economies, we observe a clear inverse relationship between energy intensity and GDP per capita. Countries with high GDP per capita use relatively less energy per unit of output produced. But the decline of energy intensity does not follow a continuous trend. Mulder and de Groot (2012) indicate that changes in the sectoral composition of the economy account for a considerable part of aggregate energy intensity dynamics.

To see how aggregate energy intensity relates to the economy's sectoral composition, think of it as the sum of sectoral energy efficiency levels weighted by their sectoral shares. As the economy shifts production across sectors, aggregate energy intensity changes even if the intensity of each sector is constant. For example, in the early stages of development, most of the economic activity occurs in the agricultural sector. In low-income countries, agricultural production is, in general, labor-intensive with low adoption of capital and energy. As the economy grows, production reallocates mainly towards the manufacturing sector, which is energy-intensive and the aggregate energy intensity of the economy rises. In the later stages of economic growth, production reallocates from manufacturing to services that require less energy to produce. Thus, shifts towards services reduce the overall requirement of energy. Consequently, aggregated GDP scenarios that do not capture a sectoral composition may abstract of important factors when deriving energy demand scenarios. This pattern relating GDP per capita, energy use, and energy intensity have been widely documented in the literature (e.g., Deichmann et al. (2019)).

In the following we specify and illustrate the patterns of structural change by looking at historical data. We use country-level data from 1990-2015 from the World Bank and the International Energy Agency (IEA). Population data, aggregate output, which is PPP-adjusted GDP (US$2017), and sectoral data on employment and on value-added in constant prices are from the World Bank's World Development Indicators (WDI)[1]. The energy data, expressed in kilotonnes of oil equivalent (ktoe), is from the IEA's Energy Balances database[2]. We combine the "final consumption" series with "energy industry own use and losses" to map into our broad sectors. The shares of labor are the total number of workers in a sector divided by the total number of workers in a country and the energy shares are sectoral energy use divided by total energy use. While we use country-level data for the regression in the next section, for the illustrative purpose in this section data are aggregated to a world-region level (see section 4 for the definition of the twelve world regions).

Figure 1 shows the well-known patterns of sectoral reallocation. With increasing income, less labor is allocated to the agricultural sector and more to the service sector. The share of labor in manufacturing follows a hump-shaped curve. The peak of manufacturing labor share at a level slightly above 25 % occurs with a GDP per capita of around 10000 PPP-adjusted 2017 international dollars (9.2 on the log scale). The shares of value-added follow a similar pattern (Figure 2), but they are less distinct and peak earlier. They are, in general, higher than the labor shares in the manufacturing sector and lower in the

[1]Accessed May 6 2021 at https://databank.worldbank.org/source/world-development-indicators
[2]Procured in 2018.

agricultural sector, indicating higher labor productivity of manufacturing.

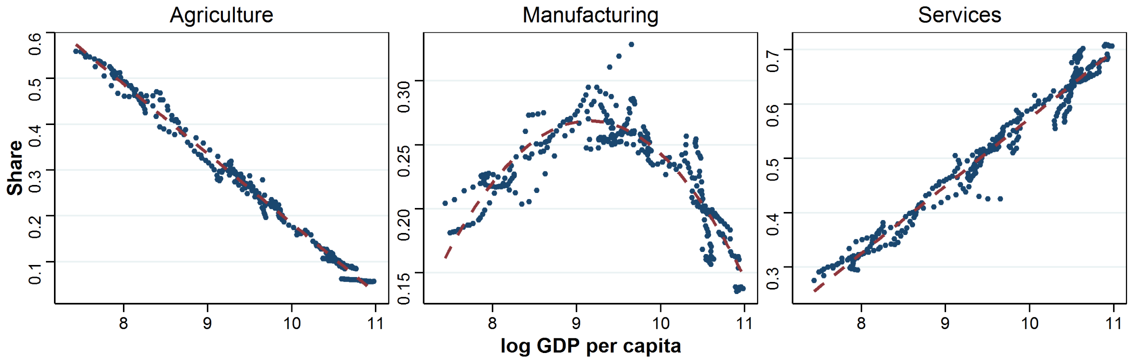

Figure 1: Share of Labor per Sector (data is partialled out of country fixed effects)

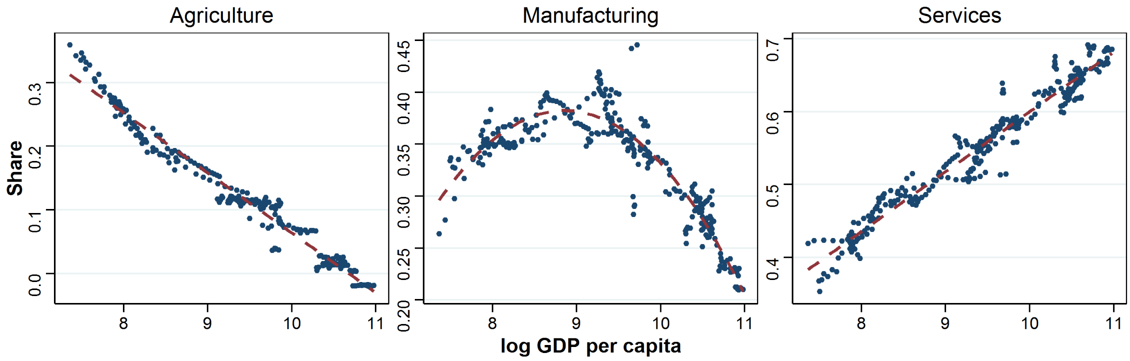

Figure 2: Share of Value-Added per Sector (data is partialled out of country fixed effects)

Looking at the shares of energy use per sector (Figure 3), we observe that the energy share in manufacturing also increases at lower levels of income and decreases at higher levels. The peak level above 40 %, which is higher than the peak share of labor, occurs at GDP per capita of around 15000 PPP-adjusted 2017 international dollars (9.6 on the log scale). The energy share of services follows a U-shape, decreasing at lower income levels and increasing at higher. The energy share in agriculture declines slightly with income[3].

To relate the dynamics of labor and energy, notice that both measures correspond to the production side of the economy. First, even though the share of energy in agriculture is declining like that of labor, the share level of energy is much smaller. Second, the close association between labor and energy manufacturing shares suggests that structural change is key to understanding the sectoral energy use patterns. The share of energy use peaks at a higher output than the labor share, but their dynamics are fairly close. Finally, notice that the bottom of the services energy share happens at about the same

[3]The inverse relationship between agricultural energy use share and income is significant only when considering country fixed effects. In the absence of country fixed effects, there is no apparent relationship.

GDP per capita level as the maximum of the manufacturing energy share because of the low energy use in agriculture.

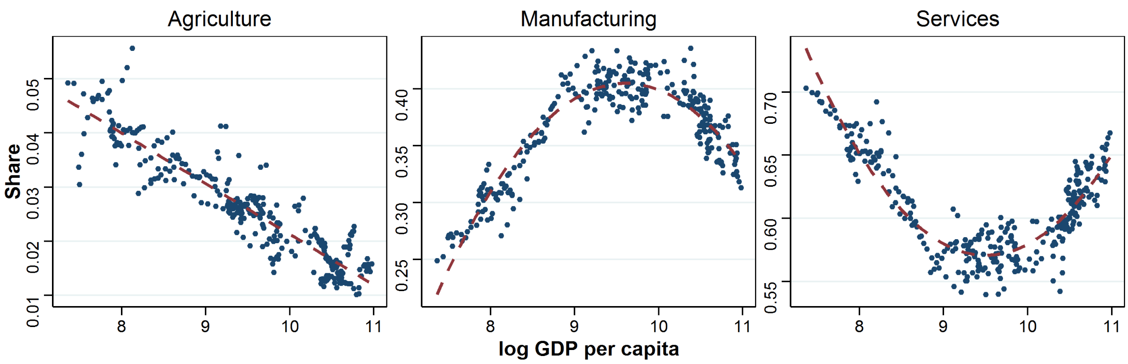

Figure 3: Share of Energy per Sector (data is partialled out of country fixed effects)

3 Polynomial regression model

We develop structural change scenarios that are available for each of the five SSPs and cover the three broad economic sectors: agriculture, manufacturing, and services. We follow the economic literature (see Maddison (1980) and Herrendorf et al. (2014)) and represent structural change by share variables - namely shares of labor, value-added, and energy. In contrast to absolute level values, share values can much easier be adopted by other models because they are independent of the unit of the data sources.

To construct future paths of the structural change variables, we take advantage of their clear patterns throughout the growth process. We apply a polynomial that fits well the patterns observed between 1990 and 2015, restricting the structural change variables to relate solely to independent variables whose projections are available from the SSPs such as GDP and population. We pin down the parameter values of the polynomial using a standard cross-country fixed effects regression. Finally, the structural change scenarios are constructed using the estimated coefficients of the polynomial combined with the projections from the five SSPs scenarios.

Let $x_i \in \{l_i, v_i, e_i\}$ correspond to the shares of labor, value-added and energy of each sector $i \in \{a, m, s\}$ - agriculture, manufacturing and services - and y to the GDP per capita. With j corresponding to the country and t to the year, the country-fixed effects regressions for sectors $i \in \{a, s\}$ are:

$$\ln\left(\frac{x_{ij,t}}{x_{mj,t}}\right) = \beta_{0i} + \beta_{1i}\ln(y_{j,t}) + \beta_{2i}\left(\ln(y_{j,t})\right)^2 + \beta_{3i}\left(\ln(y_{j,t})\right)^3 + \mu_{ij} + \epsilon_{ij,t} \tag{1}$$

where μ_{ij} is the fixed effect of country j and ϵ is an error term. The quadratic and cubic terms capture non-linear relations between structural change variables and GDP per capita[4] Notice that equation (1) is based on the relative sectoral allocation x_{ij}/x_{mj} since the dynamics of structural change depend on interaction between the different sectors, not on one isolated.

The regression is estimated with a standard cross-country OLS method using country data from WDI and IEA as introduced in the previous section. Around 4000 data points enter the regression for each variable.The estimated coefficients $\hat{\beta}$ are displayed in Table 1. The attached statistics provide the significance of all three independent variables. While the the R^2 statistic is poor, in particular for the energy share variable, the impact of most independent variables and the related correlation coefficients is highly significant. The corresponding standard errors are low and also the F statistic indicates high significance.

	labor share		value-added share		energy share	
	$\ln\left(\frac{l_a}{l_m}\right)$	$\ln\left(\frac{l_s}{l_m}\right)$	$\ln\left(\frac{va_a}{va_m}\right)$	$\ln\left(\frac{va_s}{va_m}\right)$	$\ln\left(\frac{e_a}{e_m}\right)$	$\ln\left(\frac{e_s}{e_m}\right)$
$\ln(y)$	7.64***	5.54***	-5.24***	2.92***	12.1***	-1.09
	(0.95)	(0.75)	(0.95)	(0.84)	(3.13)	(0.85)
$\ln(y)^2$	-0.89***	-0.75***	0.41***	-0.41***	-1.44***	-0.04
	(0.103)	(0.081)	(0.104)	(0.092)	(0.341)	(0.093)
$\ln(y)^3$	0.031***	0.033***	-0.012***	0.018***	0.054***	0.007**
	(0.004)	(0.003)	(0.004)	(0.003)	(0.012)	(0.003)
Observations	4186	4186	4083	3902	3979	4542
R^2	029	0.15	0.33	0.014	0.013	0.003
Adj. R^2	0.26	0.12	0.30	−0.03	−0.03	−0.04
F Statistic	2006***	1055***	2967***	161***	115***	671***

Table 1: Regression Results

Notes: Table (1) reports the results of the cross-country fixed effects regressions based on equation (1). Standard errors are reported in parenthesis. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Having in hand the estimated values $\hat{\beta}$ and the projections for GDP per capita y_j until 2050, projections for the designated structural change variables are derived by the following algorithm[5]:

1. Given initial $(x_{ij,0}, y_{j,0})$ from the data and future paths on $(y_{j,t})$, calculate the

[4]The cubic term improves the fit of the model to the historical data, especially for high-income countries. Looking ahead in the paper, without the cubic term, the model projects a flattening in the fall of manufacturing share variables in high-income countries which has not been observed in the past.

[5]In the SSPs each period t is constituted of five years.

projected growth of the structural change variables as:

$$\Delta \ln\left(\frac{x_{ij,t}}{x_{mj,t}}\right) = \hat{\beta}_{1i}\Delta\ln(y_{j,t}) + \hat{\beta}_{2i}\Delta\left(\ln(y_{j,t})\right)^2 + \hat{\beta}_{3i}\Delta\left(\ln(y_{j,t})\right)^3 \tag{2}$$

assuming the notation $\Delta w_t = w_t - w_{t-1}$ for any variable w.

2. Calculate recursively the sequence of $\ln(x_{i,t}/x_{m,t})$ for $t \geq 1$ as:

$$\ln\left(\frac{x_{ij,t}}{x_{mj,t}}\right) = \ln\left(\frac{x_{ij,t-1}}{x_{mj,t-1}}\right) + \Delta\ln\left(\frac{x_{ij,t}}{x_{mj,t}}\right) \tag{3}$$

taking $\Delta\ln(x_{ij,t}/x_{mj,t})$ as given from step 1.

3. Given the feasibility constraint

$$x_{aj,t} + x_{mj,t} + x_{sj,t} = 1 \tag{4}$$

and defining $\ln(x_{i,t}/x_{m,t}) = z_{im,t}$ calculate the relevant variables for each period according to:

$$x_{mj,t} = \frac{1}{1 + e^{z_{aj,t}} + e^{z_{sj,t}}}, \quad x_{aj,t} = e^{z_{aj,t}}x_{mj,t}, \quad x_{sj,t} = e^{z_{sj,t}}x_{mj,t} \tag{5}$$

Notice that in the algorithm, the logarithmic formulation constrains the variables to be positive, and step 3 restricts them to sum up to one for any projected growth of GDP per capita[6].

While we do not regard our generated scenarios as predictions, nor do we claim to uncover causal relationships through the regression, we consider the model's capability to reproduce historical structural change patterns as a main evaluation criteria (and use it to put the low R^2 into perspective). Therefore we compute the Mean Absolute Error (MAE). Let $\hat{x}_{ij,t}$ refer to the model's allocation in period t, then MAE is given by:

$$\text{MAE}\left(x_{ij}\right) = \frac{1}{N_{ij}}\sum_{j\in J}\sum_{t=1998}^{2015}\text{abs}\left(\hat{x}_{ij,t} - x_{ij,t}\right) \tag{6}$$

where N_{ij} refers to the number of observations for a maximum of 191 countries and 18 periods. The result of each variable is reported in Table 2.

[6]Following a different procedure in which the left-hand side of equation (1) depends solely on x_i imposes some difficulties. For example, with the projection of continuous growth of GDP per capita, the share in agriculture may turn negative, and the share in services may become larger than one. However, there is no clear way to impose additional constraints for the variables to be positive and sum up to one.

l_a	l_m	l_s	va_a	va_m	va_s	e_a	e_m	e_s
2.4%	1.8%	3.0%	1.1%	2.2%	2.2%	0.8%	3.1%	2.9%

Table 2: Mean Absolute Error

On average, the method successfully reproduces the reallocation behavior observed in the data. The MAE for the shares of labor, the shares of energy and the shares of value-added is roughly in the range between 1% and 3%. We consider these results as reassuring of the method's capability to construct possible projections of the structural change variables.

Within the Appendix (A.1), we present a comparison of model results and empirical data on a world-region level and for each structural change variable (see next section for the definition of world regions). Overall, it again demonstrates a good fit and the robustness of the structural change pattern which support our approach of a regression based scenario method.

4 Structural change scenarios

4.1 Shared socio-economic pathways

The structural change projections offer an extension of the current SSPs. There are five different SSPs. Each of them follows a different narrative of future development resulting in worlds that largely differ with regard to their climate change mitigation and adaptation challenges (O'Neill et al. (2014)). Each narrative is translated into a set of consistent socio-economic assumptions that can be adopted by models to run climate change analyses. SSP1 ("Sustainability") characterizes a world that makes progress towards sustainability, including the rapid development of low-income countries and relatively high urbanization rates. SSP2 as the "middle of the road Scenario" is meant to continue historical trends with a medium level of per capita GDP growth and urbanization. The narrative of SSP3 ("Regional Rivalry") sketches a strongly fragmented world characterized by a high level of poverty, a high level of the rural population, and subject to high mitigation and adaptation challenges. SSP4 ("Inequality") represents a highly unequal world with a strong divide of rich and poor people between countries as well as within countries. This divide additionally appears in urban areas that grow comparatively fast. Finally, SSP5 ("Fossil-fueled development") characterizes a growth-oriented world with large technological progress and high urbanization rates. The energy supply relies largely on fossil fuel-based energy conversion technologies and therefore causes high mitigation challenges. Similar to SSP1, in SSP5, per capita income across regions is also expected to converge. But to a higher level and within a longer time horizon. A summary of the major characteristics of the relevant SSP parameters is given in Table 3.

	SSP1	SSP2	SSP3	SSP4	SSP5
GDP per capita growth	medium	medium	low	medium	high
speed of convergence	high	medium	low	medium (low for low income countries)	high

Table 3: Characteristics of SSP scenarios (cf. Leimbach et al. (2017))

Given data of initial shares on labor, value-added, and energy for 2015, the projections depend essentially on SSP scenarios of GDP per capita. Such scenarios are available in the SSP database[7]. While they are widely used in the community, they do not include short-term adjustments. We updated GDP projections in order to reflect most recent developments (cf. Koch and Leimbach (2022)) and to avoid including uncertainty into the projections in periods without real-world uncertainty. The construction of updated SSP GDP scenarios is described in the Appendix (A.2). Data from these scenarios may particularly be useful for analyses explicitly seeking engagement with near-term phenomena as well as longer term path dependencies caused by them. In the same way as the original SSP GDP scenarios, the updated SSP GDP scenarios can be conceived as plausible interpretations of the underlying narratives in form of alternative long-term projections starting from empirical data. While using the updated SSP GDP scenarios for the construction of structural change scenarios reduces the comparability with the original scenarios, the nature of the structural change scenario variables as dimensionless figures allows to use them in combination with different GDP scenarios and metrics.

4.2 Projections of sectoral shares

We compute structural change scenarios until 2050 for almost 200 countries and each SSP by following the three steps of the algorithm described in the previous section[8]. For the purpose of presenting illustrative results, we aggregated the country-level scenario data for twelve world regions:

1. USA - USA
2. EUR - EU27 and United Kingdom

[7] https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=about

[8] All scenario and input data (including the updated SSP GDP projections) are available on Zenodo: https://doi.org/10.5281/zenodo.7433139.

3. JPN - Japan
4. CHA - China and Hongkong
5. IND - India
6. REF - Reforming economies including Russia
7. SSA - Sub-Saharan Africa (including Republic of South Africa)
8. MEA - Middle East and North Africa
9. LAM - Latin America
10. OAS - Other Asia (Central and South-East Asia)
11. CAZ - Canada, Australia, New Zealand
12. NEU - Non-EU European countries.

In Figures (4), (5) and (6), we present the results of structural change projections for four selected countries and world regions, respectively, which are at different stages of development - United States, India, China, and Sub Saharan Africa (SSA). Corresponding figures for all world regions are presented in the Appendix (A.3).

There are some common patterns of future structural change across all regions. Due to the applied construction method of scenarios, future structural change follows historical pattern. Given the assumption that these patterns are robusts[9], we consider the constructed scenarios as plausible quantifications with uncertainty covered by SSP variation. Across all regions, we project decreasing labor shares in the agricultural sectors and increasing shares in the service sectors. The same applies to the value-added shares in the two sectors. However, the rate of change is quite different across the regions and the different SSPs. In countries at advanced stage of development, like the USA, the shares neither change substantially over time nor vary significantly across the SSPs. On the other hand, fast developing countries, like China, show substantial changes over time and moderate variation across SSPs. Between 2015 and 2050, the labor shares in China are projected to decrease by up to 25 percentage points in the agricultural sector, and to increase by up to 40 percentage points in the services sector. The figures are somewhat smaller for the value-added shares. The projections for India and SSA include significant changes over time and substantial variation across the SSPs for the agricultural and service sector. While this typically characterizes developing regions undergoing substantial structural change, it also points to the challenges these regions will face to catch up with more developed economies. As a general pattern across all regions, we create the fastest changes under SSP5 and slowest under SSP3. That is directly related to the GDP per capita growth characteristic of these scenarios.

[9]Note the empirical robustness of the structural change pattern. It has been observed since the early 19th century (Herrendorf, Rogerson and Valentinyi (2014), Maddison (1980)).

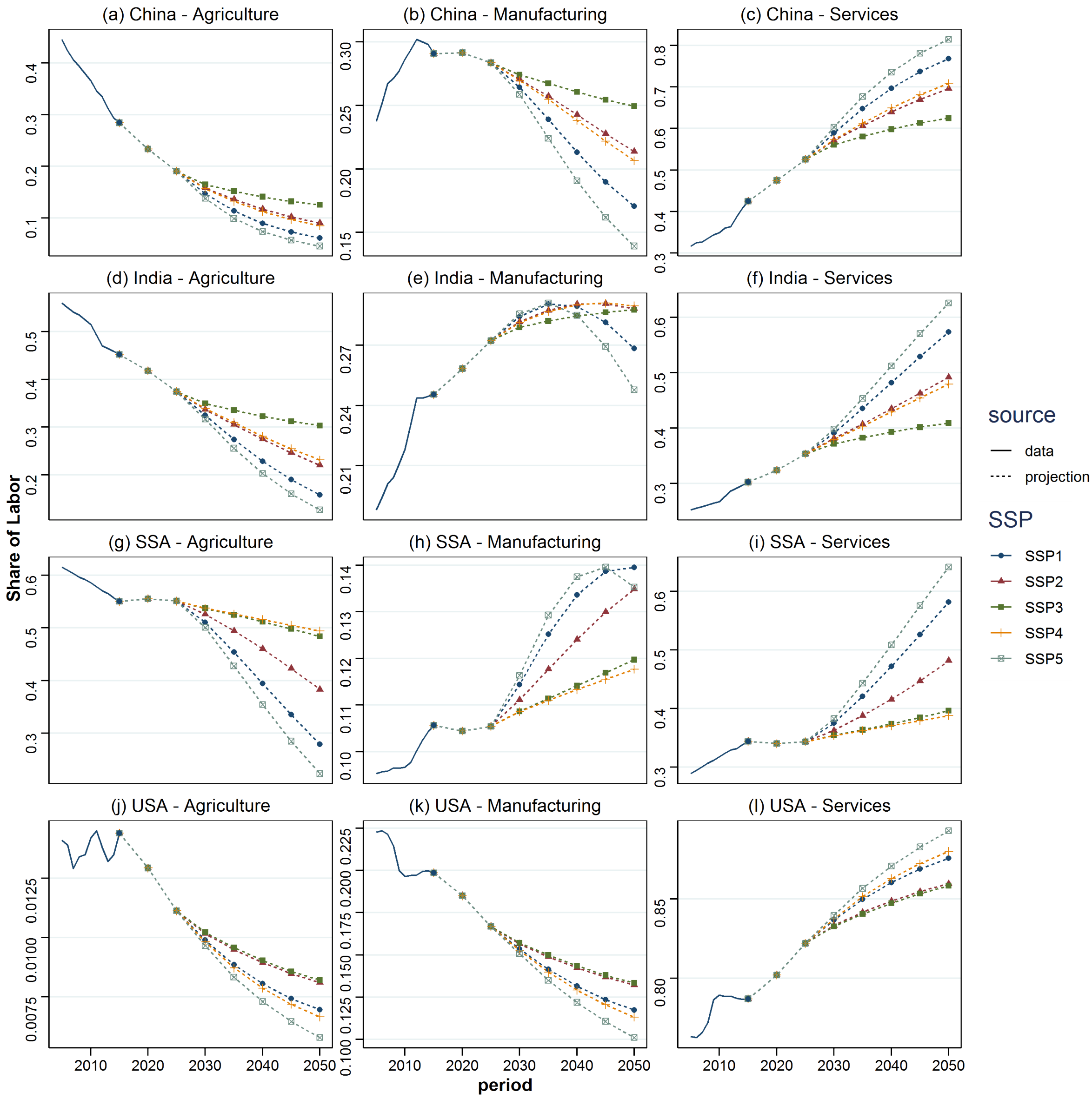

Figure 4: Sectoral shares on total employees across SSPs (historical data are shown until 2015)

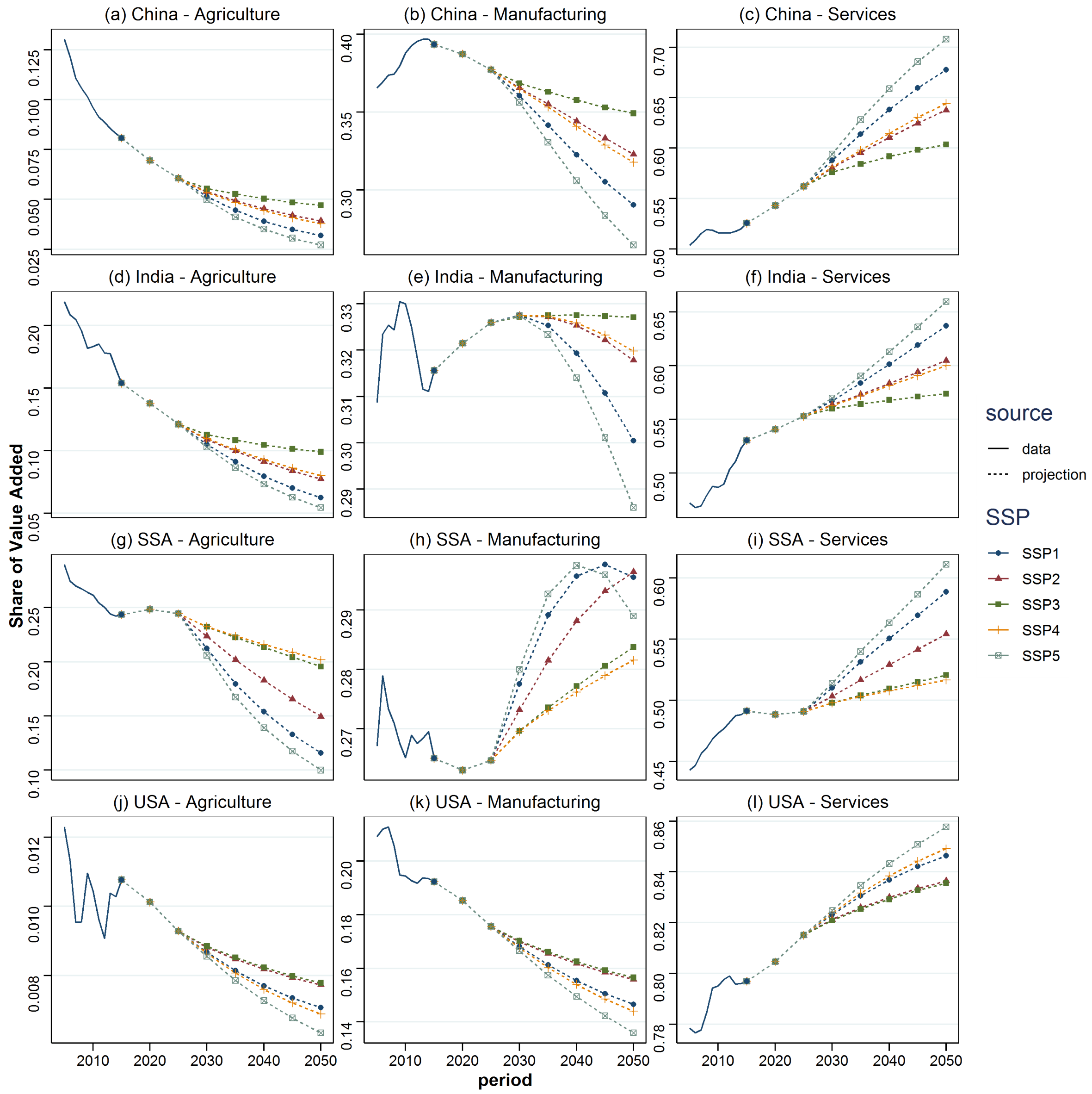

Figure 5: Sectoral shares on total value-added across SSPs (historical data are shown until 2015)

Labor and value-added shares

While the USA see low labor and value-added shares in the agricultural sector of almost less than 1% already today, an ongoing reduction of these shares can be expected in the other regions, in particular in India and SSA under SSP1 and SSP5. Projected reductions compared to the levels today amount to 20-30 percentage points. The associated reallocation of labor is immense and cannot be compared in magnitude to any job market impacts that, for example, climate change and climate change mitigation will have. This reallocation will pose a major challenge if high levels of labor immobility in many of the affected countries persist. However, the labor shares in agriculture remain at around 30 and 50 percent in India and SSA, respectively, under SSP3 in 2050. And, in this manner, agriculture will still be the primary source of income for the world's poor. In contrast, it is less than 0.5% in the USA. Thus, SSP3 is constructed as a scenario with a very slow-paced structural change process in developing countries and consequently with limited perspectives of reducing the number of people living in poverty. This is in line with the SSP3 narrative.

Within the manufacturing sector, we create different patterns across the regions. The applied model is able to reproduce the hump-shaped curve that the empirical and theoretical literature has identified for this sector. Figures (4) and (5) nicely show how the different regions move along the humped-shaped curve with a time-shift among them. While for the USA and most other developed countries, the labor shares in the manufacturing sector peaked in the past, our scenarios see this peak today in China. In India, we expect a persistent increase in manufacturing labor shares up to a peak of around 30%, similar to China's, in the next 15-30 years. The value-added shares are projected to even peak earlier.

While for all regions the projections expose smaller changes of value-added shares over time and smaller variations across SSPs than for the labor shares, the ratio of changes in labor and value-added shares is different across more developed (USA, China) and less developed (India, SSA) regions. The former display declining shares of value-added and even more rapidly declining labor shares in the manufacturing sector. This is a reasonable feature assuming that in rich countries labor productivity grows faster in manufacturing than in services. We expect a contrasting pattern in the manufacturing sector of less developed countries. For example, in India we project decreasing value-added shares combined with partly increasing labor shares (India) and in SSA nearly constant value-added shares associated with continuously increasing labor shares (SSA). Explanations of this divergent pattern is the high degree of industrial automation in more advanced economies, with less workers employed, the low value-added industry that first moves from developed towards developing economies, and the process of deindustrialization (Rodrik (2016), Alvarez-Cuadrado et al. (2018), Lee and McKibbin (2018)).

In SSA, the peak in labor and value-added shares in the manufacturing sector is projected further ahead and happens at lower levels than in other regions. In many countries of this region, today there is not yet a significant increasing trend of this structural change indicator. This, one the one hand, corresponds to findings from empirical studies (McMillan et al. (2014), Carmignani and Mandeville (2014), Rodrik (2016)) that also address the risk of premature deindustrialization. Under SSP3 and SSP4, we project this kind of stagnation for nearly all countries of this region. On the other hand, several studies show that manufacturing is still an engine of growth, and the development perspectives strongly depend on a take-off of the industrial production (Szirmai and Verspagen (2015), Cantore et al. (2017), Gabriel and de Santana Ribeiro (2019)). The early stages of economic growth are associated with significant accumulation of capital (e.g., infrastructure investments), which has to be provided by the manufacturing sector[10]. The take-off, projected particularly under SSP1 and SSP5, reflects the narrative of improved development perspectives.

While in the early stages of economic transformation, labor moves from agriculture to manufacturing and services, in the later stages, the service sector attracts labor from both other sectors. Thus, independent of the growth stage, labor and value-added shares in the service sector increase in all regions and under all SSPs. While the difference between the patterns of structural change between SSP3 and SSP5 is significant in all sectors, it is most substantial in the service sector. The difference of projected values of labor share in the final year amounts to more than 20 percentage points in China, India and SSA. In 2050, the service sector has the largest labor, value-added, and energy shares in all world regions and under all SSPs. The only exception are the agricultural labor shares under SSP3 and SSP4 in SSA.

Energy shares

The energy shares in the agricultural sector are on low levels of below 5 % across all regions and all SSPs (see Figure 6). In the manufacturing sector however, the constructed scenarios project comparatively high energy shares (e.g., China and India), which increase and then decrease with advanced development stages - in line with the empirical pattern. China and India feature energy shares between 40 and 55 percent over a long time span, whereas the corresponding labor shares are below 30%. This indicates the high energy intensity of the manufacturing sector and the challenge that is posed to climate policies related to energy transition.

In the developing region SSA (and initially also in India), the SSPs with the largest projected energy shares in the manufacturing sector are SSP1 and SSP5. In contrast, the SSP1 and SSP5 manufacturing energy shares in more developed regions are projected to be the lowest of all SSPs. Nevertheless, the manufacturing energy share in SSA in 2050 (below 22%) is relatively low compared to that of the other regions. This coincides with the low level of economic activity in SSA in manufacturing discussed previously. The scenario feature, that manufacturing energy shares under SSP1 and SSP5 peak at this relatively low level, is based on the implicit assumption that the SSA region can leapfrog, i.e. use technological spillovers to avoid the historically energy-intensive industrialization patterns of other world regions. For the other SSPs, energy shares will slowly increase and may exceed this level beyond the projection horizon. In the more developed regions (China, USA), the energy shares are projected to decrease in manufacturing and increase

[10]See García-Santana et al. (2021).

in services. This reallocation of production from manufacturing towards services reduces the overall energy intensity of the economies.

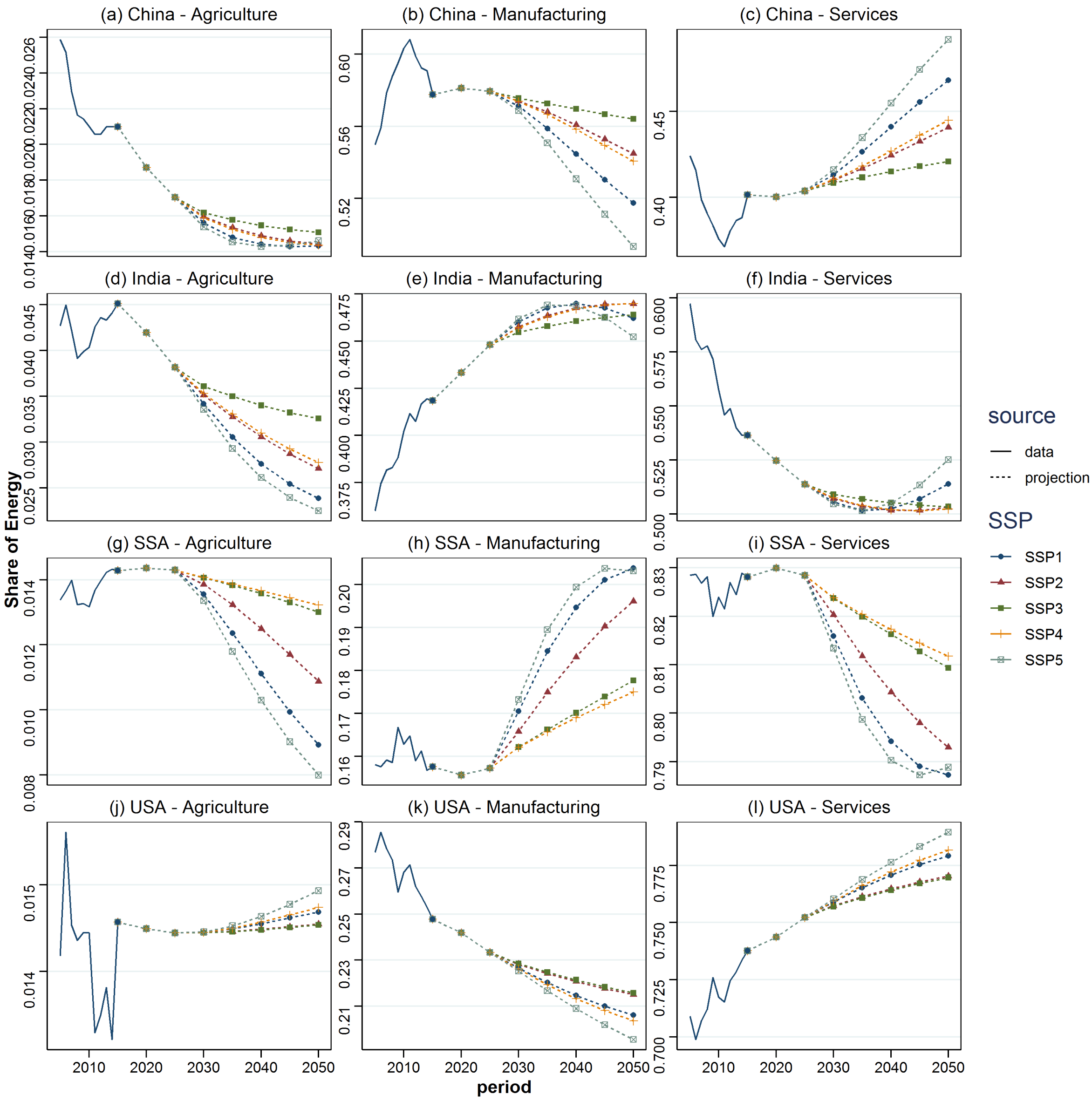

Figure 6: Sectoral shares on total final energy across SSPs (historical data are shown until 2015)

The moderate increase of the energy shares of advanced economies (USA) in the agricultural sector (in particular under SSP5), while at a low level and mainly triggered by the decrease of manufacturing shares, seems to be in contrast with empirical data (cf. Figure 3). By looking at the absolute level of energy use (see Figure 7), we add another SSP specific dimension that helps to put the results of this structural change parameter into perspective. We compute the level of total final energy consumption by multiplying the sectoral shares with SSP specific energy demand projections from the

EDGE model (Baumstark et al. (2021), Levesque et al. (2018)). The result illustrates both the low levels of energy use in the agricultural sector, and the characteristic of SSP5 as the scenario with the highest energy demand. Even in sectors where SSP5 has the lowest energy share of all SSPs (agriculture and services in SSA, manufacturing in China and USA), the absolute level of energy use is almost always the largest.

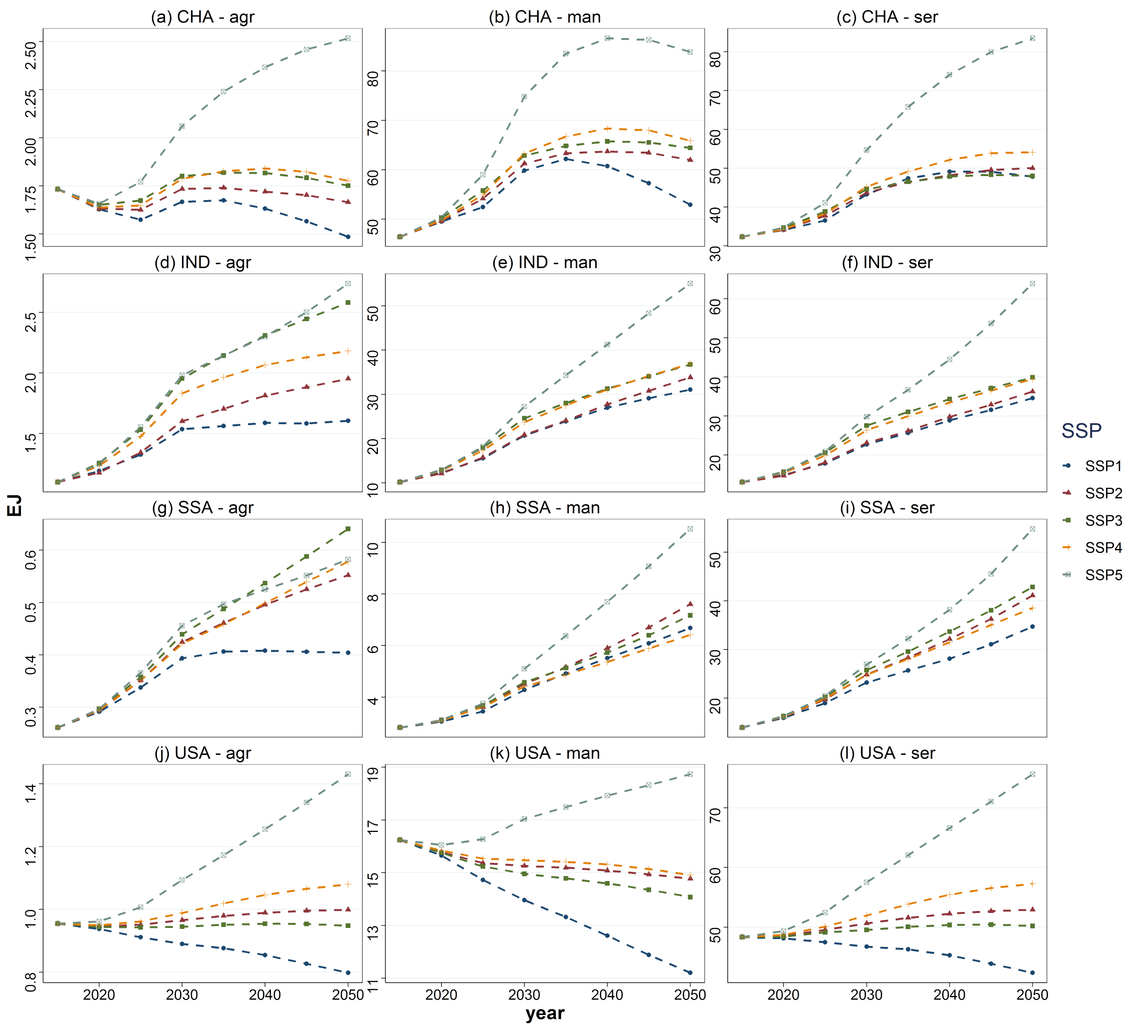

Figure 7: Consumption of total final energy across SSPs (historical data are shown until 2015)

4.3 A further look at the projections

For the example of India, we provide a further look into the model's capability to construct scenarios consistent with the historical patterns of structural change. So far, we discussed the projections based on their time paths until 2050, which we see as the main variable of interest for other researchers in the field. However, the stylized facts of structural change are established relative to GDP per capita as shown in section (2).

In Figure (8), we show the projections for India with the log of GDP per capita in the x-axis and the shares in the y-axis. We observe that the model's projections reflect the structural change patterns. The labor shares follow their typical behavior with the manufacturing displaying a hump-shape with a peak at the log of GDP per capita of around 9.7[11]. Moreover, the energy share in manufacturing also displays a hump-shape while that of services a U-shape. Finally, the value-added share in agriculture persistently declines while in services increases. We see these results as additional evidence of the soundness of the model to generate credible structural change scenarios.

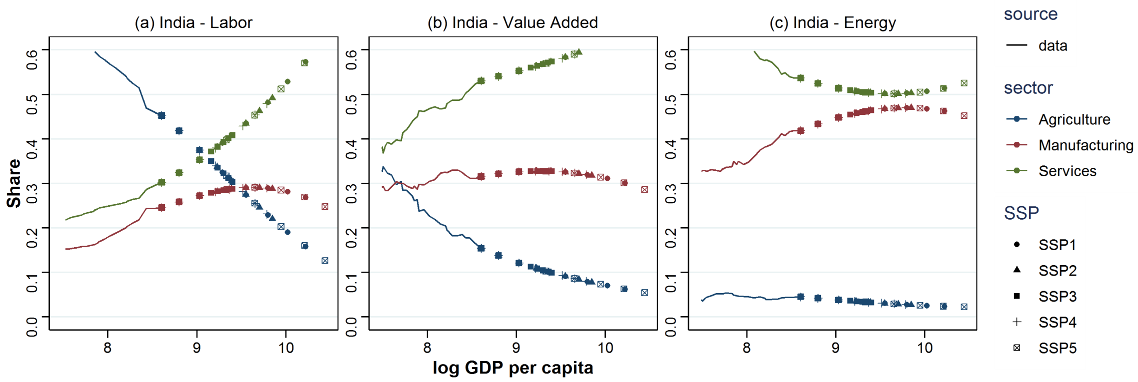

Figure 8: Projections of structural change in India

4.4 Covid impact on long-term projections

The new structural change scenarios are linked to updated SSP GDP scenarios. While these include short-term corrections due to the impact of the the Corona pandemics, the original SSP GDP scenarios do not take this into account. We analyze to which extent this short-term phenomenon has a long-term impact on our projections. The figures in Appendix A.4 present the differences in labor, value-added and energy shares between scenarios with Covid taken into account and without[12]. These differences are provided for the twelve world regions in the years 2020 and 2050. Aggregated results are summarized in Table 4.

The comparison shows that the scenarios differ only marginally. The absolute differences averaged across all regions, SSPs and sectors are far below 1 percentage point in 2050. This even applies to the maximum values. In general, the differences are larger in 2020 and also larger for the labor shares than for the value-added and energy shares. We find a maximum difference of 1.5 percentage points for India in 2020. Without the covid

[11] Recall that in the data the peak happened at log GDP per capita of around 9.2.

[12] The scenario in which Covid is not taken into account, was constructed in the same manner as the updated SSP GDP scenarios (see A.2), with the following difference: instead of using WDI data until 2020 and current IMF projections for the years until 2025, it uses WDI data until 2019 and IMF projections from the year 2019 (pre-covid) for the years 2019-2025.

	labor share		value-added share		energy share	
	mean	max	mean	max	mean	max
2020	0.0033	0.015	0.0016	0.0060	0.00084	0.0054
2050	0.0024	0.0076	0.0013	0.0046	0.00076	0.0031

Table 4: Mean and maximum absolute differences between covid and no-covid scenarios for the years 2020 and 2050. The mean is computed as average over regions, sectors and SSPs.

effect taken into account, less labor of the corresponding amount is projected to work in the agricultural sector which in 2020 is the sector with largest labor share in India. Overall, we find that the projections of structural change are robust against the near-term covid shock. For the long-term projection there is hardly any impact. Furthermore, we also can't detect any systematic bias of the covid shock effect to changes of structural change in a particular SSP.

5 Conclusions

With this study, we present a new set of structural change scenarios and the method of scenario construction. We provide structural change scenarios, represented as shares of labor, value-added, and energy in the sectors agriculture, manufacturing, and services, for each of the five SSPs. They extend the set of socio-economic drivers and parameters for which climate change impact and mitigation analyses can avoid ad-hoc assumptions. These new scenarios represent a disaggregation of the existing SSP GDP scenarios and can be used in combination with them or with other GDP scenarios. While we presented the scenarios for selected world regions, we applied the described approach to construct structural change scenarios on a country level as well. The structural change scenarios presented are based on updated GDP scenarios. The applied method, however, can be used with any available set of SSP GDP per capita projections.

The method of scenario construction is based on a rather simple regression model. We do not claim that this model reveals any causality. Yet, we could demonstrate that the model, reproduces the historical pattern of structural change quite well. This does not only apply to the direct comparison of empirical and model data for the historic time horizon, but also to future projections. By constructing structural change scenarios, patterns observed in advanced economies in the past are reproduced in developing countries today or in the future, in particular with respect to the manufacturing sector. While the reproduction of historical patterns is a major advantage of the applied method, providing a good starting point for the quantification of scenarios, it is at the same time also a weakness. The method mainly assumes that historic patterns persist and all variation across the SSPs is adopted from SSP GDP scenarios. The new structural change scenarios are not robust against breaks with historical patterns.

Given the methodological limitation and supported by the empirical robustness of the underlying structural change pattern over time, we use the presented scenario method in an extended thought exercise of exploring possible future structural changes. The developed scenarios expose significant differences in structural change under different SSPs. For example, the transformation process is always the fastest in a SSP5 world, whereas it is the slowest in a SSP3 world. Developing countries, in particular, are challenged in either world. In the one case, under SSP5 (also under SSP1), the loss of employment in the agricultural sector until 2050 is immense. In the other case, as shown in Sub-Saharan Africa, it turns out that there is hardly any structural change but almost constant share variables under SSP3. This potential lack of structural transformation and build-up of industrial capacities may intensify the problems developing countries have with adapting to climate change and investing in climate change mitigation.

The presented approach covers the major determinant of structural change, but there are certainly more. While additional regression factors can easily extend the applied methodological approach, the major limitation is the availability of scenarios that differentiate additional independent variables along the SSP dimension[13]. Furthermore, future research on structural change scenarios has to go beyond the econometric approach and projection methods based on historical patterns. Not all factors that will impact structural change in the future will be covered by historical data. This for example applies to the impact of the digital transformation on sectoral energy consumption or the process of reindustrialization of developed countries based on uncertainties about the global geopolitical situation. Future research on structural change scenarios should be directed to overcome these limitations. Moreover, a further sectoral disaggregation could help to increase the range of application of structural change scenarios, particularly for climate impact and vulnerability studies.

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[13]We already included urbanization rates (Jiang and O'Neill (2017)), but the updated data are not publicly available. Preliminary results based on that show just a moderate impact on the projection of sectoral shares.

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A Appendix

A.1 Comparison of model results and empirical data

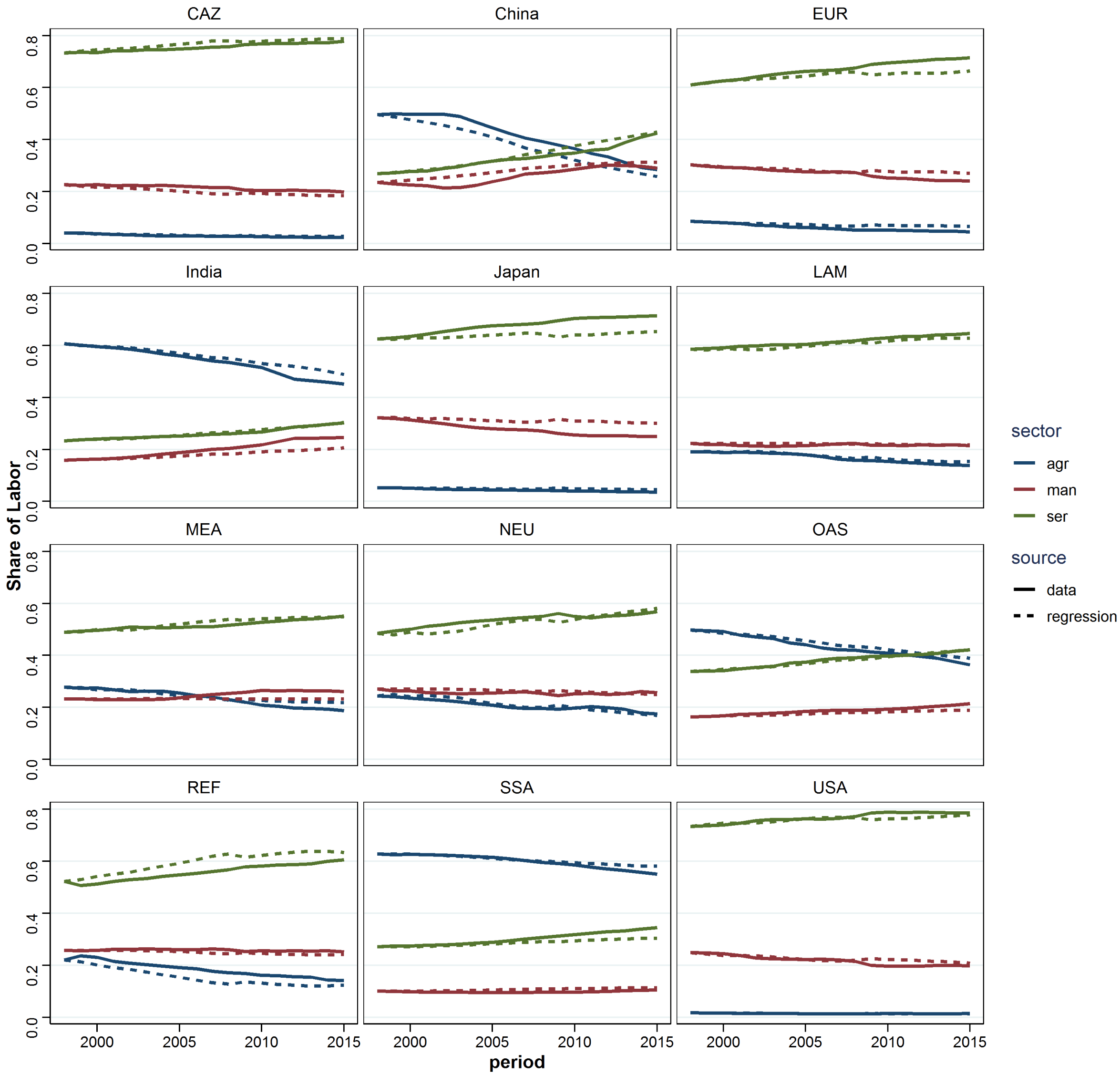

Figure 9: Labor share (solid lines represent empirical data, dotted lines represent model data)

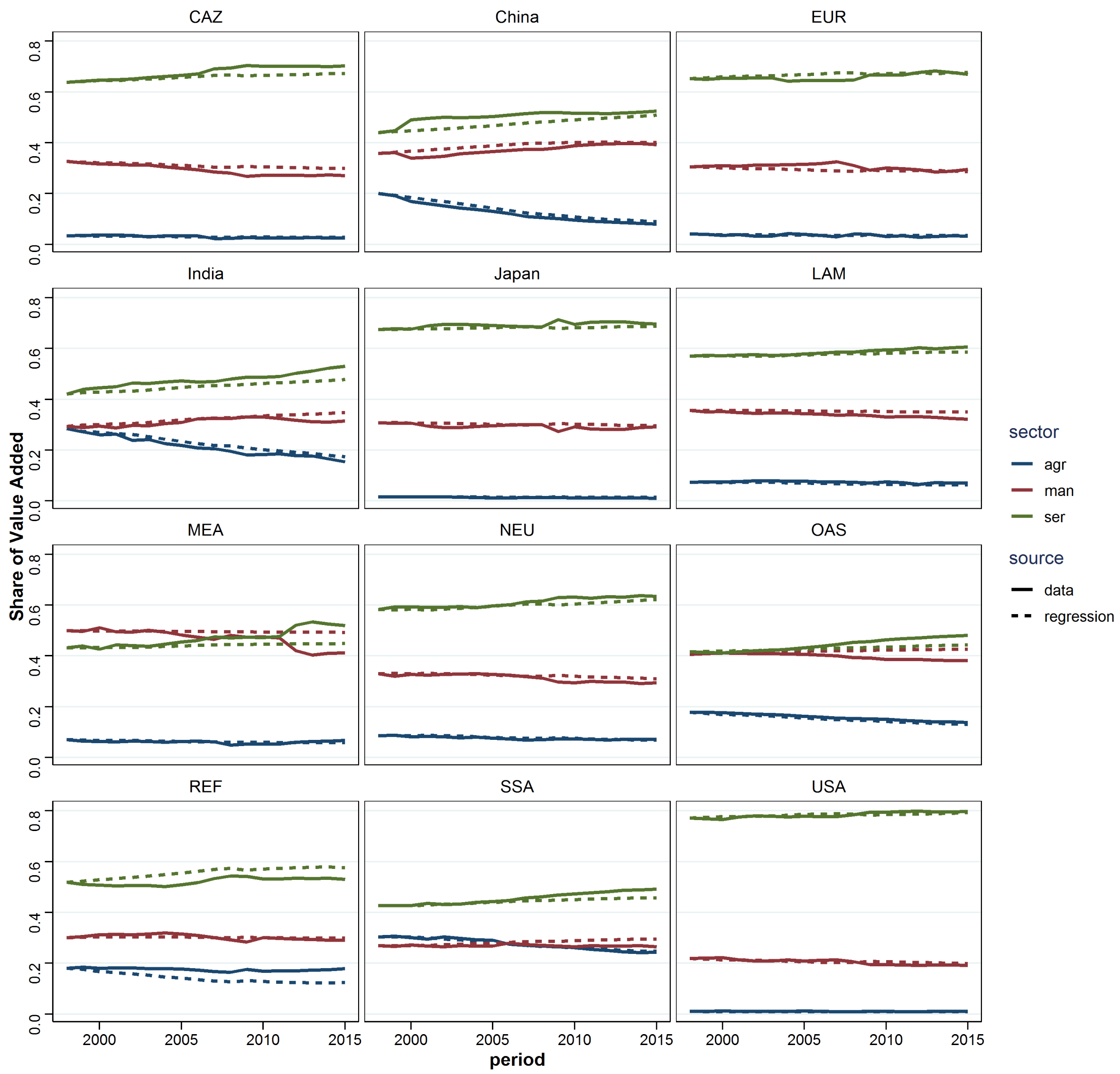

Figure 10: Value-added share (solid lines represent empirical data, dotted lines represent model data)

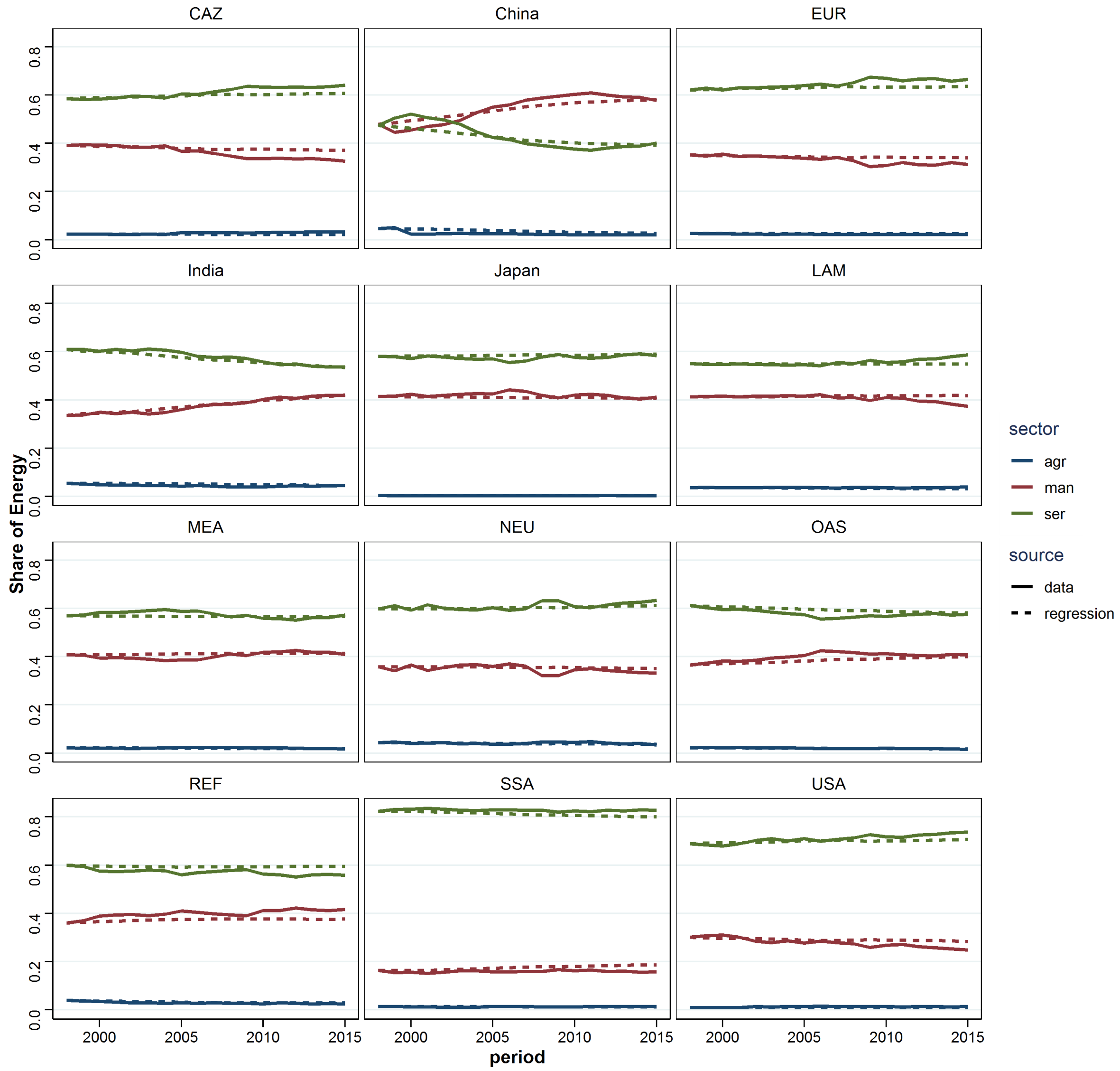

Figure 11: Energy share (solid lines represent empirical data, dotted lines represent model data)

A.2 Construction of SSP GDP projections

The data set of updated SSP GDP per capita scenarios (see Koch and Leimbach (2022)) was constructed by harmonizing the original SSP projections (Dellink et al. (2017)) with recent data from the World Bank's (WB) World Development Indicator Database[14] and the International Monetary Fund's (IMF) World Economic Outlook of October 2021.

The original SSP projections are in constant 2005 international dollars at purchasing power parity (PPP) (short-notation: 2005$PPP), and cover the time period between 2010 and 2100, in 5 year time steps. The WB has data until the year 2020, and the IMF has short-term projections until 2025. The data from the WB and IMF is given in 2017$PPP. The base year 2017 corresponds to the year of the most recent International Comparison Program report (World Bank (2020)) that provides the PPP estimates. In order to harmonize the projections with the most recent data, we decided to express the SSP projections in 2017$PPP. The updated SSP projections have the same time-resolution as the original projections. For the years 2010 and 2015, they match the data from the WDI. For the year 2020, they correspond to the 2018-2022 average, and for the year 2025 they correspond to the WEO's short-term estimates of GDP per capita growth. Between 2025 and 2100, the scenarios follow a path that, by 2100, leads them back to the same GDP per capita relative to that of the USA, as in the original scenarios.

Depending on whether the GDP per capita in 2025 of the updated scenarios is higher or lower than that of the original SSP projections, the convergence back to the same GDP per capita relative to that of the USA, is either accelerated or prolonged. In the case of lower GDP per capita, SSP1 and SSP5 start converging right away, i.e. by 2025, SSP2 starts by 2030, and SSP3 and SSP4 by 2035. In the case of higher GDP per capita, the convergence behavior is reversed: SSP3 and SSP4 start converging right away, SSP2 by 2030, and SSP1 and SSP5 by 2035. Until convergence is commenced, the SSPs use the same growth rate as the original projections, thus avoiding substantial changes in the growth rates. This SSP specific convergence behavior was implemented following the underlying SSP story-lines: in SSP1 and SSP5, high GDP per capita growth is expected, therefore faster catch-up (or slower slow-down) is a reasonable assumption. The inverse is true for SSP3 and SSP4.

The updated SSP GDP projections are the product of the updated SSP GDP per capita projections and updated SSP population projections provided by Lutz et al. (2018); KC. (2020), that we harmonized to the most recent WB data. For the years 2010 and 2015 the projections match WB data. For the years 2020 and 2025 the projections follow short-term WB population growth estimates from the Population Estimates and Projections database [15]. Between 2025 and 2100, the projections use the Lutz et al. (2018); KC.

[14]Accessed Mai 6 2021 at https://databank.worldbank.org/source/world-development-indicators
[15]Accessed Mai 6 2021 at https://databank.worldbank.org/source/population-estimates

(2020) growth rates.

A.3 Structural change scenarios for all world regions

Labor shares

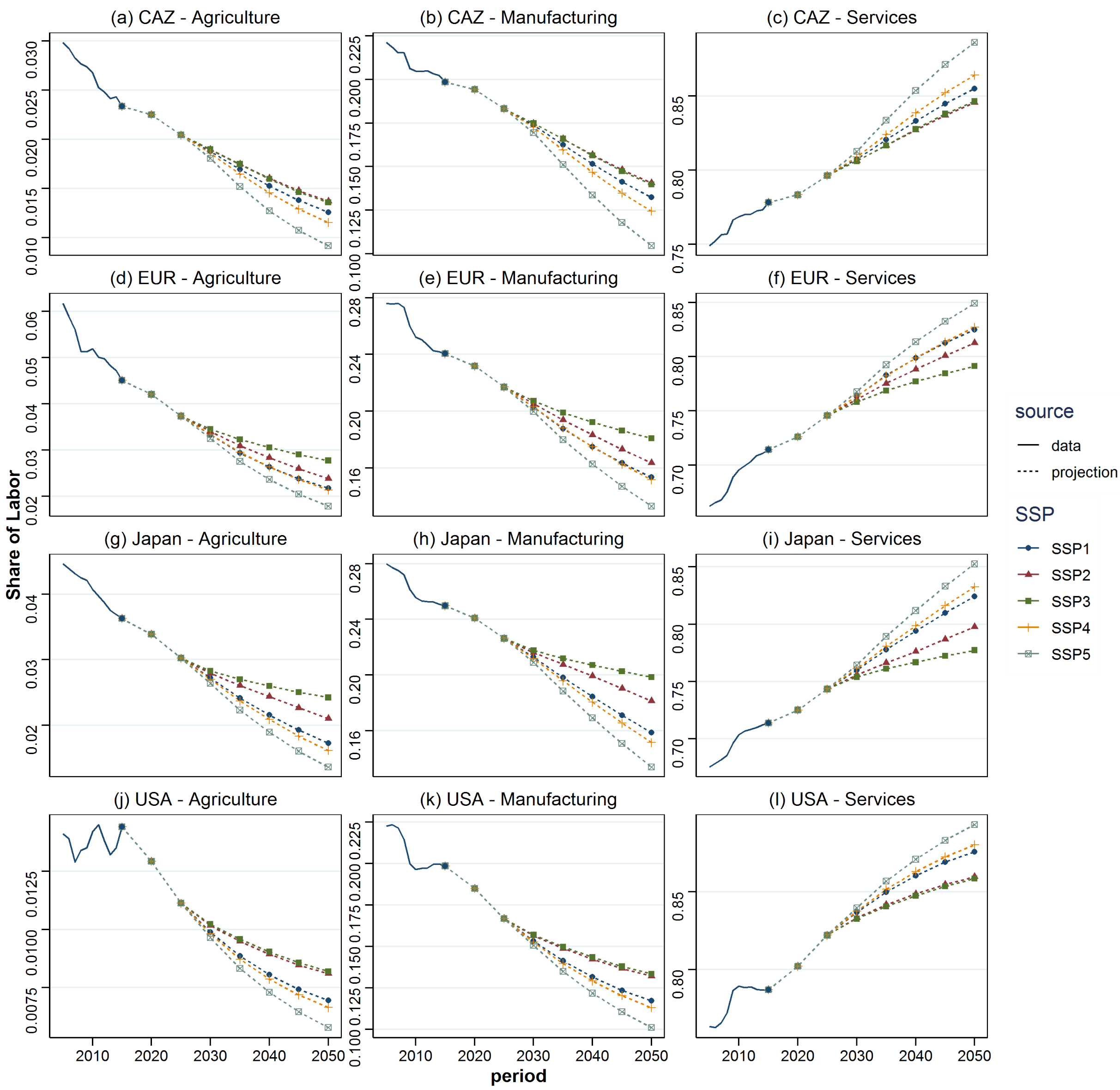

Figure 12: Sectoral labor shares (historical data are shown until 2015)

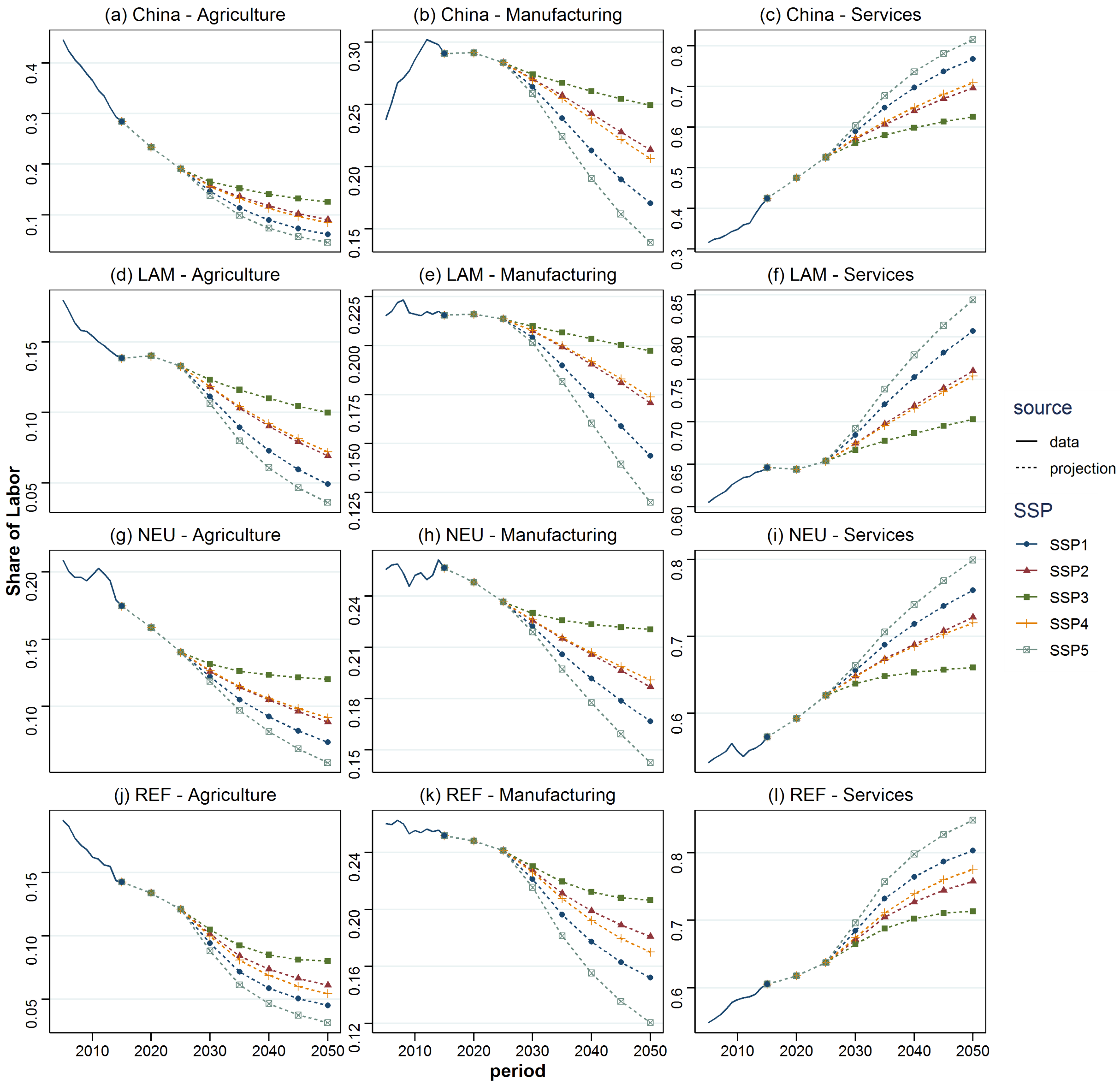

Figure 13: Sectoral labor shares (historical data are shown until 2015)

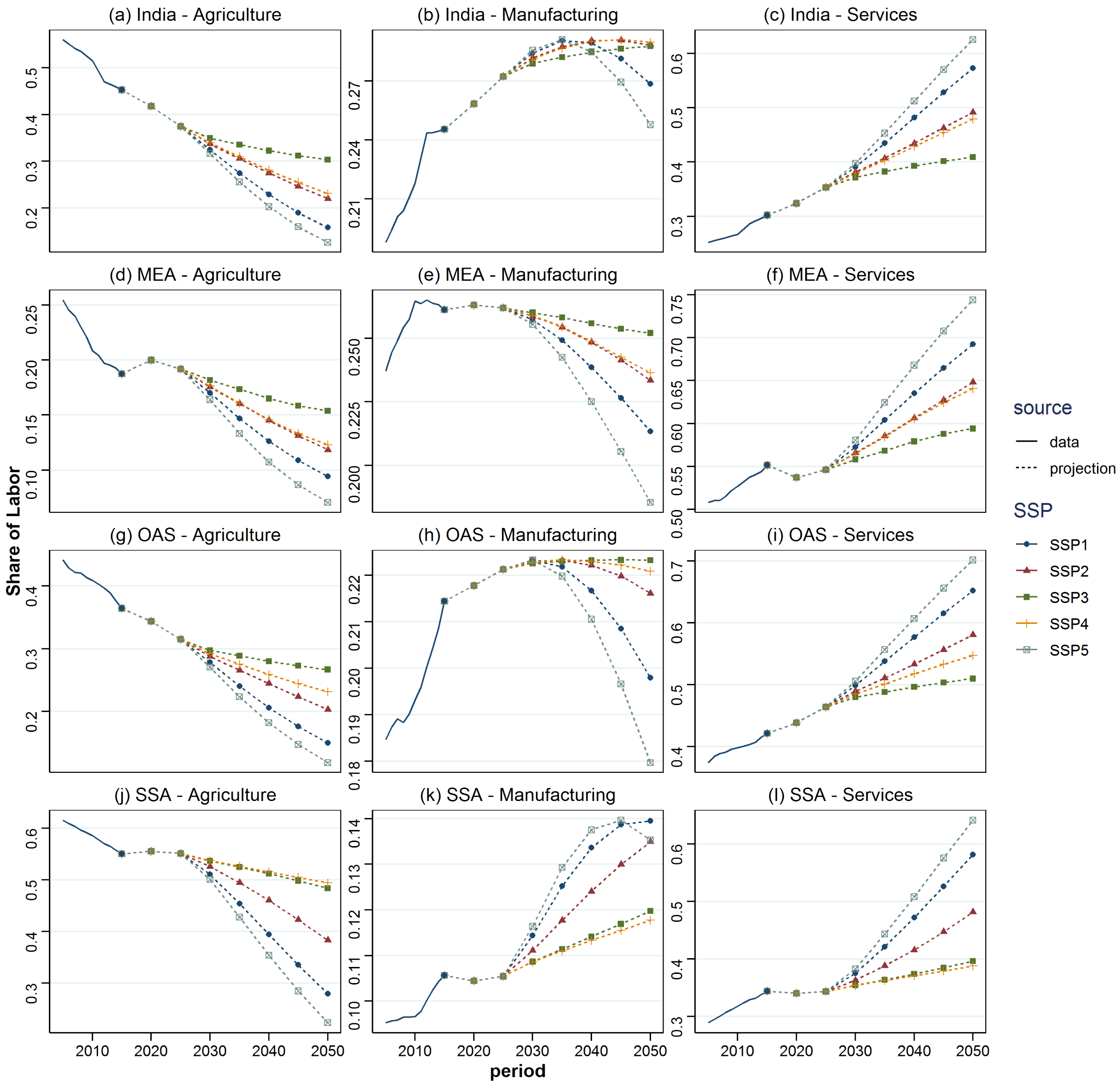

Figure 14: Sectoral labor shares (historical data are shown until 2015)

Value-added Shares

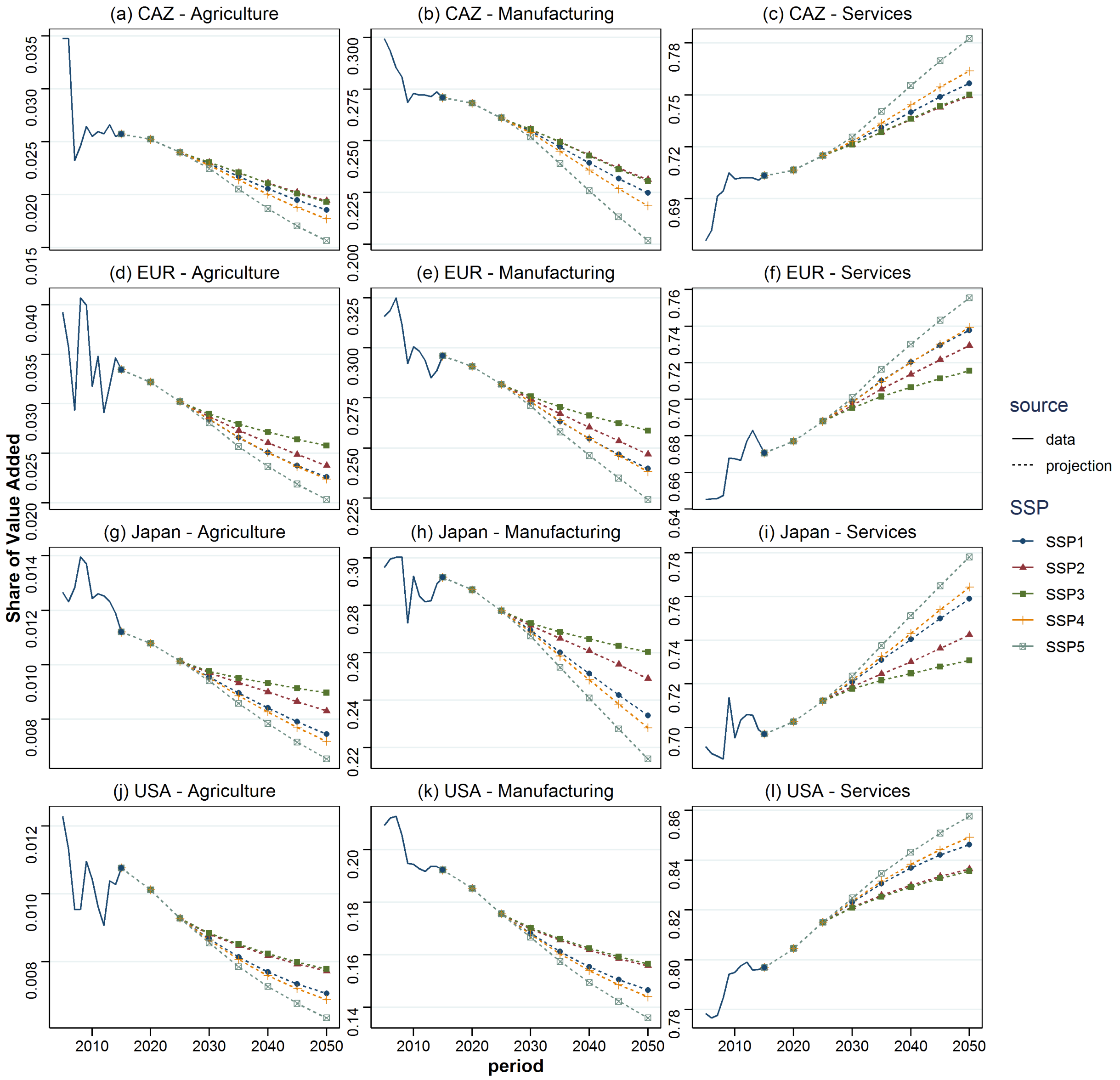

Figure 15: Sectoral value-added shares (historical data are shown until 2015)

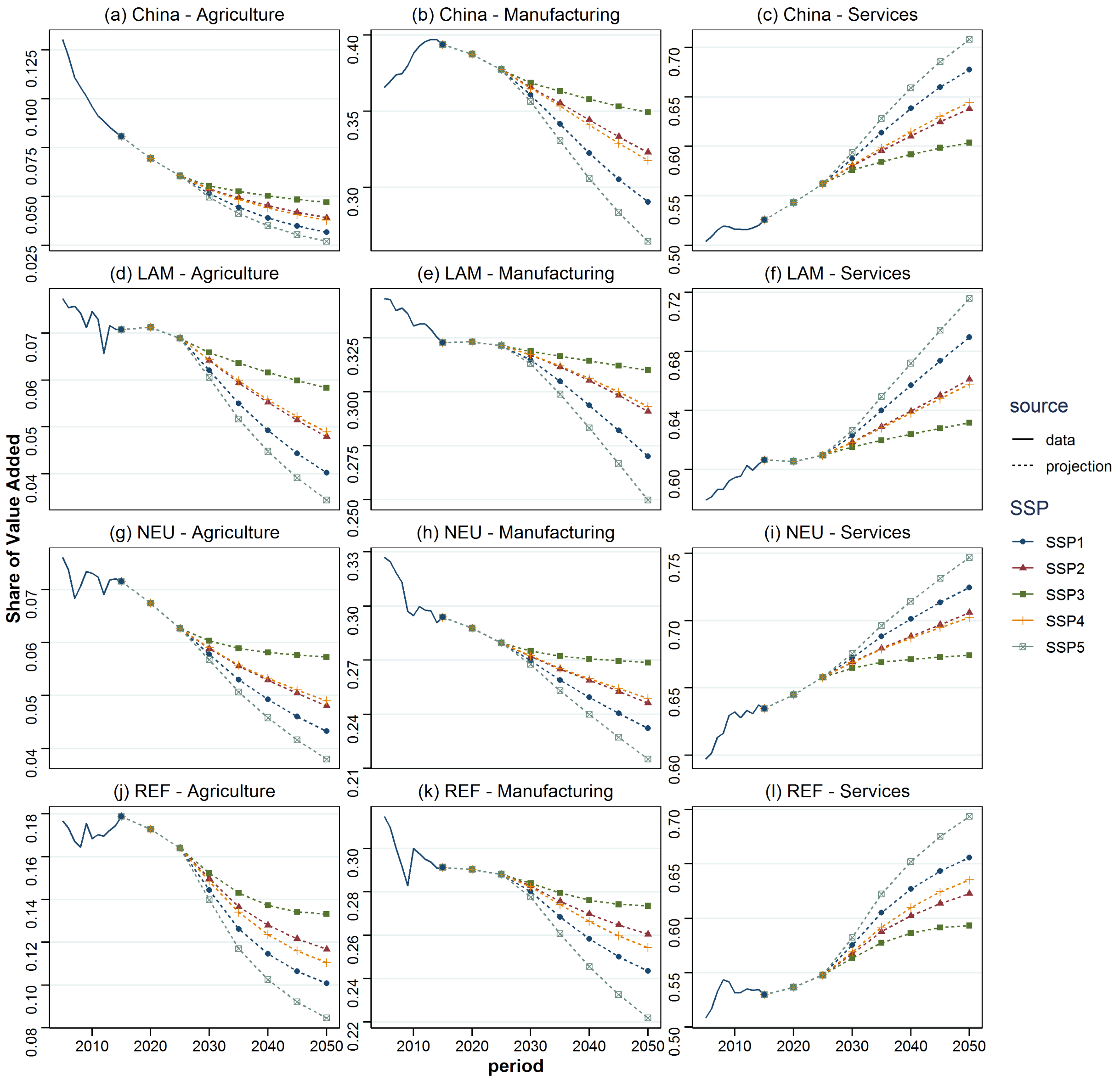

Figure 16: Sectoral value-added shares (historical data are shown until 2015)

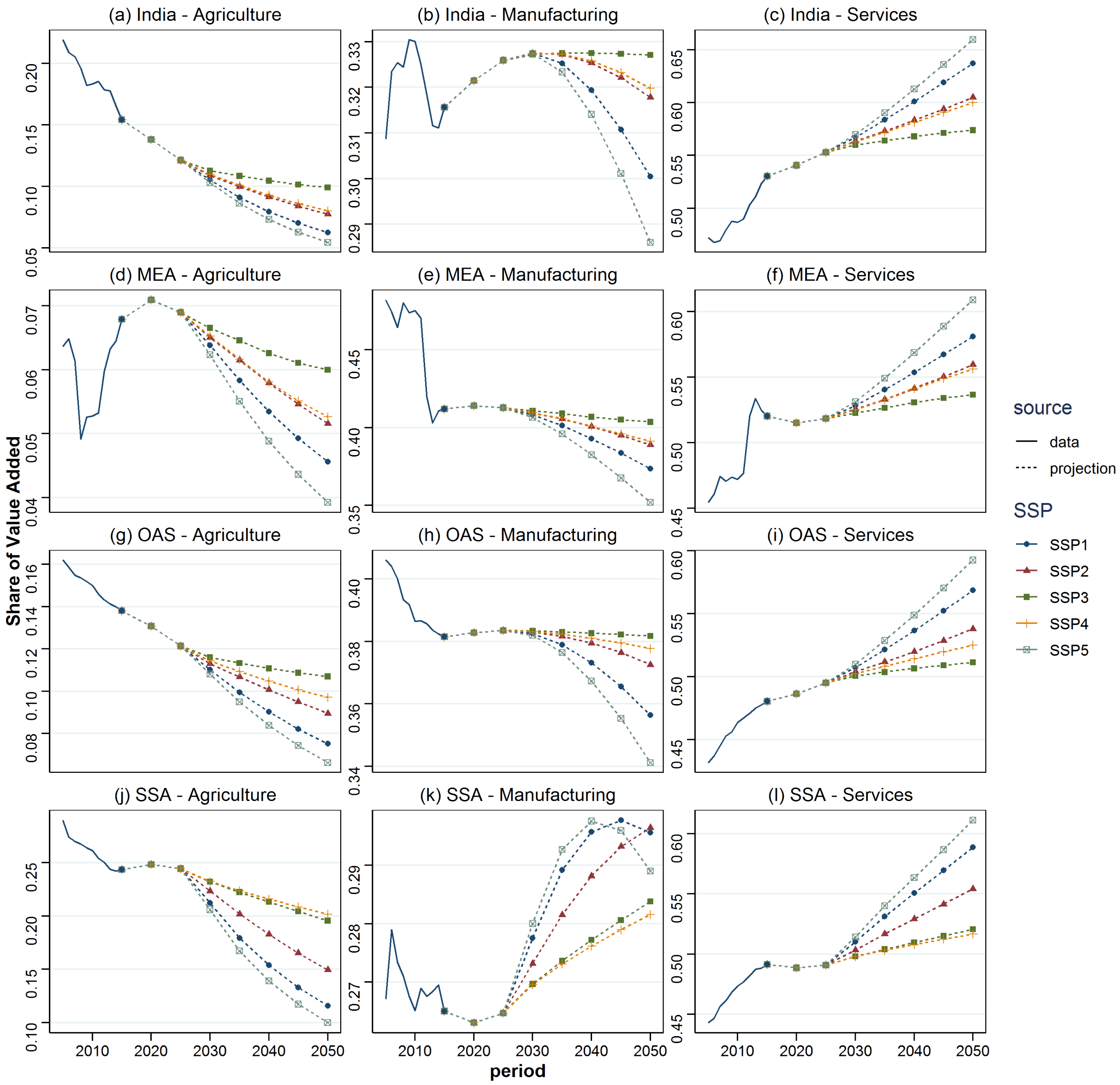

Figure 17: Sectoral value-added shares (historical data are shown until 2015)

Energy Shares

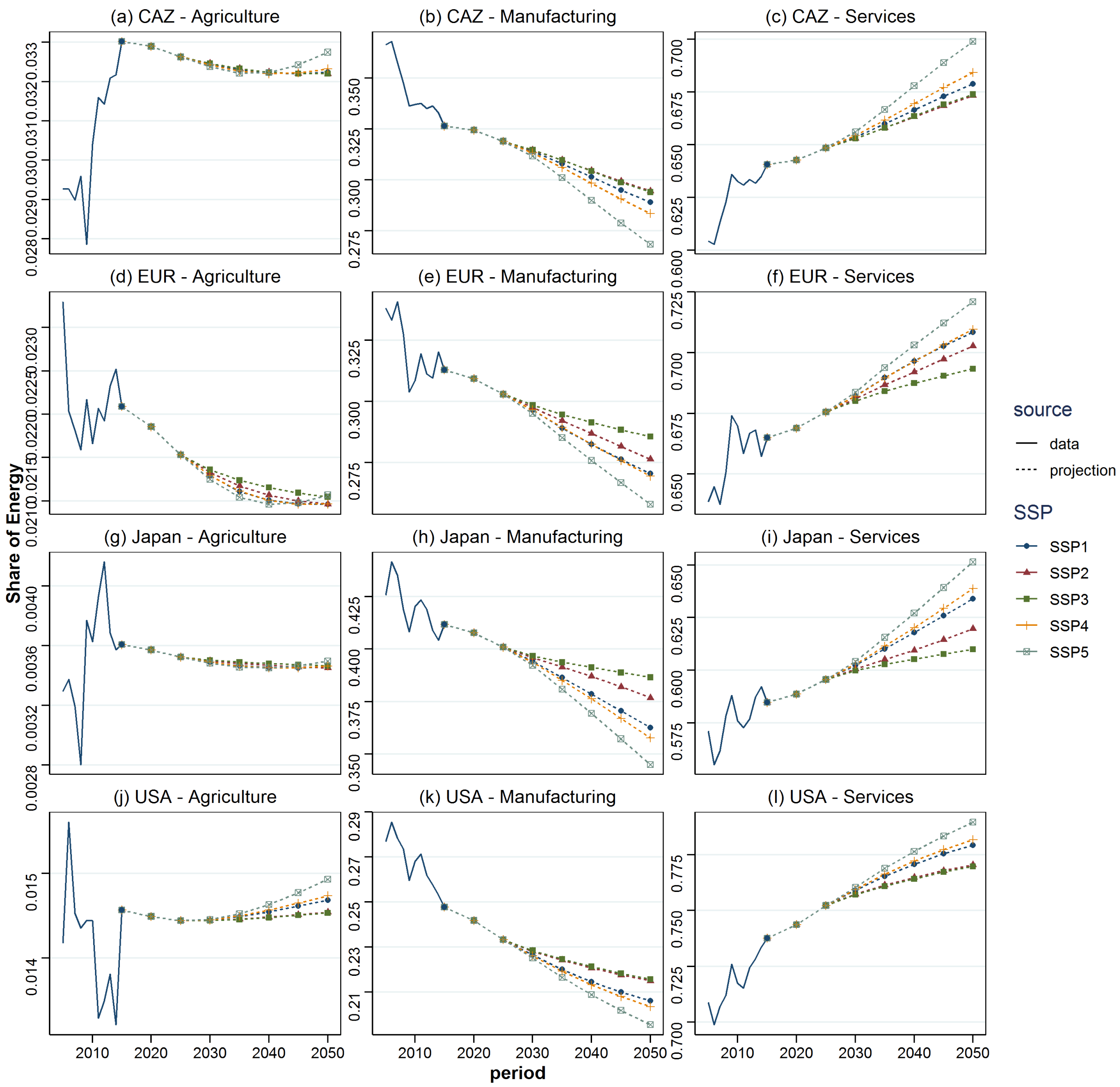

Figure 18: Sectoral energy shares (historical data are shown until 2015)

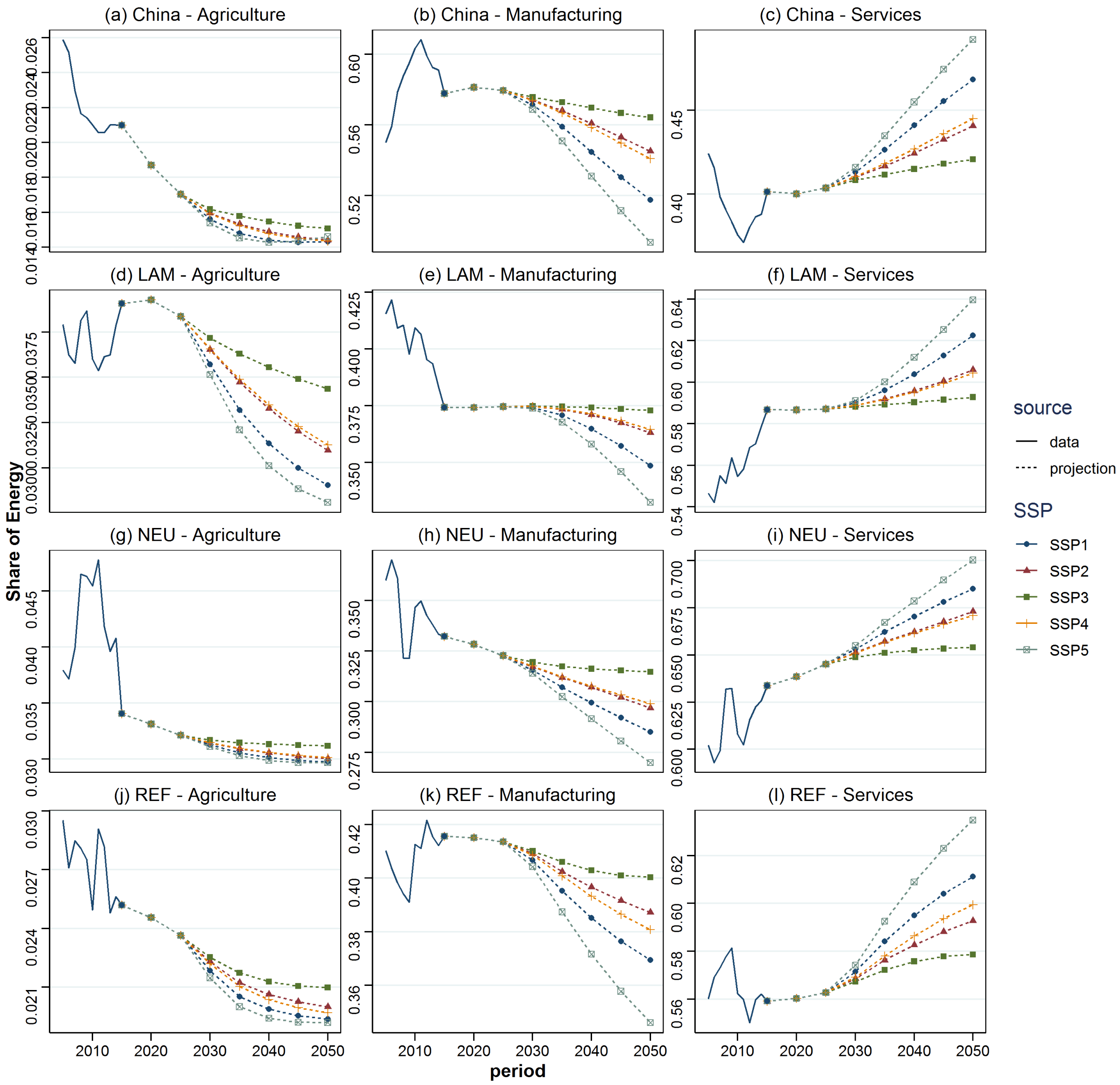

Figure 19: Sectoral energy shares (historical data are shown until 2015)

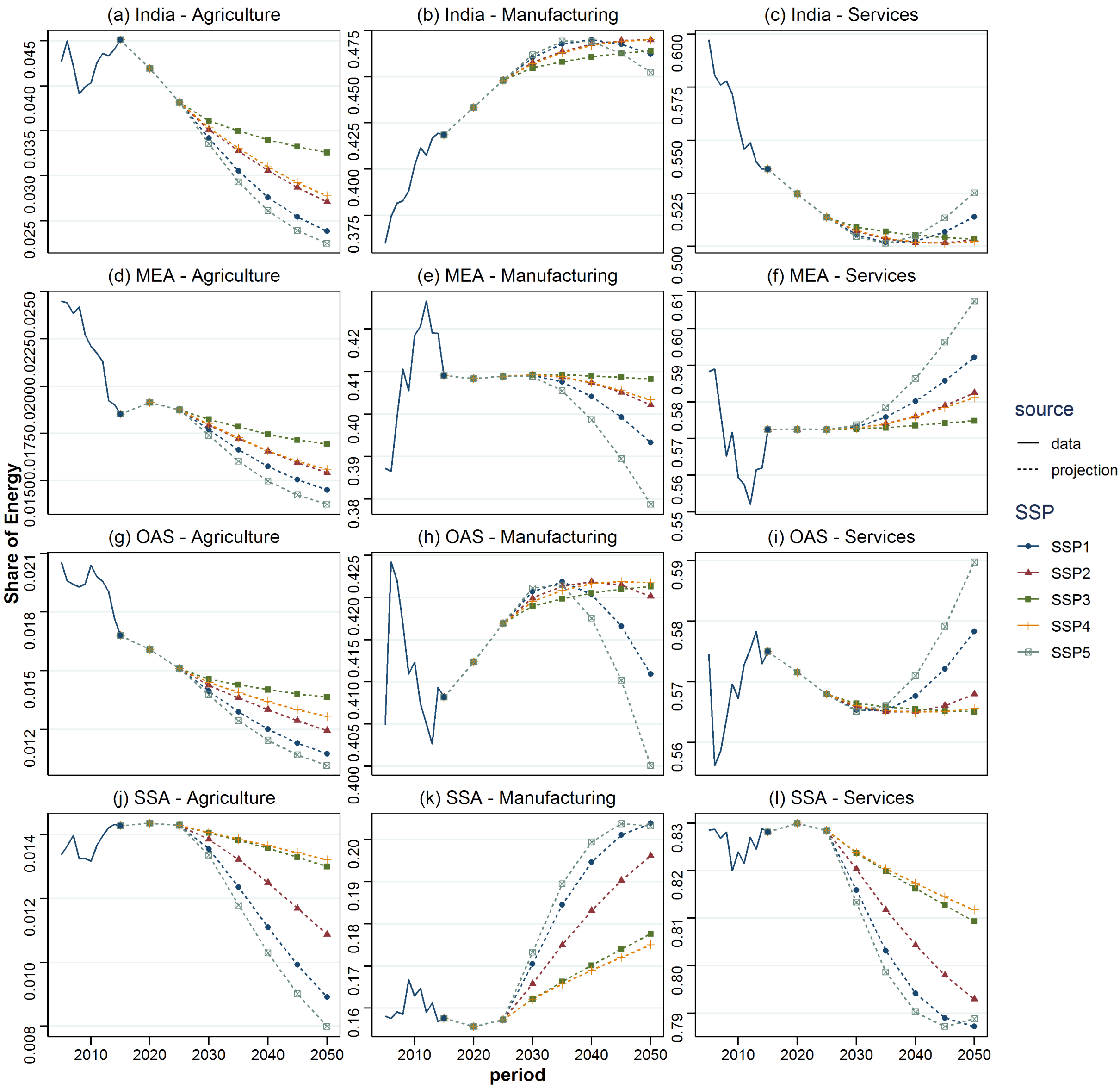

Figure 20: Sectoral energy shares (historical data are shown until 2015)

A.4 Robustness against covid shock

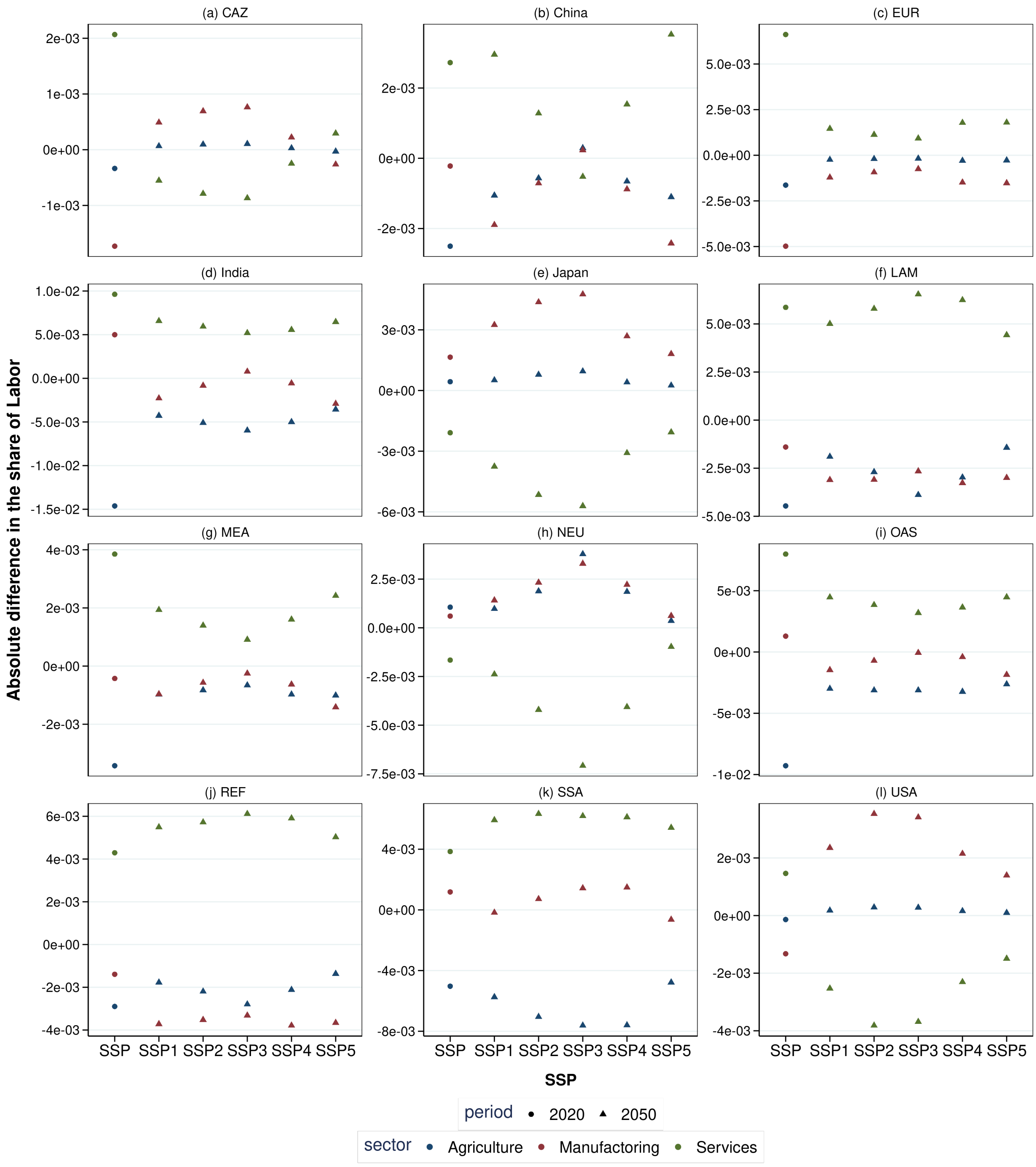

Figure 21: Differences in labor shares between projections with the covid shock either taken or not taken into account. 1e-03 corresponds to 0.1 percentage points. Values in 2020 are the same across all SSPs (labeled by "SSP" on the x-axis)

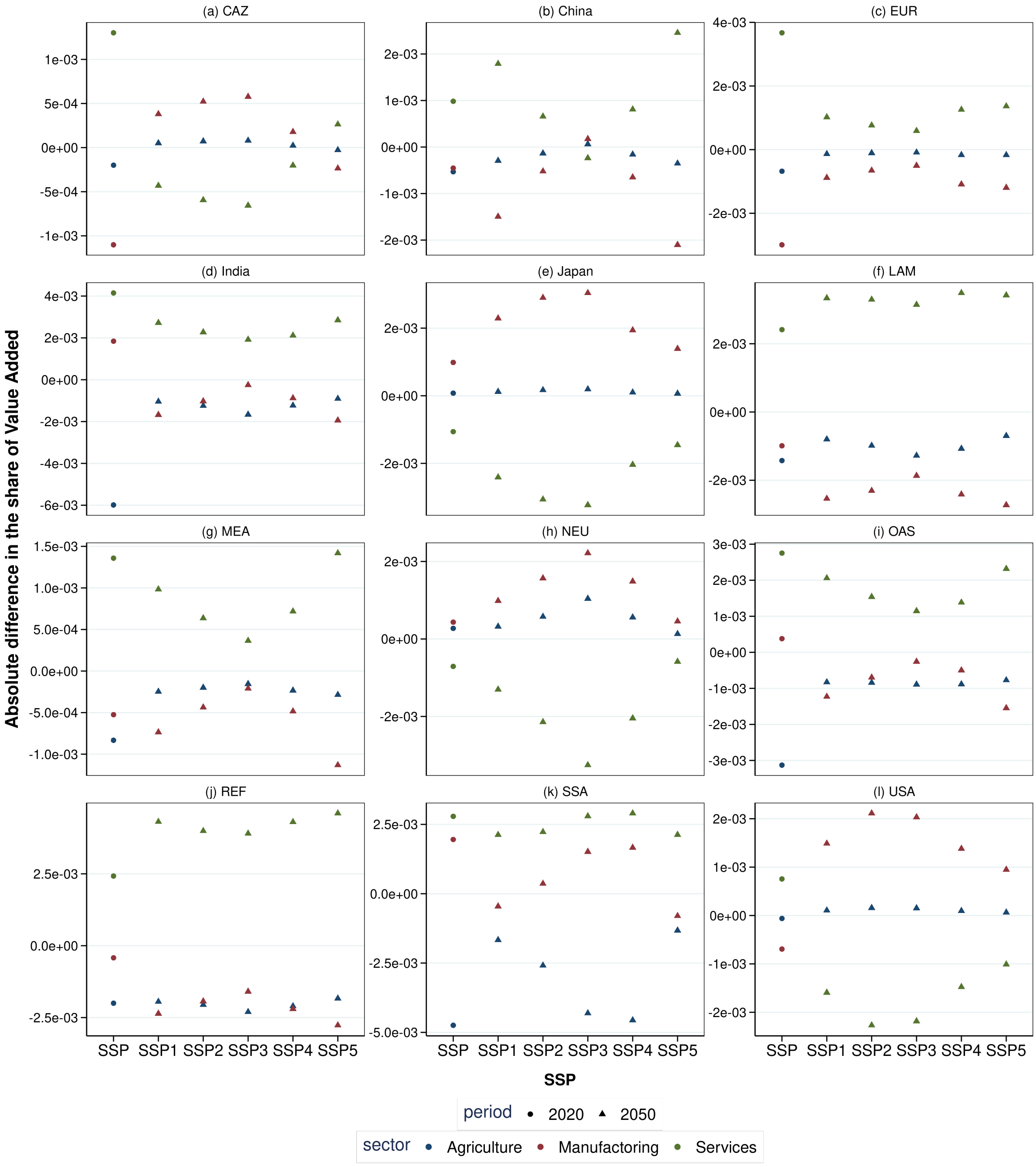

Figure 22: Differences in value-added shares between projections with the covid shock either taken or not taken into account. 1e-03 corresponds to 0.1 percentage points. Values in 2020 are the same across all SSPs (labeled by "SSP" on the x-axis)

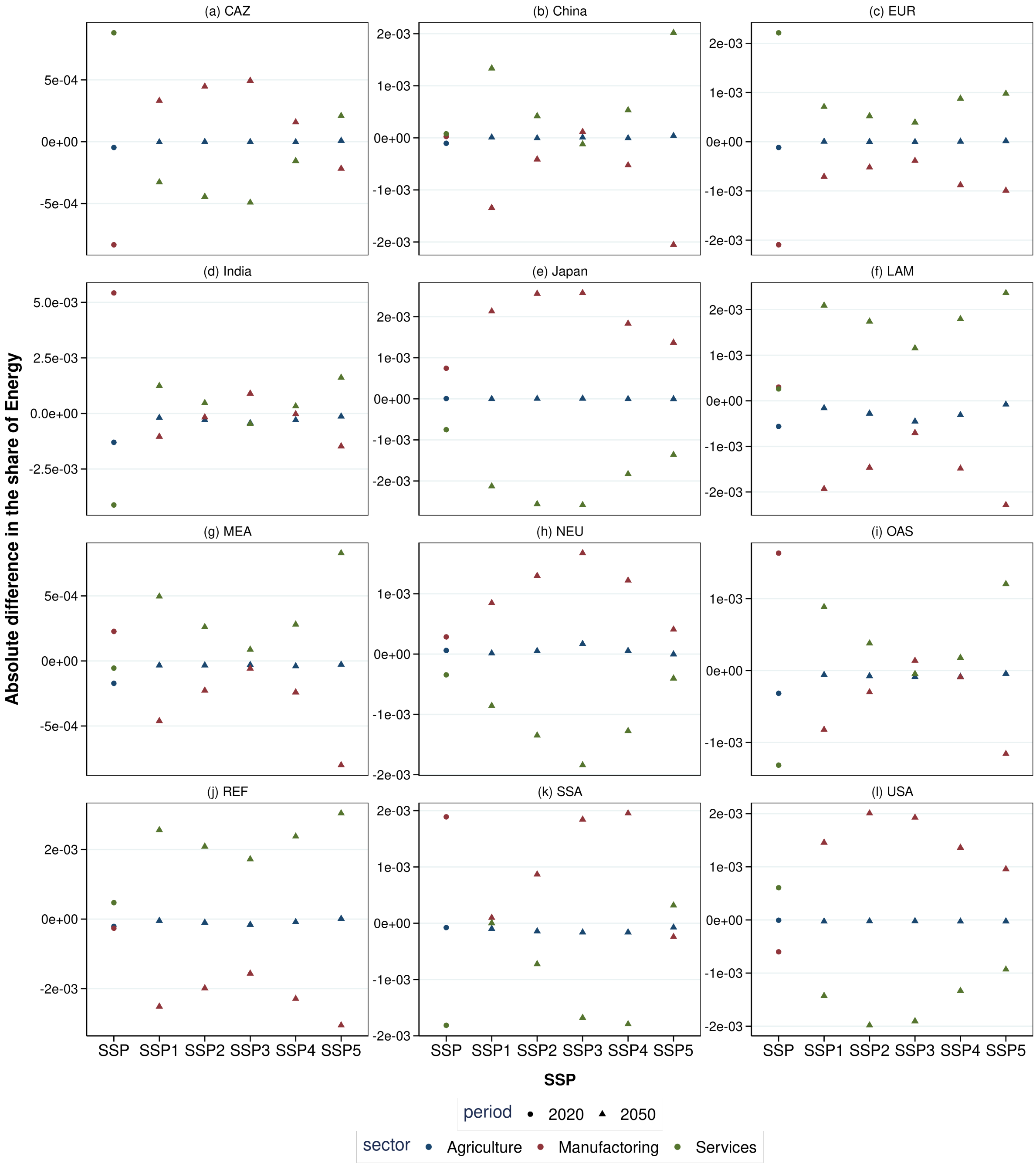

Figure 23: Differences in energy shares between projections with the covid shock either taken or not taken into account. 1e-03 corresponds to 0.1 percentage points. Values in 2020 are the same across all SSPs (labeled by "SSP" on the x-axis)