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Interregional Diffusion in the Analytic Climate Economy

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Interregional Diffusion in the Analytic Climate Economy

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Acknowledgments

Writing this sentence means a lot to me. It symbolizes that I have almost completed my thesis, thus wrapping up one of the more stimulating periods of my life so far. In navigating through this process, I have too often felt like the character Clark Griswold in the classic movie Christmas Vacation, trying to identify the broken bulb after decorating the entire house with lights and reindeer, only for his wife to discover that a silly mistake caused the whole issue. That is exactly what it feels like to calibrate a model.

First, I must thank my genius supervisor Christian Traeger for giving me the opportunity to work closely with him on current research. You have been like a mentor for me the last couple of years, and I have learned a lot from you. I greatly appreciate all your help and support.

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Abstract

In this thesis, I calibrate a North-South multi-sector integrated assessment model with explicit energy production and analyze the consequences of technology diffusion between regions. Using data from public sources, I sort countries into two regions based on income and degree of electrification. Then I calibrate five separate energy sectors and electricity that goes into the production of three final good sectors for each region. I introduce a simple exogenous inter-regional diffusion mechanism to the base model. Then I apply this model to analyze the effects of inter-regional diffusion on the welfare in each region, emissions and temperature increase, the composition of energy use within the economies.

I find the welfare effect of diffusion to be between 40 billion and 370 billion US dollars for the richer region. These effects are only indirect, through lower global temperature and lower climate-related damages. The low-income region has a welfare effect between 190 billion and 1800 billion US dollars. The energy composition and emissions of the richer region are not changing in diffusion, so the welfare effects on the low-income region are strictly local and direct. These results depend crucially on the potential for inter-fuel substitution within the production electricity, represented by the elasticity of substitution.

This thesis contributes to the literature on specifically analytic types of integrated assessment models. Analytical models are easily interpretable and permit a large state-space with fast solution mechanism, which enables quick computation of model results. By calibrating the present model, I look to narrow the gap between the simplicity and transparency of analytical models, and the accuracy and richness of more complex numerical models. I hope that this work lays a foundation for further explorations of the possibilities within numerical use of analytical models.

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Chapter 1

Introduction

Energy is the link between climate change and our welfare. For much of human history, we used a modest amount of energy. This changed during and after the industrial revolution. Anthropogenic emissions increased as we discovered how to effectively use coal instead of charcoal for fuel. With the later additions of oil products and natural gas, fossil fuels gradually replaced pre-industrial energy sources in all sectors in the industrialized world. However, that large-scale burning of relatively cheap fossil fuels does not come without consequences.

The Intergovernmental Panel on Climate Change (IPCC) has since the early nineties published reports on the state of climate change. They are currently in their sixth assessment cycle (AR6) and published their latest reports not long before I am writing this sentence. The IPCC (Masson-Delmotte et al., 2021) finds that human activities already have caused climate change in all areas on the planet. The average global temperature is estimated to already be more than 1 degree Celcius above pre-industrial levels, and it is only increasing as we continue to break yearly emission records. The IPCC warns that we might cause irreversible changes to our planet, which can adversely affect millions, if not billions of people (and other living creatures). Thus, there are huge potential welfare costs from climate change.

The most straight-forward way to emit less is to consume and produce fewer carbon-intensive goods and services. However, reducing consumption by a marginal unit has different consequences depending on your existing level of consumption. For a rich person, skipping a vacation abroad or trading in a large SUV with an internal combustion engine (ICE) for a similar but electric vehicle (EV) may not matter much. This is especially true if ICEs and EVs become more similar means of transportation and their substitutability increases. For people with very low consumption, however, reducing consumption could mean to go hungry or worse. Countries have recognized this potential injustice and have agreed to financial transfers from wealthy to poor countries to help with emission mitigation and climate change adaptation (Harvey, 2021).

Developing countries without access to modern infrastructure do not have to follow path of industrialized nations. They can potentially skip some of the fossil-fuel dependence that characterized the modern energy history of the industrialized world. Such a path of technology adoption is sometimes called technology leapfrogging. The argument is that falling prices for renewable sources, abundant local potential for renewable energy supply and political preference for avoidance of local pollution and foreign fossil fuel imports all point to a future in which growth in important sectors will be supplied emission-free in developing countries (Bond et al., 2020, Bond et al., 2021). As a contrasting scenario, developing countries may travel along a path leading to so-called carbon lock-in. This term refers to the self-perpetuating path-dependency of a fossil-fuel based energy system. Network externalities, sunk investments into infrastructure, capital vintages, habits, institutions and so on, 'locks in' fossil fuels as the main energy source, similar to what have been seen in the industrialized world (Unruh, 2000). There are many other potential futures, of course, but these to constitute two interesting future paths on each end of the spectrum of possibilities for a country transitioning from using traditional energy sources to modern ones.

It is not energy use per se that causes emission, but the carbon intensity of the energy use. Therefore, if developing countries could transition from traditional energy sources to modern renewables, they could enjoy higher consumption without paying the cost in terms of carbon taxes or climate-related damages[1]. Modern renewable energy systems require a lot of investment, political will, technology and knowledge that does not come for free, even in richer countries. But richer countries can make the energy transition in developing countries smoother by sharing technological knowledge. On the other side of the coin is the political economy of developing countries. It may (Bond et al., 2020) or may not (Newell and Pizer, 2003) be in the best interest of incumbent leaders to invest in renewable energy systems, to import foreign resources or to allocate resources efficiently. All these economical, political and technological factors are part of a technology- diffusion mechanism, where knowledge, policy and ideas flow between countries.

In this thesis, I calibrate a North-South multi-sector integrated assessment model (IAM) with explicit energy production and analyze the consequences of technology diffusion between regions. Researchers use IAMs to analyze the interaction between the economy and the climate system in order to inform climate policy. Such models are used to estimate or calculate various important figures, such as the social cost of carbon (SCC), likely future emission paths, the cost of climate change adaption, the benefit of mitigation and so on. They are called integrated because they use models of the economy, the climate system, energy and sometimes agriculture and land use in a combined framework to analyze the complex connections between these areas, and because they combine insights from several different fields (IAM Consortium, 2022).

Using data from several different public sources, I sort countries into two regions based on income and degree of electrification. Then I calibrate five separate energy sectors plus electricity that goes into the production of three final good sectors for each region. My motivation for calibrating this model is to analyze and quantify the sector- and fuel- dependent effects of different policy scenarios. To do this, I introduce an exogenous inter-regional diffusion mechanism to the base model, in which one region can import technology from another and improve their own technology levels. Then I apply this model to analyze the effects of inter-regional diffusion on the welfare in each region, emissions and temperature increase, the composition of energy use within the economies.

This thesis contributes to the literature on specifically analytic types of integrated assessment models. These models have closed-form solutions which usually limits the functional form choice and descriptive accuracy compared to more complex numerical models. Analytical models are easily interpretable and permit a large state-space with fast solution mechanism, which is especially important when analyzing issues like uncertainty – which I don't go into in this thesis. By calibrating the present model, I look to slightly narrow the gap between the simplicity and transparency of analytical models, and the accuracy and richness of more detailed models. I hope that this work lays a foundation for further explorations of the possibilities within numerical use of analytical models.

The rest of the thesis proceeds as follows: In chapter 2, I present the background and review the relevant literature on integrated assessment models, technological transitions and diffusion and on analytical IAMs. In chapter 3, I explain the model, the theoretical assumptions and the motivation behind the model structure. I also introduce the diffusion model. In chapter 4, I go through the calibration process. First, I explain the calibration process and list the

[1] Given that consumption goods also are produced with renewable or low-emission sources.

parameters I will calibrate. Second, I present the numerous data sources I use for calibration, and the assumptions and interpolations I make in cases of missing or incomplete data. Finally, I discuss how I pick the important elasticity of substitution parameters. In chapter 5, I discuss the calibration results and simplifying assumption I make in the calibration process. Then I discuss the numerical results of three main cases: (i) business-as-usual vs. optimal tax implementation; (ii) the effects of technological growth in the renewable sector and; (iii) the welfare effects of high and low technological diffusion. I end the chapter with a brief sensitivity analysis. I conclude in chapter 6.

I have collected detailed mathematical derivations, supplementary tables and figures and the programming codes in the Appendix. I use Matlab for all programming purposes: wrangling and compiling raw data for further analysis, missing data interpolations, sorting countries into regions, calculating the calibrated parameters, solving the model and running simulations.

Chapter 2

Background

In this chapter I will first give a brief history and description of different kinds of IAMs. Second, I will give a short literature review on IAMs that analyze the energy transition in developing countries and those that use technological diffusion models. Finally, I will give background and a literature review on analytical IAMs and place my contribution in context.

2.1 Integrated assessment models

Integrated assessment modeling grew out of the 1970's energy modeling community, as described in a nice field history by William Nordhaus (2011). The most well-known IAM is perhaps the DICE model for which the same Nordhaus (1993) was awarded the Nobel Memorial Prize in Economic Sciences in 2018. IAMs have not become less relevant since then: The IPCC (IPCC, 2001) uses several different IAMs in their most recent report on the mitigation of climate change, such as WITCH (2006), AIM (Fujimori et al., 2017) and MESSAGE-GLOBIOM (Krey et al., 2020). Some countries use IAMs to inform their local carbon tax policy, e.g., the Interagency Working Group on the Social Cost of Carbon in the US (2021) uses DICE, PAGE (Hope, 2006) and FUND (Waldhoff et al., 2014).

IAMs come in many shapes and forms. There is no single framework that is best suited in all cases and for all uses. Which model type, solution method or assumptions to use all depend on the problem on hand. The IPCC (IPCC, 2001) gives a comprehensive and readable overview of IAM taxonomies[1]. I will give a brief summary of the most relevant general distinctions they use.

First, models have different solution methods. Simulation models specify equations and parameters to represent likely future paths of the economy and corresponding emissions, and analyze the different outcomes given expert specification of these parameters. Optimization models selects some control variables optimally given the constraints of the system in order to maximize utility (for cost-benefit analyses) or minimize system costs (for cost-effectiveness analyses). The model on which I base this thesis, ACE (Traeger, 2022a), is a cost-benefit based optimization model. Such models uses a damage function to close the feedback loop between the economy and the climate system, where economic activities require energy that generates emissions which increase temperatures, which in turn harms the economy and human welfare. But I will also evaluate potential future paths similar to simulation models, where I specify

[1]See also Farmer et al. (2015), Bosetti (2021) and N. Stern (2022) for comprehensive reviews of the history, taxonomy and common critiques of IAMs. For detailed and pointed critiques, see Pindyck (2013, 2017) and Pindyck (2019)

different levels of diffusion and inter-fuel substitutability. The benefit of using an optimization model as the basis for this analysis is that I can calculate the welfare effects as the difference between an optimal base-line path and a optimized variation on that path.

Second, dynamics are handled differently within the optimization models category. Inter-temporal dynamic models find the optimal path to follow to maximize the present utility value, or minimize the total discounted system costs. Such models can assume either assume perfect foresight, or allow for uncertain futures in which case agents maximize expected present values (see e.g. Traeger (2018)). In contrast, recursive-dynamic models optimize within one period, but do so sequentially. The state of the world changes over time but the agents do not take into account the consequences their actions have on future states of the world and there is no trade-off between future and present. There are hybrid models that assume varying degrees of imperfect foresight. I use a inter-temporal dynamic model in this thesis.

A final main distinction is whether the model relies on a general equilibrium framework where all prices in the economy adjust to equate supply and demand in every market, or if the researcher analyses a single or a few markets in a partial equilibrium while keeping the effects on other markets constant. I use a general equilibrium framework in this thesis.

In addition to the more technical differences mentioned previously, models also vary in their degree of detail and underlying assumptions. The first version of DICE (1993), for example, was a global model, but it was later extended to the regional RICE (Nordhaus and Yang, 1996) model, increasing the level of detail. The current version of DICE has a single-good economy produced in each region with capital, labor and two different energy types. REMIND (Baumstark et al., 2021), however, uses the same basic macro-economic variables, but has a detailed bottom-up specification of the energy sector with more than 50 different technologies. AIM also has a detailed energy sector, but also has several different industrial and agricultural end-use sectors. Another regional model with a single-good economy is WITCH (Bosetti et al., 2006), but that model allow for endogenous investments in technology which captures strategic game-theoretic effects between regions or groups of regions.

2.2 Numerical IAMs analyzing the energy transition in developing countries

There is a rich literature analyzing energy transition in the developing world using IAMs. Lucas et al. (2015) use the models in the LIMITS project[2] to analyze African emission scenarios under various assumptions. Using the same LIMITS framework McCOLLUM et al. (2013) find that most supply-side capital investments should flow to developing countries in the two-degree scenario. In particular, investments should shift from upstream fossil fuels to downstream electricity generation. There exist several other LIMITS project papers (e.g. Van Der Zwaan et al. (2013)). These papers are thorough and very useful for detailed insights in the necessary future energy system mix in developing countries, how to obtain that mix, and the corresponding emission paths. They also show through detailed modelling that the energy transition in developing countries indeed is feasible. In the same spirit, Leimbach et al. (2018) quantify the costs and benefit of climate policy in Sub-Saharan Africa, using REMIND. Their context is the "favorable conditions" for renewable energy on the continent and they include international fossil fuels markets and technology diffusion. They find emission pathways Sub-Saharan Africa consistent with two degrees warming at a net zero cost, given equitable burden sharing by international transfers.

Clarke et al. (2012) explore how different models in the Asian Modeling Exercise (AME) vary in their energy system assumptions. Many of the models use production functions that are

[2]LIMITS is inter-model study of policies consistent with a maximum warming of maximum 2 degrees Celsius.

calibrated to base-year shares. Some models in AME vary parameters over time, allowing them to represent predicted changes in technology, infrastructure and so on. The paper includes a comprehensive overview of the implied constraints on and costs of key technologies and if (and how) base-year shares are calibrated in the models.

All these models are much more complex and rich than the present model. However, they are solved numerically and in that respect differ from the present thesis.

2.3 Technological diffusion models

Zhang et al. (2020) augment REMIND to include regional technological improvement and diffusion. They ask how multi-level learning affect the regional mitigation costs and technology diffusion. This paper is an extension from a earlier paper by Zhang et al. (2014) that looked at different regional investment costs, but did not include multi-scale learning. Four different approaches are investigated: full international spillover, no spillovers and two intermediate cases with varying degree of market efficiencies. The crucial exogenous parameter in their model is the learning rate.

Gu et al. (2021) develop a numerical multi-sectoral and regional IAM that models bottom-up low-carbon technology diffusion between regions and (exogenous) R&D investments. They use this model to identify the effects endogenous technology transfer can have on optimal regional carbon emissions. The use only Cobb-Douglas or Leontief production functions.

Cai et al. (2015) combines a top-down dynamic computable general equilibrium model with a bottom-up model of energy production and consumption. The result is a hybrid IAM called GTEM-C[3]. They want to keep the general equilibrium framework, while permitting more realistic technological development. To do this they use constant ratios of elasticities of substitution for homothetic (CRESH) functions for a set of disaggregated energy technologies and household energy preferences. A CRESH function allows for heterogeneous substitutability between input factors in the same production functions. I use the simpler but more constraining constant elasticity of substitution (CES) production function. An interesting extension to the model in this thesis is try to introduce CRESH production functions. -

Gu et al. (2021) analyze the possible carbon mitigation caused by technology diffusion between countries. The base model, CIECIA (Wang et al., 2016), is a multi-sector, multi-country general equilibrium model with a damage function, endogenous technology and free trade in capital and commodities. Gu et al. (2021) add a bottom-up technological diffusion block to CIECIA in which every sector in each country search for, select, learn and imitate technology from corresponding sectors in other countries. First, sectors find the feasible imitable technologies and then select among those to find imitation targets. The higher the intellectual property protection, the narrowed the imitation range becomes. Each imitation target is represented their "attractiviness", or the magnitutude of the technology gap and the economic gap plus the severeness of path dependency. The selection is governed by a probability distribution where higher probability of selection are given to countries with higher attractiveness. After having selected a supplier country, the imitating country gets accelerated energy-saving R%D in the process technology for the given sector. Progress in "processing" is modeled by a looping stochastic logarithmic shock mechanism that affect the intermediate input coefficients in the production functions. The technology is self-selected by the sector if the shocks have caused lower unit costs. Analytical models are suited for analyzing uncertainty. Another interesting extension is to model inter-regional diffusion more in line with their approach an incorporate uncertainty in

[3]GTEM-C is built on top of the Global Trade and Environment Model , which is the Global Trade Analysis Project's (GTAP) IAM

the diffusion model. This is beyond the scope of this thesis, however.

Furthermore, Gu et al. (2021) find that technology transfer has significant mitigation effects. They analyze four different intellectual property regimes. The ideal regime is where low-carbon technologies are freely shared to the public. Decreasing the technology transfer threshold, so that more technology becomes imitable, will significantly increase diffusion and mitigation. While this effect is strongest for technology transfers from developed to developing countries, the authors point out the importance of technology sharing between developed countries as well. Finally, Gu et al. (2021) interact diffusion with various exogenous R%D investment shares and find that the combination gives the highest mitigation, particularly in developing countries. Even with no patent barriers, a relatively low knowledge stock creates a drag on low-carbon technology progression in developing countries.

2.4 Analytical IAMs

The complexity of all the models mentioned in earlier in this chapter require numerical solutions. Solving such large and detailed models became feasible only after the major improvements in computing power during the final decades of the previous century. Analytic and semi-analytic models, in contrast, permit closed-form model solutions. Thus, they allow transparent analyses of the crucial trade-offs and economic mechanisms inherent in the problem of climate change. While the qualitative closed-forms expressions are often quantified to inform policy, the necessary analytic tractability requires closed-from solution, thereby limiting functional form choise and descriptive accuracy.

Analytic models are especially useful when handling uncertainty[4]. They permit large state-spaces that break the "Bellman curse-of-dimensionality", referring to the exponentially increasing computing power needed when adding states in numerically solved models (see e.g. Traeger (2018) for a state-of-the-art analytical model of closely related structure, with uncertainty).

An important landmark in the field was when Golosov et al. (2014), building on the analytic macro-model of Brock and Mirman (1972), included a heterogeneous energy sector with emission feedback into production damages[5]. This flexible but robust framework has supported several extensions, such as a closed-form general equilibrium version of RICE (Hassler and Krusell, 2012), the pricing of uncertain catastrophic events (Gerlagh and Liski, 2018b), game-theoretic approaches to time-inconsistent preferences (Gerlagh and Liski, 2018a; Iverson and Karp, 2021) and distortionary fiscal policy (Barrage, 2019).

Traeger (2022a) made further progress by generalizing the economy, including the energy sector, while explicitly modeling and improving climate dynamics and thus enabling a clearer analysis of the economics of climate change. In the appendix of the same paper, Traeger proposes a production structure in which several sectors produce final goods in Cobb-Douglas function of capital, labor and an CES function of intermediate energy. Traeger (2022b) further develops the multi-sector specification.

The present thesis relies on the analytic structure in Traeger (2022a) and production functions in Traeger (2022b) to solve the inter-temporal optimization problem characterizing regionally optimal carbon prices[6]. My main contributions are (i) to calibrate the production function

[4]Several early analytic contributions indeed focus on tackling uncertainty in climate-economic models (Pizer, 1999; Schauer, 1995). Later papers make use of linear-quadratic functions to obtain relevant closed-form expressions (Hoel and Karp, 2002; Karp and Traeger, 2021; Karp and Zhang, 2006, 2012). These are stylized benefit-cost models without production or energy sectors.

[5]Van Der Ploeg and Withagen (2014) developed a similar but slightly more general model around the same time. Other generalizations are found in Rezai and Van der Ploeg (2016) and van den Bijgaart et al. (2016)

[6]I assume that regions takes into account only their own future damages, not the damages to other regions.

proposed in Traeger (2022b) (ii) to find, gather and clean the data used in this calibration exercise and (iii) to analyze the effects on welfare and energy composition from technological diffusion in a two-region version of the model. To my knowledge, this is the first analytical integrated assessment model calibrated to this level of detail.

Chapter 3

The Model

The model is based on the ACE-model by Traeger (2022a) with the multi-sector production function specification in Traeger (2022b). In this chapter, I will first present the economy with the accompanying nested production function. Second, I give a brief explanation of the climate system. Third, I introduce a simple but general exogenous technological diffusion model for the energy sectors across regions. Finally, I briefly explain how to solve the model.

3.1 The Economy

There are two social planners in this model, one for each region $j \in J = \{L, H\}$. Region L is low-income and region H is high-income. There is no trade between the regions. They are connected (i) through the carbon-stock in the atmosphere, into which the fossil fuel energy sectors in both regions emit CO_2 and (ii) by the exogenous diffusion of technical knowledge from region H to regions L. Each social planner cares only about her own region's consumption, but they affect the other region's welfare indirectly through the future damages inflicted on each other by climate-change related damages. If the social planners had a way to credibly commit, they could agree to lower their own emissions to the benefit of the other social planner, and to the potential net benefit for both social planners[1]. I assume, however, that there are no such commitment vehicles, and that both social planners therefore have an incentive to free-ride on the other's mitigation. Region H, however will be endowed with a positive but small price on emissions, to reflect the current state of carbon pricing in the World. It is in this setting I analyze different technological diffusion scenarios and their welfare effects.

The social planners maximize their discounted infinite stream of (their own) utility from the consumption of an aggregated good

$$\max \sum_{t=0}^{\infty} \beta^t \log C_t, \tag{3.1}$$

with the discount factor $\beta = \frac{1}{1+\delta} \approx 0.87$, where the pure rate of time preference δ determines how much the social planner discounts future utility, and is I crucial parameter in integrated assessment models (see e.g. Drupp et al. (2018) for an expert survey and discussion). I suppress regional indexing j for brevity, but will include it wherever necessary to avoid confusion.

[1]Even if the social planners could credibly commit, it is not given that commitment is in the best interest of their populations.

The single good ACE-model has simple logarithmic utility, which implies a unitary intertemporal elasticity of substitution. The present model, as explained in the appendix to Traeger (2022a), weakens this assumption by disaggregating consumption using the constant elasticity of substitution (CES) composite

$$Y_t = A_t \Big(\sum_{l \in N_c} a_{l,t} \left(c_{l,t}\right)^s \Big)^{\frac{1}{s}}, \tag{3.2}$$

where $\sum_l a_{l,t} = 1$ and the substitutability index $s \leq 1$ indicating that all final consumption goods $c_{l,t}$ are necessary in consumption. The final goods are transportation, industry and other, with $l \in N_c = \{tr, in, ot\}$ respectively. I choose these sectors because they approximately consume a third each of the total World energy consumption (International Energy Agency, 2019), and because they have different dominating energy inputs with varying degrees of potential interfuel substitutability. The constant A_t makes sure C_t is measured in calibration-period money metric utility units.

Each final good sector have Cobb-Douglas production functions of technology $A_{l,t}$, capital, $K_{l,t}$, labor $N_{l,t}$ and the intermediate energy input $d_{l,t}$

$$c_{l,t} = A_{l,t} K_{l,t}^{\alpha_l} N_{l,t}^{1-\alpha_l-\nu_l} d_{l,t}^{\nu_l}, \tag{3.3}$$

where ν_l is sector dependent. The overall production function must be homogeneous in capital to get a closed-form solution (Traeger, 2022a), which means $\alpha \equiv \alpha_l$ must be sector-independent.

The intermediate energy good $d_{l,t}$ represents the energy composite used in production of final good l. It can be interpreted as a generalized mean of various refined energy inputs $e_{i,l,t}$ combined according to the CES production function

$$d_{l,t} = \tilde{A}_{l,t} \Big(\sum_{i \in N_d} \tilde{a}_{l,i,t} e_{l,i,t}^{\tilde{s}_l} \Big)^{\frac{1}{\tilde{s}_l}} \quad \forall l \in N_d, \tag{3.4}$$

where $\tilde{a}_{l,i,t}$ are CES share coefficients with $\sum_i \tilde{a}_{l,i,t} = 1$ for each sector, and where $\tilde{A}_{l,t}$ is a constant turning the function money-metric in calibration-period USD. The notation $e_{i,l,t}$ reads 'refined energy input i in sector l in period t'. The refined energy sources available to sector l is a sector-specific subset of $N_d = \{c, o, g, b, el\}$, the elements of which corresponds to coal, oil products, natural gas, bioenergy and electricity, respectively. Note that the substitutability parameter $\tilde{s}_l$ is sector-dependent[2]. The model can therefore distinguish between the arguably harder-to-substitute inputs to the transportation sector, where oil products especially in heavy transport currently dominates electricity, and the more substitutable other-sector, where fuels for e.g. heating are easier to switch out.

Electricity production, indexed with both $i = 0$ and $l = 0$ and where $\tilde{a}_{0,0,t} = 0$, happens in a special in-between transformation sector that uses refined energy from the set $N_e = \{c, o, g, b, r\}$, where r is renewable energy:

$$e_{0,t} = \tilde{A}_{0,t} \Big(\sum_{i \in N_e} \tilde{a}_{0,i,t} e_{0,i,t} \Big)^{\frac{1}{\tilde{s}_{0,t}}}, \tag{3.5}$$

[2]An earlier version of the thesis had time-dependent substitutability as well. This feature allows the degree of substitution to increase over time. This is particularly interesting in the transportation sector, where we are in the middle of a technological development that makes non-emission vehicles, ships and airplanes more similar to their combustion engine counterparts. Kaya et al. (2017) point out that many IAMs in effect forces a preservation of the technology mix. The reason is the use of constant elasticity of substitution (CES) production functions. This, argues Kaya et al. (2017), does not match with empirical data on historical diffusive transitions. They suggest several methods to alleviate this issue, one of which is to allow the constant elasticity of substituion vary over time. I removed this feature, however, to simplify the present analysis. In general, substitutability can also vary between regions and this model permits it. But I have left this feature out for the same reason.

with the CES coefficients and the constant $\tilde{A}_{0,t}$ have the same roles as the production function in (3.4). Electricity has the same notation as other refined energy inputs, but differ in inputs and functional form.

The refined energy products coal, oil products, natural gas, bioenergy and renewable energy are all produced in the Cobb-Douglas-Leontief-hybrid production function of technology, $\bar{A}_{i,t}$, capital, $\bar{K}$, labor, $\bar{N}$ and emissions $E_{i,t}$:

$$e_{i,t} = \bar{A}_{i,t}\bar{K}_{i,t}^{\bar{\alpha}_i} \min\left\{\bar{N}_{i,t}, \bar{a}_{i,t}E_{i,t}\right\}^{1-\bar{\alpha}_i} \quad \forall i \in N_e, \tag{3.6}$$

where I define $E_{i,t} \equiv \frac{\bar{N}_{i,t}}{\bar{a}_{i,t}}$ and where $\bar{a}_{i,t}$ is a calibrated parameter making the units of labor and emissions comparable. The motivation for using this functional form merits some explanation. Traeger (2022b) introduces the general production function $e_{i,t} = g_{i,t}(\bar{A}_{i,t}, \bar{K}_{i,t}, \bar{N}_{i,t}, E_{i,t})$, increasing in all inputs. If there is no saturation mechanism, cost or other constraint on $E_{i,t}$ it will be a free factor in the absence of carbon pricing, which implies an infinite demand in optimum. This is not particularly realistic, however. Even with low global average carbon prices, we are not currently emitting infinite amounts of CO_2, nor have we ever done so. This warrants some sort of saturation in emissions. Traeger (2022b) have several suggestions to ensure finite optimal factor demand, among them the functional form in equation (3.6). This specification ensures that labor and emissions are perfect complements in production of refined energy. Then, to get infinite emissions, one would need infinite labor in the fossil fuel sectors. The perfect complementarity introduces an implicit price on emissions, which helps the model in reproducing a more realistic 'business-as-usual' scenario. Finally, note that the capital share of output, in this case $\bar{\alpha} \equiv \bar{\alpha}_i$, must yet again be constant across refined energy, for the same reasons as explained above.

Finally, to ensure that total supply equals total demand in each of the energy sectors, let

$$e_{i,t} = \sum_{l \in N_c} e_{l,i,t} \quad \forall i \in N_e \cup N_d.$$

The aggregate capital stock, K_t, does not depreciate fully over the decadal timestep but is allowed to persist as a stock in the economy, as introduced to analytical IAMs by Traeger (2022a). Capital's equation of motion is

$$K_{t+1} = I_t \left[\frac{1 + g_{k,t}}{\delta_k + g_{k,t}}\right] \quad \text{were} \quad I_t = Y_t[1 - D(T_{1,t})] - C_t,$$

where δ_k is the depreciation factor and $g_{k,t}$ is an exogenous approximation of the capital growth rate. The social planner distributes the accumulated capital optimally in each period.

A fraction of GDP is destroyed each year by climate change related damages

$$D(T_{1,t}) = 1 - \exp\left[-\xi_0 \exp(\xi_1 T_{1,t}) + \xi_0\right], \ \xi_0 \in \mathbb{R}, \tag{3.7}$$

where $T_{1,t}$ is the increase in atmospheric temperature in period t, compared to year 1900. ξ_0 and ξ_1 are damage parameters calibrated to Howard and Sterner (2017). While country per-capita income levels show some geographical correlation, I assume for simplicity that increasing temperature damages both regions in the same way.

3.2 The Climate System

The climate system in this model is taken from Traeger (2022a). Fossil-based energy production emits CO_2 into the atmosphere where it accumulates and causes increased radiative forcing (or greenhouse effect). This in turn increases atmospheric temperatures which causes damages.

Let the global CO_2-emissions in each period be $E_t \equiv E_{L,t} + E_{H,t}$, where $E_{j,t} = \sum_{i \in I^d} E_{j,i,t}$, and where I have collected fossil-based energy sources in the set I^d. These emissions flow into the atmosphere, from where they can flow between different reservoirs in the carbon stock vector

$$\boldsymbol{M}_{t+1} = \boldsymbol{\Phi}\boldsymbol{M}_t + \boldsymbol{e}_1(E_t + E_t^{exo}), \tag{3.8}$$

where E_t^{exo} are exogenous global non-energy related emissions. $\boldsymbol{e}_1$ is the unit vector reflecting that emissions initially only go into the atmosphere, and the transition matrix $\boldsymbol{\Phi}$ governs carbon flow between reservoirs.

Increasing levels of carbon in the atmosphere causes a greenhouse effect, also called radiative forcing

$$F_t = \eta \frac{\log \frac{M_{1,t}+G_t}{M_{pre}}}{\log 2},$$

where $M_{1,t}$ is the level of CO_2 in the atmosphere, G_t are exogenous non-CO_2 emissions, M_{pre} is the pre-industrial level of atmospheric CO_2 and η is a parameter that captures the radiative forcing intensity.

There are three temperature layers in the model: atmosphere and the upper and deep oceans, corresponding to $i = 1, 2, 3$. The 0^{th} layer is defined to be the long-term equilibrium temperature in the atmosphere, which is increasing in the strength of the greenhouse effect

$$T_{0,t} \equiv \frac{s}{\eta} F_t,$$

and where climate sensitivity parameter s captures the response of temperature equilibrium to a doubling of atmospheric CO_2 levels compared to pre-industrial times. For the other layers, the temperature equation of motion is a non-linear mean of own- and adjacent temperatures

$$\begin{aligned} T_{i,t+1} = \frac{1}{\xi_i} \log \Big(&(1-\sigma_{i,i+1}-\sigma_{i,i-1})\exp[\xi_i T_{i,t}] \\ &+ \sigma_{i,i+1}\exp[\xi_i w_i^{-1} T_{i-1,t}] + \sigma_{i,i-1}\exp[\xi_i w_{i+1} T_{i+1,t}] \Big) \end{aligned} \tag{3.9}$$

with parameters $\xi_1 = \frac{\log 2}{s} \approx \frac{1}{4}$ and $\xi_{i+1} = w_i \xi_i = \frac{T_{eq}^{i-1}}{T_{eq}^{i}} \xi_i$. The weight matrix $\boldsymbol{\sigma}$ captures heat exchange between layers. There are only three layers, so $\sigma_{3,4} = 0$. Using this specification, atmospheric temperature is affected by the current temperature, the long-term equilibrium temperature and the upper ocean temperature. The current atmospheric temperature enters the damage function in equation (3.7), which closes the economy-climate feedback loop.

3.3 Technological Diffusion

Remember equation (3.6) which for renewable energy ($i = ren$) reads

$$e_{ren,t} = \bar{A}_{ren,t} \bar{K}_{ren,t}^{\bar{\alpha}} \bar{N}_{ren,t}^{1-\bar{\alpha}},$$

noting that renewable energy has no emissions (in energy production) so that $\min\left\{\bar{N}_{i,t}, \bar{a}_{i,t} E_{i,t}\right\} = \bar{N}_{i,t}$, and where $\bar{A}_{ren,t}$ is technology in production of renewable energy. Since the production function is Cobb-Douglas, technological change is Hicks-neutral and will not be factor-augmenting. Growth in the absolute technology level will mean that more output can be produced for the same level of capital and labor. Furthermore, I let the technology levels for the other energy sources be constant. This keeps the model as simple as possible while capturing that fast relative growth in renewable energy versus other sources (International Energy Agency, 2021b). For a more general version of the model, see the Appendix.

Define the growth rate of technology in renewable energy production as

$$g_t \equiv \frac{\bar{A}_{ren,t+1} - \bar{A}_{ren,t}}{\bar{A}_{ren,t}}. \tag{3.10}$$

Then, let each region $j \in \{L, H\}$ have the growth rate $g_{j,t}$, capturing that the growth rates of renewable power technology can be different in different regions.

Inspired by Acemoglu (2009), I propose the following model of technological diffusion between the two-regions. Let region H be the world leader. Then, let

$$g_{L,t} = \theta_L \hat{A}_{L,t} + \lambda_L \quad \text{and} \tag{3.11}$$

$$g_{H,t} = \theta_H \hat{A}_{H,t} + \lambda_H \tag{3.12}$$

where $\hat{A}_{j,t} \equiv \frac{\bar{A}_{H,t} - \bar{A}_{j,t}}{\bar{A}_{j,t}} \in [0, \infty)$ is the rate of difference in technology levels in renewable energy production between the regions, expressed as a rate. The technology absorption rate or diffusion parameter $\theta_j \in [0, 1]$ captures the varying degrees with which regions are able to import various technologies given their policies, institutions and other economic and social factors. This rate is exogenous in the current model, but it is possible to endogenize it as a function of e.g. human capital (see Acemoglu (2009)). The absorption rate captures the delay or imperfectness with which technology becomes available across the world. For $\theta_j = 0$, there is no diffusion. For $\theta_j = 1$ the region catch up to the World frontier without delay. For example, if the level of technology in region H is five times region L, $\theta_L = 0.01$ and $\lambda_L = 0$, then $g_{L,t} = 0.05$. There is no diffusion effect for region H, since $\hat{A}_{H,t} = 0$. The local innovation parameter λ_j determines the locally sourced growth rate in technology. It captures how fast a region uses it existing knowledge A_j to improve technology, remembering that technology here means relative to fossil fuels.

3.4 Sketch of model solution

Traeger (2022a) solves a version of the present model with a general production function. I will only give an heuristic explanation of his solution method and point the interested reader to his working paper for details. His closed-form solution relies on homogeneity of capital in the production functions using capital. Therefore, I will show that this requirement holds for this multi-sector model but that it restricts the parameter space of the model.

To solve the model, Traeger (2022a) makes use of the Bellman equation. Here, the control variables in each period are chosen by the social planner such that she (i) maximizes the sum of present-period utility and the discounted value of all future utility streams, and (ii) that the value of this maximization is equal in all periods. First, Traeger (2022a) transforms all endogenous state variables such that their equations of motions become linear in the transformed states. This step is important, because it makes an affine solution to the Bellman equation possible. The first order conditions will then provide optimal controls that do not depend on the states but only on coefficients of parameters and shadow values. Thus, when the optimal controls are inserted back into the Bellman equation, it is possible to collect terms so that the states are each a linear function of these coefficients. Second, to make the Bellman equation hold in each period the state-coefficients must all equal 0. The coefficients are therefore manipulated so that this requirement holds, which will also provide the shadow values along the optimal path as function of parameters only. Finally, one can solve for the optimal control paths also as functions of parameters only. It is the shadow value on the carbon stock that will, when transformed from utils to consumption units, inform the value of the social cost of carbon.

The production function in this model has (for each region j)

$$Y_t = F(A_{l,t}, K_{l,t}, N_{l,t}, d_{l,t}) = A_t \Big(\sum_{l \in N_c} a_{l,t} \left(c_{l,t}\right)^s \Big)^{\frac{1}{s}} = A_t \Big(\sum_{l \in N_c} a_{l,t} \left(A_{l,t} K_{l,t}^{\alpha_l} N_{l,t}^{1-\alpha_l-\nu_l} d_{l,t}^{\nu_l} \right)^s \Big)^{\frac{1}{s}}$$

Then, multiply capital by γ

$$F(A_{l,t}, \gamma K_{l,t}, N_{l,t}, d_{l,t}) = A_{l,t} \left(\gamma K_{l,t}\right)^{\alpha_l} N_{l,t}^{1-\alpha_l-\nu_l} d_{l,t}^{\nu_l}$$

If $\bar{\alpha_i} \equiv \bar{\alpha}$ then

$$\begin{aligned} F(A_{l,t}, \gamma K_{l,t}, N_{l,t}, d_{l,t}) &= \gamma^{\bar{\alpha}} A_t \Big(\sum_{l \in N_c} a_{l,t} \left(A_{l,t} K_{l,t}^{\alpha_l} N_{l,t}^{1-\alpha_l-\nu_l} d_{l,t}^{\nu_l} \right)^s \Big)^{\frac{1}{s}} \\ &= \gamma^{\bar{\alpha}} F(A_{l,t}, K_{l,t}, N_{l,t}, d_{l,t}), \end{aligned}$$

which shows that the production function is homogeneous in capital if all sectors have the same α. One can use the same method to show that the production of the refined energy goods also are homogeneous in capital.

Chapter 4

Calibration and Data

In chapter 3, the social planners allocated the resources in an optimal utility-maximizing way. To match this theoretical construct into a construct that permits the use of real data, I transform the social planner's problems into the corresponding decentralized cost-minimization problem for representative firms. By doing so, I can derive their respective compensated demand equations, which, when inverted, provides the equations for the calibration targets. For a detailed mathematical derivation of these equations, see Appendix A.

This chapter proceeds as follows: First, I briefly explain the practical calibration process. Second, I list the parameters to be calibrated. Third, I present and discuss the different data I use. And finally, I discuss the most important but also most elusive production function parameters: the elasticities of substitution. The calibration results are in the next chapter.

4.1 Calibration procedure

A significant part of this thesis is the calibration process. My first step in this process is to find and collect relevant data. Second, I clean and compile the data and read it into arrays and tables in Matlab. See Appendix E for the wrangling script. Third, I perform interpolations in cases where there is missing data. Fourth, I aggregate the data into the two regions I will use. Fifth, I use the regional arrays as inputs to the calibration equations in order to calculate the numerical values of the parameters. See Appendix F for the calibration script which is appended with the diffusion model. I omit the graph-producing code.

I calibrate a total of 44 parameters, see table 4.1 for an overview. These parameters are then fed into a numerical optimizer in Matlab (provided by my supervisor) along with an initial guess of the optimal solution controls, as informed by the data. The optimizer produces a result that should, if the calibration is done correctly, replicate the structure of the data as they were read into the calibration script initially. If the model do not reproduce the data, I search for bugs, typos, calculus-errors or similar until the calibration improves. See chapter 5.1 for a discussion of the final calibration results.

4.2 Data sources

There is no single source that can provide up-to-date data covering all the needs in the calibration process. Therefore, I must collect data from several different sources, then pre-process and combine them to a usable form. All the data sources I use are based on country-level data,

Table 4.1: Parameters to calibrate – one set for each region

Parameter	Domain	Explanation	Equation
$\alpha_l \equiv \alpha$	$l \in N_c$	Capital share in final good sectors	(A.5)
ν_l	$l \in N_c$	Energy share in final good sector l	(A.4)
$\bar{\alpha}_l \equiv \bar{\alpha}$	$i \in N_e$	Capital share in energy production	(A.12)
$a_{l,t}$	$l \in N_c$	CES-shares in final good aggregation	(A.2)
$\tilde{a}_{l,i,t}$	$l \in N_c,\ i \in N_d$	CES-shares in intermediate energy good	(A.7)
$\tilde{a}_{0,i,t}$	$i \in N_e$	CES-shares in electricity production	(A.8)
A_t		TFP in aggregation sector	(A.2)
$A_{l,t}$	$l \in N_c$	TFP in final goods sector	(A.6)
$\tilde{A}_{l,t}$	$l \in N_c$	TFP intermediate energy sector	(A.7)
$\tilde{A}_{0,t}$		TFP in electricity sector	(A.8)
$\bar{A}_{i,t}$	$i \in N_e$	TFP in refined energy sector	(A.13)
$\bar{a}_{i,t}$	$i \in I^d$	Leontief parameter in energy production	(A.11)

which means that my two-region model can be easily extended. The model is already calibrated to the RICE-regions and can, with some adjustments and additional data, be used as a country-level model. However, not all countries provide detailed enough data, so the calibration process rely on regional interpolations where necessary.

The following section has the following structure: First, I set the income cut-off that defines the two regions. Second, I present the volume data sources. Third, I present price data sources and the conversions and assumptions I make. Finally, I calculate emission factors and the regional emission prices.

4.2.1 Region classification

Countries are sorted into two regions: high income and low income, with corresponding region indices $j = H$ and $j = L$. I would like to sort countries to the degree to which they use electricity, and use GDP per capita as a proxy. I sort the list of countries by PPP GDP per capita, and set the cut-off such that China with a GDP per capita in 2019 of 14 031 PPP USD is included in the group of high-income countries. This is contrary the common definition of ´developing' and ´developed' countries, where the cut-off normally is set higher. Excluding China, however, which has a very high degree of electrification (International Energy Agency, 2019) seems unnatural. India, a large country with a low degree of electrification, is then included in the low-income group, as are many African countries and poorer countries in South America and Asia. See table D.1 for a complete list of countries.

4.2.2 Volume data

The base-year for calibration is 2019 and all gathered data corresponds to that year unless otherwise specified. I use the Penn World Tables (Feenstra et al., 2015) for data on country-level real GDP, capital stock and employment for 183 countries[1]. All values are denoted in current purchasing power parities (PPP) in millions of 2017 US dollars, which enable cross-country comparisons in a given year (OECD and Eurostat, 2012). There are missing capital

[1]The Penn World Tables have only sparse data for average hours worked per year but good data for number of persons employed. I will therefore use the latter measurement of labor throughout.

and employment data for some smaller countries in the Penn World Tables. For these countries I use the regional average ratios of capital/GDP and employment/GDP for interpolation. The interpolating regions are based on the 12 RICE regions (Nordhaus and Yang, 1996). I find the average yearly growth rate of GDP between 2010 and 2019 by regressing log GDP on year for each region. I use this growth rate as total factor productivity (TFP) growth in the model, which I assume is falling over time. The socio-economic data is collected in table 4.2.

Table 4.2: Macroeconomic data

Variable	Unit	Region L	Region H
No. Countries	.	89	94
GDP	Trillion PPP 2017USD	27,6	97,3
Capital stock	Trillion PPP 2017USD	110	452
Employed	Million	1553	1764
Emissions	$GtCO_2$	6,7	27.5
Share of output	Transport	0,07	0,05
Share of output	Industry	0,44	0,42
Share of output	Other	0,49	0,53
Share of labor	Transport	0,06	0,06
Share of labor	Industry	0,20	0,25
Share of labor	Other	0,74	0,68
Share of capital	Transport	0,06	0,06
Share of capital	Industry	0,16	0,15
Share of capital	Other	0,77	0,79
TFP growth rates	.	3,1%	2,2%

The Penn World tables do not have data per economic sector, only country-level GDP. GDP is a value-added concept, and is meant to measure the value added by all the economic activities within a country in a given period. The value added is defined as output minus the value of intermediate goods used in production, and GDP thus avoids double-counting economic activities. In my model, however, the three sectors are kept separate and do not provide inputs for each other except indirectly through the possibility of capital accumulation. The production of final good $c_{l,t}$ should therefore be interpreted as sector output less the value of the energy consumption good. But since the energy sectors do not use any intermediate goods, it holds that output and value added are equivalent measures in my model. However, I cannot use data for value added by economic sector to calibrate my model, nor only use output data. The first reason is that this will reduce the relative importance of sectors that in reality may use few intermediate goods but provide many services for other sectors in the economy. The second reason is that total output will exceed total GDP, which will double count production and therefore total emissions. My solution is to find output shares of total output by sectors using UN (United Nations Statistics Division, 2022) and WIOD data (Timmer et al., 2015). Then, I use these output shares to find sector shares of GDP in each region based on macro data from the Penn World Tables. UN and WIOD data cover in total 102 countries, and I use regional average interpolation for missing sector share data. Some poorer countries' shares do not sum to unity. The transport and industry shares are, however, of the same magnitude as in countries with better data, whereas the 'other' sector show significantly lower shares, resulting in a less-than-unity sum of shares. Therefore, I take the 'other' share to be the difference between total economy output, transport and industry. This transformation does not matter for countries with good data, and a good second-best fix for countries with inconsistent data. I have 2019 data for most countries, and less recent data for a few countries, with the oldest being from 2014. The sector shares are fairly stable over time, which means that older data shouldn't be too far off the correct 2019 shares.

To find labor per sector, I use a similar procedure as for output. I find country-level employment shares using ILOSTAT data (International Labour Organization, 2022) and apply those share to total employment from the Penn World Tables to get labor per sector. ILOSTAT data covers 175 of the countries in the Penn World Tables. I use average regional interpolation for missing data.

There are very few countries with sufficiently detailed capital stock data. The OECD (2022) has capital data per economic sector, which I use to find the shares of total capital stock going to transport, industry and other, and to calibrate capital's share of output, α. Then, I apply these shares to the total capital stock from the Penn World Tables to find the value of capital per final goods sector. I use RICE regions for interpolation of other missing data categories, but this dataset only covers 29 OECD countries. Therefore, I use the OECD average capital shares for all countries with missing data which is obviously unrealistic. Remember, however, that α must be independent of sector to keep analytic tractability. As an implication, the sector capital values are not really needed directly in the calibration. I use them only to check ex-post if the model reproduces the state of the World from the data.

It is even more difficult to find capital data for the energy refinement sectors than for the broader economic sectors. To my knowledge, there is no data for capital in bioenergy or renewable energy production. Investment data for renewables are abundant, but it is beyond the scope of this thesis to use the perpetual inventory method needed to convert investment flows to capital stocks. These capital data goes into the calibration of capital's share in the production of the refined energy goods, $\bar{\alpha}$. Similar to α, also $\bar{\alpha}$ has to coincide across fuels to preserve tractability. Because of the mentioned lack of data, I use only fossil fuel data to calibrate $\bar{\alpha}$, and then extrapolate this parameter to bioenergy and renewables. This is perhaps not drastically unrealistic for advanced biofuel production in developed countries. Bioenergy in the poorest countries, however, often consist of agricultural waste, firewood and charcoal, which is probably much less capital intensive than fossil fuel and renewable production would be in those same countries. Furthermore, there are very few countries with detailed capital stock data in energy production, even when only considering fossil fuels. For the high-income region, I use the weighted average of US and Russian $\bar{\alpha}$. I get US capital data from US Bureau of Labor Statistics (2022). I could not find official Russian data, and based the calculation on manually collected asset data from the largest Russian oil, gas, and coal companies using publicly available information (Investopedia, 2022). Because of the uncertainty in using this method, I give the Russian $\bar{\alpha}$ only a 20% weight. For the low-income region, I use the Chinese $\bar{\alpha}$ based on data from of Statistic of China (2021). Since China is not included in the low-income group, this will be an out-of-sample extrapolation. In conclusion, there are several sources of uncertainty surrounding the calibration of $\bar{\alpha}$.

I use International Energy Agency (2019) data for energy volume balances. They provide an input-output table of energy flows between fuel sources and sector for 155 countries, and regional data for countries without individual entries. Production, imports, exports and supply changes make up the total energy supply in a country, which by definition has to equal total consumption. I divide total consumption into five groups: transport sector, industry sector, other sector, electricity sector and energy own use and losses. The latter group is the energy used in energy production itself plus losses from refinement and transport. I add this group to the other four sectors according to the relative fuel intensity of each sector. Coal, oil, natural gas and bioenergy are aggregated as such in the IEA data. I add nuclear energy, wind and solar to get an aggregated "renewable energy" input. I add electricity and heat to a single category as

Table 4.3: Energy units input-output table[1,2]

Sector (region)	Regions	Coal	Oil	Natural Gas	Bioenergy	Renewable	Electricity
Transport (L)	64	2 068	19 648 792	1 168 282	323 799	0	147 864
Industry (L)	64	9 058 048	3 540 280	5 913 090	4 598 762	2 824	6 428 874
Other (L)	64	1 411 864	5 011 278	5 412 452	24 495 134	54 981	9 307 931
Electricity (L)	64	20 116 432	2 802 371	9 977 632	1 270 319	6 925 783	16 477 436
Transport (H)	78	1 342	78 848 891	5 278 595	4 022 266	0	1 519 620
Industry (H)	78	39 411 437	9 778 205	27 649 690	6 218 485	39 028	39 404 152
Other (H)	78	5 108 055	13 326 519	31 223 891	8 380 346	2 244 821	45 814 532
Electricity (H)	78	82 150 361	4 613 042	42 752 393	7 236 553	49 695 890	91 387 683[3]

[1] International Energy Agency (2019).
[2] Units are terajoules (TJ).
[2] Electricity in electricity production is an output.

well. The processed results are in table 4.3. There are fewer individual countries covered in the IEA data than in Penn World Tables, but the data still matches when aggregated into regions since the IEA as regionally aggregated data as well.

4.2.3 Energy prices

Each energy source in this model is homogeneous and therefore will have a single price. There are of course many different refinement methods for oil (and coal and gas) which results in many different consumer products. Each of these products has different prices according to quality, transportation costs, regulation, market conditions and other factors. I use each variant's share of total supply as weights wherever there are several prices in the data.

I assume that both regions purchase fuels at the global weighted average prices, and later adjust these nominal prices with different regional purchasing power parity (PPP) price levels to match units with the Penn World Tables macro data. To create these regional price levels, I weigh the PPP price levels listed in the Penn World Tables for each country according to their GDP (in PPP) relative to the total GDP for that region. This adjustment corrects for the difference in purchasing power between the high-income and low-income regions. I use the regional share of total demand as weights whenever there are regional or country-level prices instead of World prices in the data. Ideally, each region in the model would have local nominal prices but local price data is difficult to find or very costly. It is not obvious that local prices, e.g. prices of Australian coal, only apply for that country or region since fuels are often traded on a global or super-regional market. Furthermore, I sort countries into regions based on GDP which does not necessarily group countries together based on geography or according to which regional fuel market they mostly trade in.

Coal and natural gas prices are from bp (2021) and I get monthly oil product prices from the International Energy Agency (n.d.), converted to a yearly average. Renewable energy prices are more difficult to find or conceptualize. To properly compare different energy sources in electricity production, the lifetime costs and benefits for each type should be included. This is the rationale for using the so-called levelized costs of electricity (LCOE) measure, which gives the present value for all costs including investments, operation, maintenance and fuel costs. It is the long-term break-even cost for an electricity plant. I use IRENA (2020) data to get world average LCOE for each type of renewable energy source. Then I find the single calibration renewable price by weighing each LCOE by share of total renewable production. An undesirable side-effect of using the LCOE only for renewables is that it might skew the relative prices in electricity production in favor of fossil fuels since the LCOE includes all costs, not only marginal fuel costs.

Bioenergy prices are another source of uncertainty. I use the price of wood pellets in the US (Anna Simet, 2021) as a catch-all price. In developing countries, however, bioenergy is not necessarily commercial-grade but collected and used directly from local sources. This means that it is difficult to find price data. One could use the price of labor, but it is not clear how many energy units get collected per work hour. Because of this, I assume for simplicity that bioenergy prices in the low-income region is half the high-income region price (in addition to the PPP adjustment between the regions).

I convert the idiosyncratic price units to USD per GJ according to the conversion factors in table 4.4.

Table 4.4: Energy units conversion factors[1]

Unit	GJ
1 tonne of coal equivalent	29.3
1 barrel of oil products (basket[2])	5.34
1 million British thermal units (Btu)	1.06
1 000 gallons of ethanol	84.4
1 t wood pellets	18
1 MWh	3600

[1] https://www.justintools.com/unit-conversion/energy.php
[2] bp (2021)

4.2.4 Emissions and Carbon Prices

The energy use of each fuel e_i is measured in Terajoules. I use the factors in table 4.5 to convert energy to CO_2 emissions, E_i. Note that bioenergy has a non-zero conversion factor. The reason is that burning of non-renewable waste is included in this category in the IEA data. Waste incineration is a relatively small part of the total energy use in this category (about 5%), and only a share of that is non-renewable, but it is at least as carbon intensive as oil (U.S. Environmental Protection Agency, 2022). Therefore, I assume that biofuels have 1/20 the carbon intensity of oil to capture the non-zero emissions in this category.

According to the IEA (2020), the total energy-related CO_2 emissions were 33.2 Gigatons in 2019. The energy volume data and emission factors I use gives a few percentage points too low emissions compared with the IEA estimates. The discrepancy probably comes from imprecise emissions factors. I increase all emission factors reported in table 4.5 correspondingly in order to match observed energy-related emissions exactly. This will preserves the within-fossil CO_2 intensities, but may cause a small bias in favor of renewable energy.

The price of emissions vary between countries and regions. According to the World Bank (2021), 56 carbon pricing initiatives are implemented globally in 2019, covering about 14.5 % of global emissions. I weigh the price of each initiative with its covered share of global emissions. Based on this, I find the weighted average CO2 price of covered emissions as 2.75 USD per tonne of CO_2e (in 2017 USD). Only 14.5 % of total emissions are covered, so the average price for all emissions would be about 0.40 USD/tCO_2e. No countries in region L have pricing initiatives, so $p_L^E = 0$. Region H's share of total emissions is about 80.7 %, which implies $p_H^E \approx 2.75/0.807 \approx$ 0.50 USD/tCO_2e. I correct for PPP price levels in the calibration calculations.

Table 4.5: CO_2 coefficients

Source	tCO_2/TJ[1]
Coal	91
Oil products	69[2]
Natural gas	50
Biofuels	3.5[3]
Renewables	0

[1] Source: EIA (2022), converted to units of TJ.
[2] Simple average of diesel, gasoline, jet fuel, kerosene and heating oil.
[3] ncludes non-renewable waste incineration, which causes a positive coefficient.

For regions with a positive carbon tax, the price of emissions, $p^E_{i,t}$, should already be included in the end-use energy prices $p^e_{i,t}$. The prices I find in the date are gross emission prices, though. Therefore, I add emissions prices to the observed price of energy. I calibrate $d_{l,t}$ according to $p^d_{l,t} d_{l,t} = p^e_{0,t} e_{l,0,t} + \sum_{i \in N_d} (p^e_{i,t} + p^E_{i,t}) d_{l,t}$. I measure the intermediate energy good, $d_{l,t}$, in USD which means I can normalize its prize, $p^d_{l,t}$, to 1.

4.3 On Elasticities of Substitution

The CES production functions in the model, and therefore their corresponding calibration equations, depend on the different elasticities of substitution between factor inputs, where[2] $\sigma_t \equiv \frac{1}{1-\tilde{s}_t}$. In production theory, the elasticity of substitution is heuristically defined as the ease with which a pair of input factors can be substituted for one another. The usual intuition is that σ_t measures the curvature of a given isoquant of the production function. This parameter is unambiguously defined for a two-factor production function. Blackorby and Russell (1981, 1989) show that the proper generalization from two factors to n factors is the Morishima elasticity of substitution, $MES_{i,j} = \epsilon_{j,i} - \epsilon_{i,i}$, where $\epsilon_{i,i}$ is factor i's own price elasticity and $\epsilon_{j,i}$ the cross-price elasticity between the goods i and j. This elasticity is generally asymmetric, which means that $MES_{i,j}$ is not necessarily equal to $MES_{j,i}$. However, as shown by Blackorby and Russell (1981, 1989), the constant elasticity of substitution (CES) production function is equivalent to having symmetric MES.

In the first ever meta-analysis on interfuel substitution estimates, converts the various elasticity concept into so-called shadow elasticity of substitution (SES), which is a symmetric cost-share weighted average of two asymmetric MES. The converted estimates can then be used directly in interfuel CES production functions. It is not clear, however, how to translate SES estimates between pairs of inputs to a n-good CES production function, since there is no obvious way to weigh each pair's contribution to the overall elasticity of substitution. The estimates found in D. I. Stern (2012) are often greater than 1 which imply large potential for interfuel substitutability. However, as D. I. Stern (2012) points out, the estimates in the literature vary a lot depending on several decisions and contexts in the underlying studies: econometric estimation

[2] With the risk of using confusing notation, σ_t means elasticity of substitution here even if σ denotes temperature diffusion in a previous chapter.

methods, assumptions about technology, the amount of underlying data, and so on. Some estimates in Stern's (2012) meta-regression are significantly different from neither zero nor one, meaning that neither the Leontief, the Cobb-Douglas nor the gross substitutes case can be rejected. Furthermore, the estimates are based on the local political context, market regulatory systems and factor availability. Local studies can thus not be easily extrapolated to other regions, which will be necessary in the aggregated regional model I use. These issues cause some concern for how precise the elasticities 'picked from the literature' will be.

In analyses of climate change the time horizon is very long. Therefore, integrated assessment models should use long-run estimates of sustainability. Unfortunately, such estimates are scarce and most estimates in Stern's (2012) meta-analysis are short-run. This poses an important and and difficult question of how to extrapolate from short-run elasticities to those of longer time horizons.

Because of these uncertainties, I will do significant sensitivity tests with respect to the different elasticities to identify how much the key results are affected by different assumptions. As a baseline, I pick the elasticity of substitutions as follows, and I assume equal substitutabilities across both regions for simplicity:

Transport: 0.2. This is based on the limited substitution in transport found by Serletis et al. (2010a). Bye et al. (2021) use a elasticity of 0.5 in the light-duty vehicle production function between ICE and EVs in their macroeconomic analysis climate regulations of the transportation sector. However, transportation in my model includes also aviation and shipping. There is currently impossible to do long-haul shipping, international flights or heavy-duty road freight transport using electricity, no matter the relative price change. This implies lower elasticity compared to the personal vehicle market. There are technological developments in short-haul good transport, ferries, and electric vehicles that could increase this parameter over time.

Industry: 1. Serletis et al. (2010a) find limited substitutability in the industrial sector, except for some fuels in the UK. D. I. Stern (2012) and Papageorgiou et al. (2017), however, both find greater than unity substitution between most pairs of fuels. I pick an intermediate value of 1. An elasticity larger than 1 would imply that neither input is essential in production. This assumption currently seems unrealistic. There are some subindustries with very-hard-to-abate products which is currently impossible to produce without any fossil fuel input, such as cement and steel production (International Energy Agency, 2021a). However, technological development, such as green steel (Vetter, 2021), could change this in the future.

Other: 1.2. Serletis et al. (2010b) and Jadidzadeh and Serletis (2016) find elasticities in the US and Canadian residential and commercial sectors around 1, while Serletis et al. (2010a) mostly find figures below 1. Wong et al. (2019), however, find elasticities mostly above unity. The energy use in the other sector is mainly heating, cooling, cooking, lighting and running machines and appliances in the commercial, residential and agricultural sectors. There already exists electrical alternatives to direct fossil use in these sectors, such as electric stoves instead of gas stoves, heat pumps instead of oil or gas heating, light bulbs instead of kerosene lamps.

Electricity production: 1.8. Kumar et al. (2015), Serletis et al. (2010a, 2010b) and Pelli (2012) all find less-than-one estimates. There are several reasons: most plants can only run one fuel, local availability, intermittency, and complementary since fossil electricity is often used to produce solar panels and windmills (in the beginning). Papageorgiou et al. (2017), however find it at 1.8 using a more macroeconomic approach. Technically, there should be perfect substitutability between energy sources in the production of electricity, since all the inputs are identical. But there are definely idiosyncratic factors such as market regulations, resource availability, transmission constraints that hinders the full substitutability of factors. Moreover, different fuel sources have different technical and physical constraints. Renewable energy has variable production based on weather conditions and seasons, causing potential intermittency issues in lack of sufficient storage capacity. And coal plants are expensive and time-consuming to start up and shut down, so they are best used as a peak-load input. Therefore, I pick an non-infinite elasticity, but larger than 1 to reflect that no sources should alone be necessary in production.

Empirical estimates must necessarily be based on historical data, which pins down the functional form of the production functions today. But these functions may very well change in the future. For example, Xie and Hawkes (2015) find that the elasticity of substitution between oil and electricity in the Chinese transport sector has increased steadily between the 1980s and 2010. Bye et al. (2021) calibrate their model to a low present-day elasticity, but argue for a large expected increase in the substitutability between EVs and ICEs in Norway in the coming decades. Wong et al. (2019) find that the interfuel substitution in several Chinese sector becomes easier as the country steps up the energy ladder. I omit this feature from the present analysis.

Chapter 5

Results

In this chapter I will first briefly present some of the calibrated parameters and discuss how I adjusted parameters that caused calibration issues. Then I will present graphical and numerical results from different model runs.

5.1 Calibration results

The ν_l's in table 5.1 are calibrated as described in equation (A.4). The Penn World Table has only data for capital, labor and GDP, not value of energy or resource rents. Thus, the directly calibrated α's probably include some of energy's value share. Therefore I correct these by subtracting the mean ν in the economy to get the results in table 5.1. I could not find reliable capital data for refined energy production. The initial calculation gave $\bar{\alpha}$'s that were very high and close to 1. I could not get the model calibrated correctly when using the data-based values for $\bar{\alpha}$. Therefore, I adjusted them until the model better reproduced the calibration period data. The fit improved as the values approached zero, potentially signaling that the calibration process and model do not handle capital in refined energy correctly.

Table 5.1: Calibrated parameters in base year.

	Explanation	$j = L$	$j = H$
α	Capital share in final goods production	0.209	0.336
ν_{tr}	Energy share in transport	0.454	0.334
ν_{in}	Energy share in industry	0.045	0.030
ν_{ot}	Energy share in other sector	0.066	0.025
$\bar{\alpha}$	Capital share in refined energy production[1]	0.010	0.005

[1] Assumption.

I also had to use another solution to calibrate $\bar{a}$ than equation (A.11). This Leontief parameter is supposed to convert between labor in energy and emissions to match emissions data. However, it would convert low energy use to high emissions and could not reproduce emissions. Therefore, I replace $\bar{a}$ by the vector of emissions factors in table 4.5. This will per definition convert energy units to CO_2 and solves the calibration issue. Finally, I also had issues with the calibration of A_t. Both wages and output in all three final goods sectors were off by a fixed factor. I fixed it by multiplying A_t by this factor. It was likely a bug causing this issue, but after these corrections

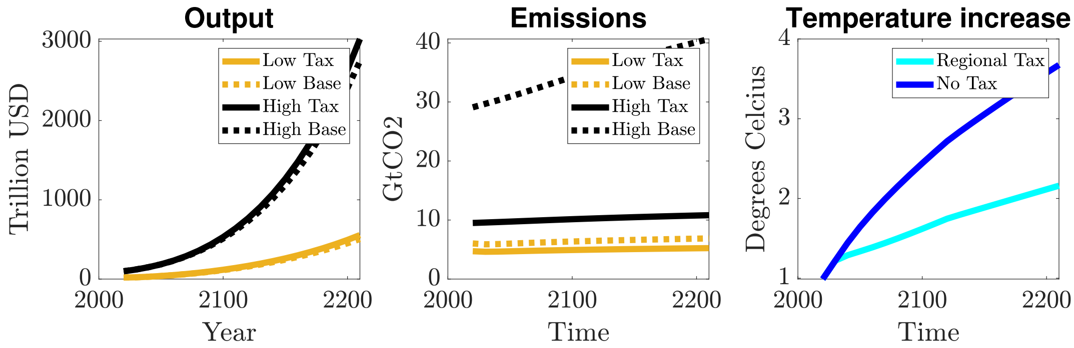

Figure 5.1: Output, emissions and temperature.

the optimized model was able to reproduce the data and the solved trajectories seems reasonable and robust. Further bug-testing was outside the scope of the thesis.

5.2 Model results

In this section I will first discuss the difference between the business-as-usual scenario and the optimal-tax scenario. This part will be brief, since it is not my main interest in this thesis. Second, I will present the results of low and high diffusion. Finally, I will do a sensitivity analysis.

5.2.1 Baseline and optimal tax

This section shows the difference between the business-as-usual baseline scenario and the optimal-tax scenario. In the former, the economy is assumed to be structured similarly to the calibration period. In the latter, each of the social planners implements an optimal carbon tax. Both have no growth in energy producing sectors and no inter-regional diffusion.

The left panel in figure 5.1 shows that outputs in both regions are increasing exponentially over time. This is a factor of the positive but decreasing TFP growth rates in both economies (see table 4.2). Region H abates relatively much compared to region L as is seen in the middle panel. One explanation is that the optimal carbon tax is equal to the social cost of carbon within each economy[1]. Still, even as a regional tax, the optimal tax causes the temperature increases to be moderate compared to the business-as-usual case, as seen in the right panel in figure 5.1.

Coal has the largest response to the optimal carbon tax in this model. Figure 5.2 shows that region L cuts coal-use almost in half, while it goes from being the most to the least used fuel in region H. The other fossil fuels fall in both regions, with oil falling the least. Waste-burning is a part of bioenergy here, which ceteris paribus should decrease its optimal usage after tax. However, there is a slight increase in both regions. One reason could be that it substitutes for more emission-intensive fuels. Renewables increases in both regions, but electricity production falls. The increase in renewable energy is not sufficient to replace the decline of fossil fuels. The difference in magnitudes between the regions could be attributed to the different SCCs.

[1]This is not a general result, but a function of how much each region internalizes the cost caused on others by themselves. I have assumed that they only care about future generations within their regions, and not in other regions.

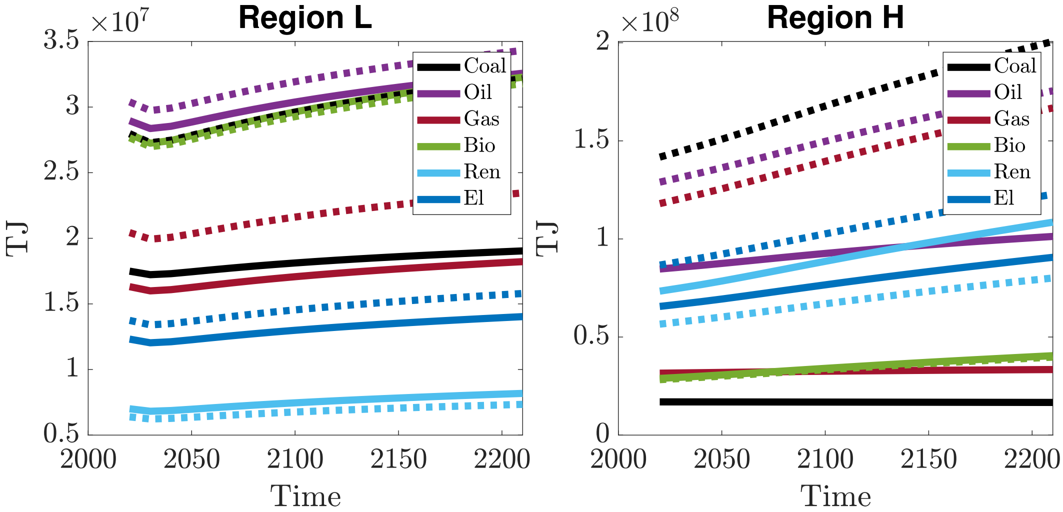

Figure 5.2: Energy by source. Dotted lines are baseline and solid lines for the case with optimal tax. Note the difference in scales.

Region H has a high SCC and therefore abates more. Also, the emissions by the poorer and lower populated region L are relatively small. Therefore, they will not cause much temperature increase and thus little damages which implies a low SCC.

Figures 5.3 and 5.4 show the energy use by sector in region L and H, respectively. These figures make the difference in magnitudes of abatement even clearer. All sectors decrease the use of fossil fuels. The largest abatement effect is in the electricity sectors.

5.2.2 Diffusion

Here I present three different comparisons. First, I compare the baseline scenario from the previous chapter to the present case with growth in renewable energy technology. Second and third, I change the baseline to be the renewable growth-case and compare it to a low- and high-diffusion scenario, respectively.

Technological growth and no diffusion: The baseline scenario is identical to the previous chapter: no carbon tax, and no growth expect for total TFP growth. I set the inherent growth rates for renewable technology in region H as $g_{H,t=2020} = \lambda_{H,t=2020} = 0.009$ in the first period, and in region L as the constant $\lambda_{L,t} = 0.001$. These parameters are then aligned with the average growth rates of wind and solar PV as percentage of the electricity supply found in the analysis of renewable energy growth rates and S-shaped transitions by Cherp et al. (2021). I let $g_{H,t}$ decline by 2% each year after the year 2030 to capture that some developed countries could be past the inflection point on an S-shaped transition curve (Cherp et al., 2021). This means that $g_{H,t=2050} = 0.006$ and $g_{H,t=2100} = 0.002$. Developing countries in region L are currently further left on the S-curve. I assume that all technological growth in excess of $\lambda_{L,t}$ are imported from region H. This mechanism is captured by the diffusion parameter θ_L. In this first scenario I set $\theta_L = 0$ and compare the scenario with technological growth to the no-growth baseline from the previous section.

Figures 5.7 and 5.8 reveal that growth in renewable energy technology increases electricity production, as is to be expected. Furthermore, as seen most clearly in the lower right panel of

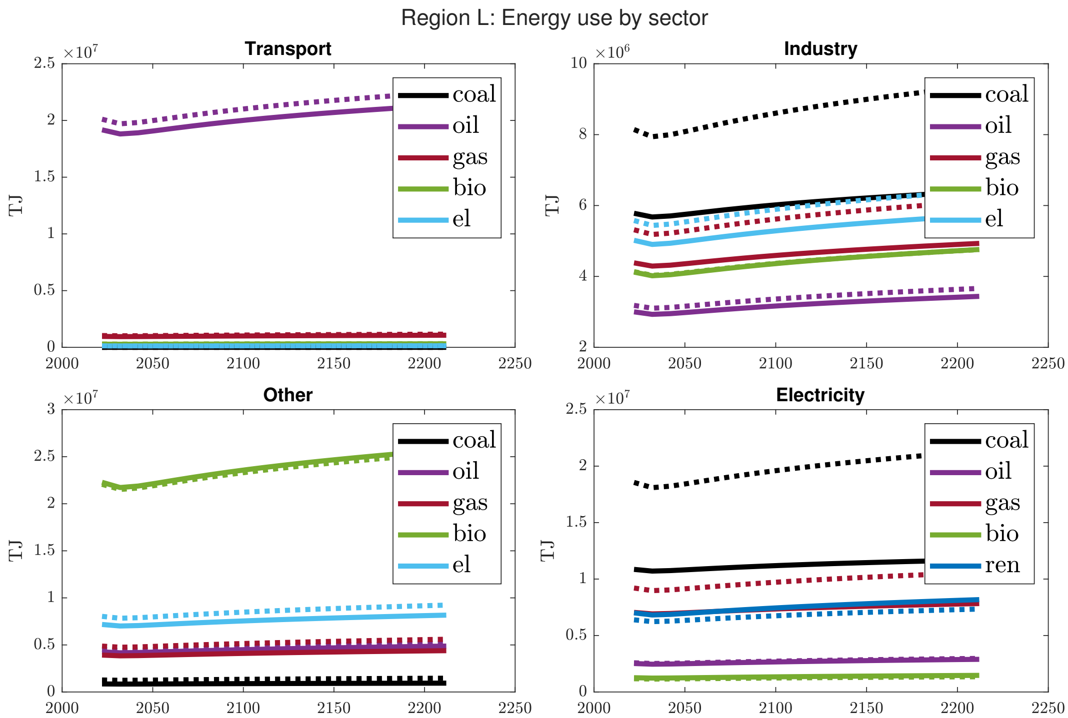

Figure 5.3: Energy by sector in region L. Dotted lines are baseline and solid lines for the case with optimal tax. Note the difference in scales.

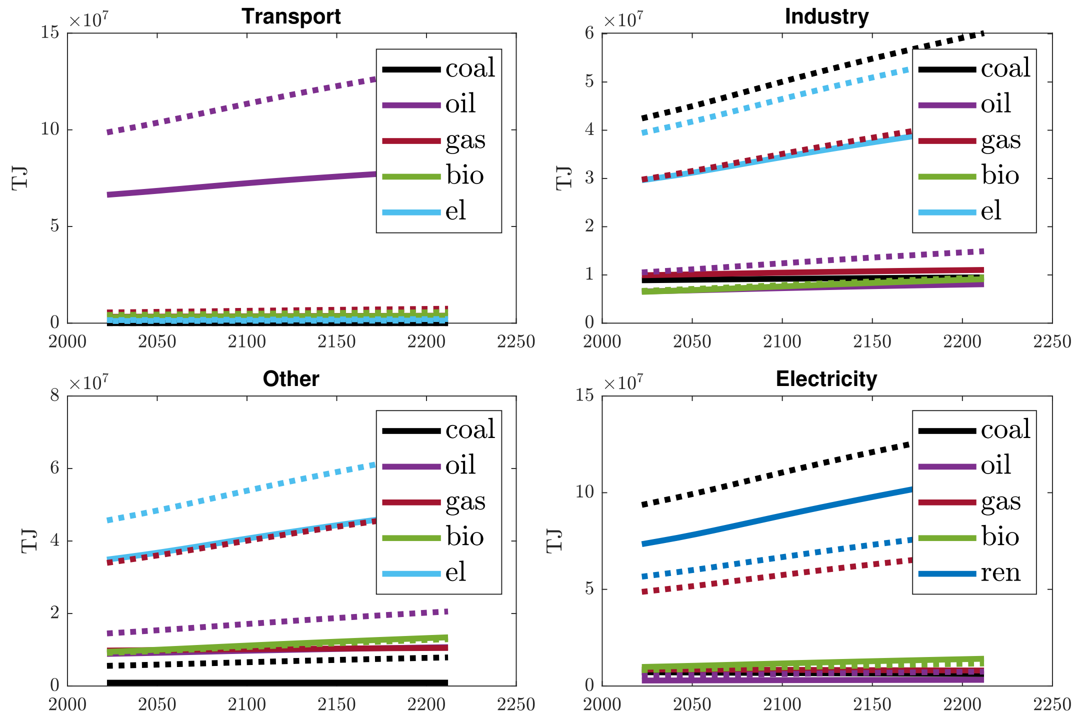

Figure 5.4: Energy by sector in region H. Dotted lines are baseline and solid lines for the case with optimal tax. Note the difference in scales.

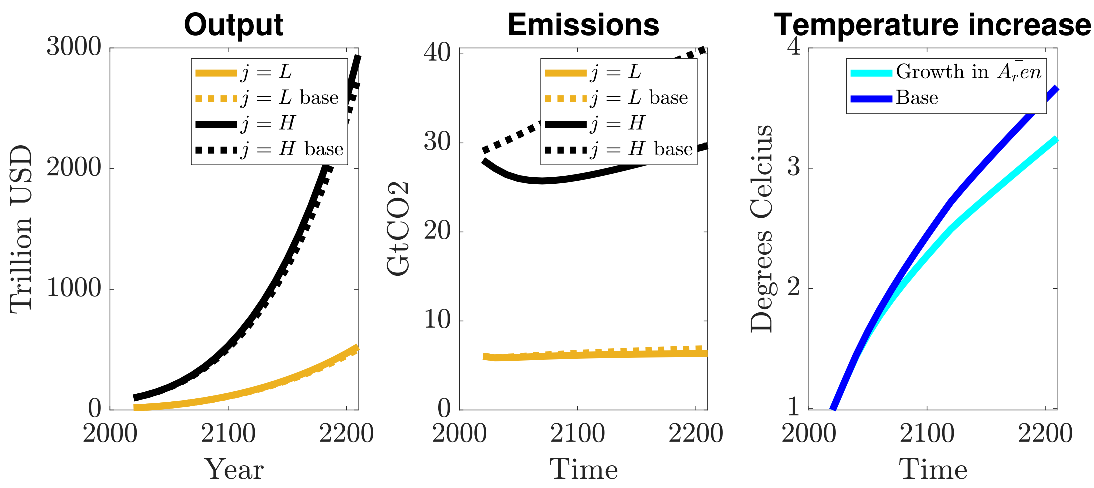

Figure 5.5: Output, emissions and temperature – with growth in renewable energy.

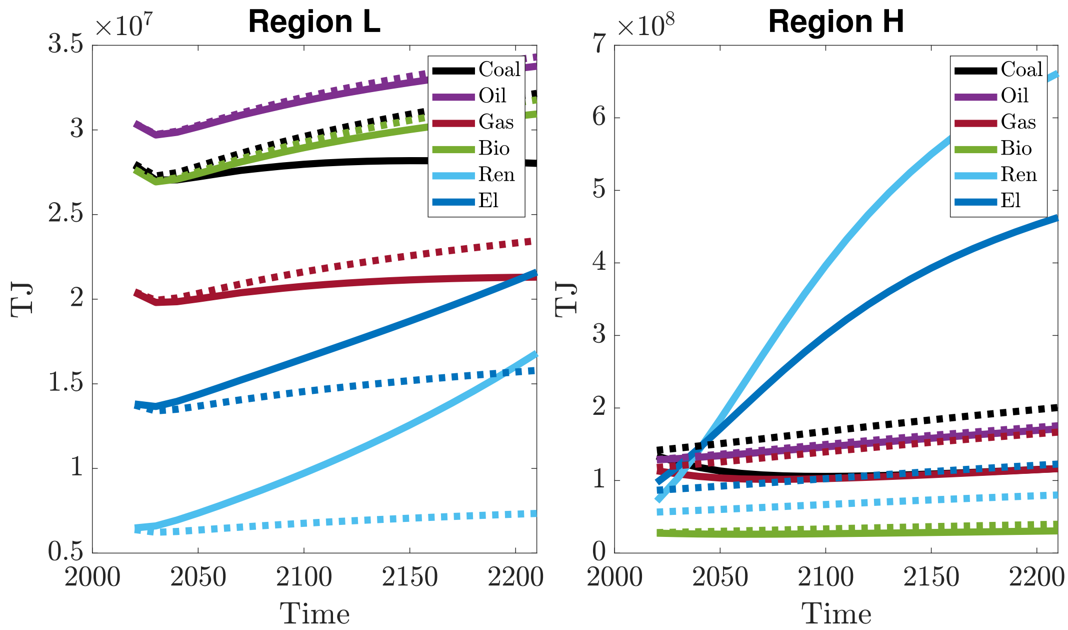

Figure 5.6: Energy by source with growth in renewable energy. Dotted lines are baseline and solid lines for the case with growth. Note the difference in scales.

figure 5.3, the increase in renewable energy causes a transition away from the other inputs to electricity production. It is not clear whether the relatively large decrease of coal use in electricity production is due to its high emission intensity or its high initial share in production.

Another interesting find is that oil use in transport is actually increasing. This is likely due to the inter-fuel complementarity in the transportation sector. The production functions are not nested between fuels, and all inputs enter on the same level. Therefore, electricity and oil are complements for an elasticity of substitution < 1. An interesting extension could be to introduce time-changing elasticity in the transportation sector to analyze how this relationship can change over time. However, total oil use decreases in both regions, as seen in figure 5.6.

Output in both regions increases and emissions decreases, causing a reduction in temperature increase. To get the the welfare in utils for both regions, I utilize the ACE numerical optimization script in Matlab. I calculate the sum of discounted welfare in each period of the planning horizon, which is 200 year. This gives me the approximate net present value of the scenario. Then I take the different of this net present value in utils and convert it to consumption equivalents in USD. I calculate the welfare effect of the assumed growth in renewable technology to be ≈ 10 trillion USD for region H and ≈ 0.9 trillion USD for region L, compared to the no-growth baseline.

Low and high diffusion: The new baseline is the previous case with growth in renewables, but without diffusion. Now I analyse two cases and compare them to the local-growth-only baseline. The results are qualitatively similar, so I only present figures for the high case here since they give clearer visual effects, and put figures for the low case in the Appendix for completeness. I set $\theta_L = 0.0001$ in the low case, and $\theta_L = 0.002$ in the high case. The rate of difference in renewable technology levels between H and L, $\bar{A}_{L,t}$, is ≈ 3.5 in 2020 for the low case. This means that $g_{L,t} = 0.0001 * 3.5 + 0.001 = 0,00135$ in the first period.

Figures 5.9 and 5.10 reveal some interesting dynamics. Firstly, growth in region H is initially

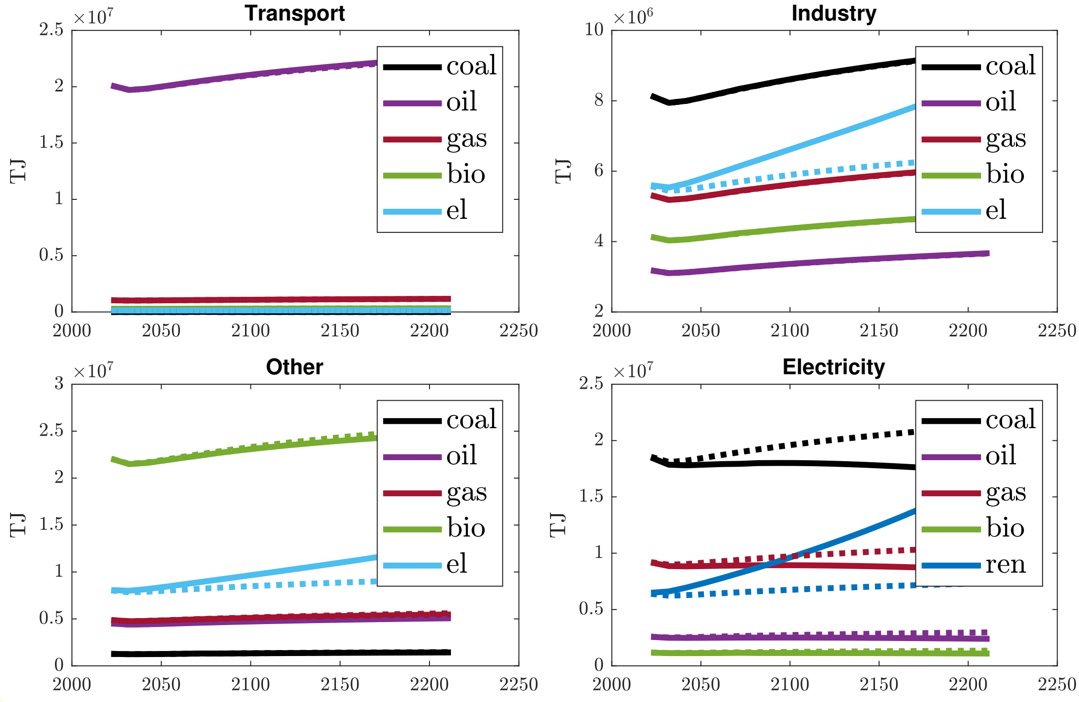

Figure 5.7: Energy by sector in region L. Dotted lines are baseline and solid lines for the case with growth. Note the difference in scales.

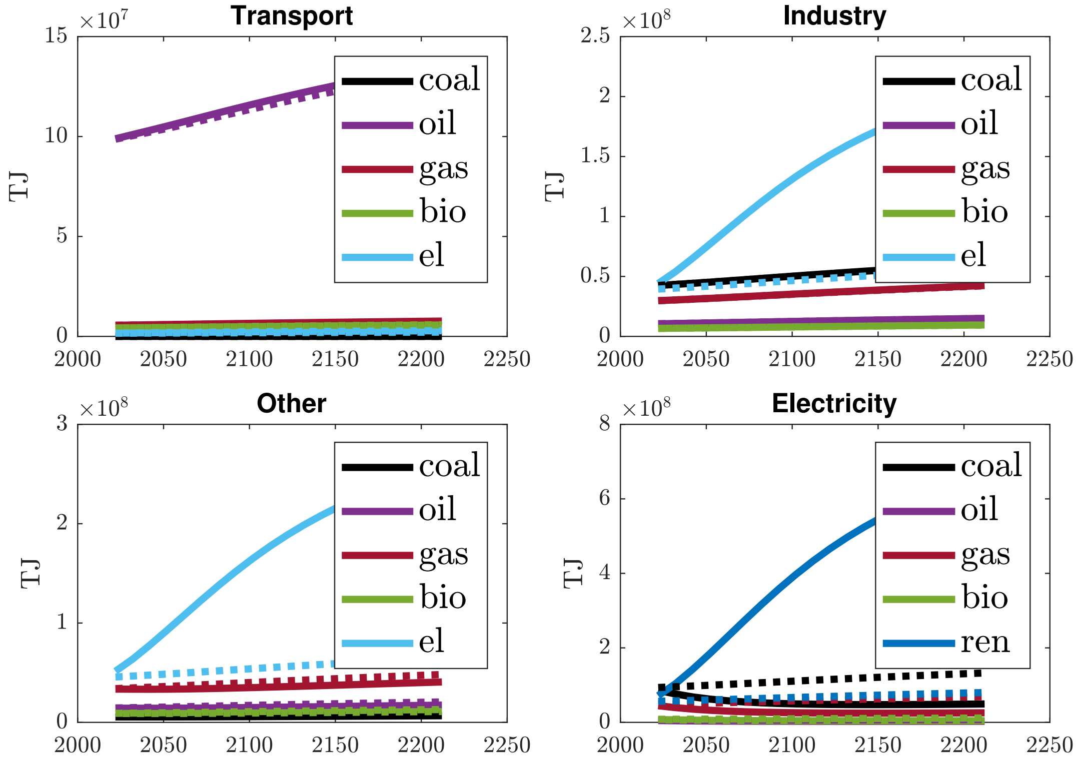

Figure 5.8: Energy by sector in region H. Dotted lines are baseline and solid lines for the case with growth. Note the difference in scales.

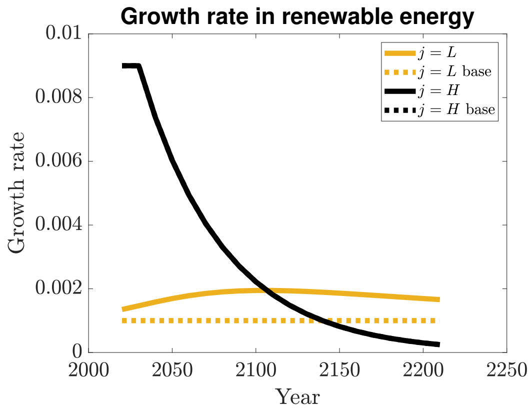

Figure 5.9: Growth rates of renewable energy technology by region (low diffusion).

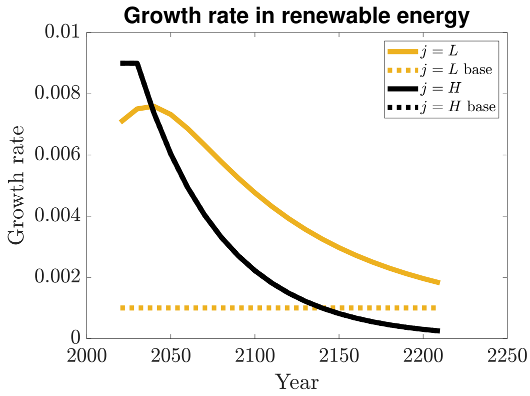

Figure 5.10: Growth rates of renewable energy technology by region (high diffusion).

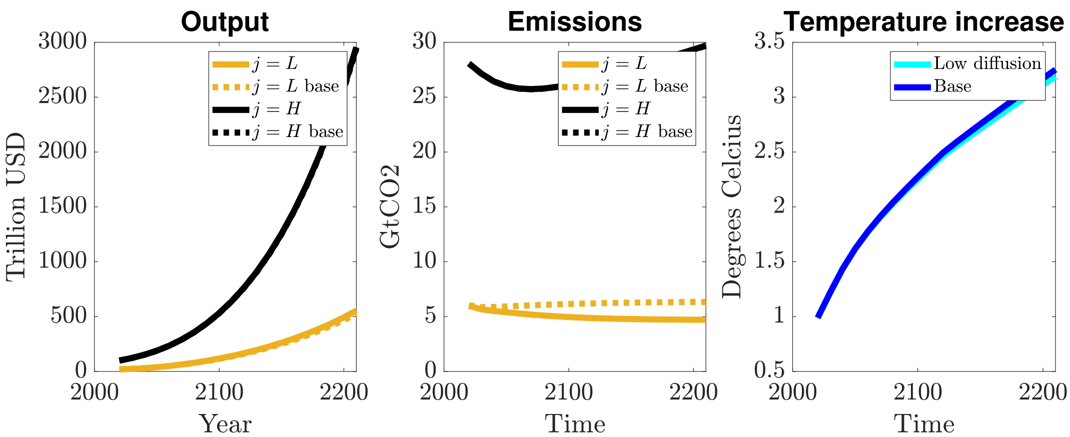

Figure 5.11: Output, emissions and temperature. No vs. high diffusion.

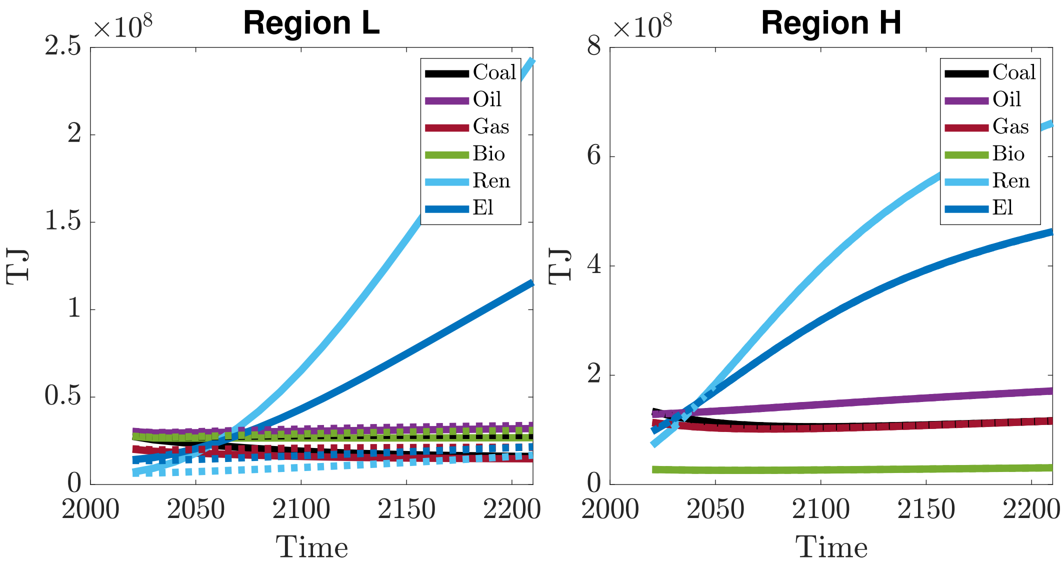

Figure 5.12: Energy by source with growth in renewable energy. Dotted lines are with no diffusion and solid lines for high diffusion. Note the difference in scales.

high, whereby it declines gradually at 2% a year in both scenarios. Secondly, for the high-diffusion case, growth in region L becomes higher than in region H and stays so for the remainder of the time horizon. This is partly an effect of the constant $\lambda_{L,t} = 0.001$, which introduces a minor inconsistency into the analysis. Without that, the growth rates should both converge to zero. More importantly, the higher growth rate captures the catching-up effect, where technologically lagging regions experiences faster growth that developed regions, because they can quickly gain technological progress by using existing innovations instead.

The right panel of figure 5.12 shows that there are no effects on energy production in region H, with the solid lines covering the dashed lines. Region H's emissions and output also stay identical as evident from figure 5.11. However, there is a positive welfare effect in region H which I calculate to be about 40 billion USD for the low case and around 370 billion USD in the high case. This comes from the indirect effect on region H welfare through lower emissions from region L. This in turn gives a lower increase in temperature which increases welfare in region H, as is seen the last panel in figure 5.11. The diffusion effect increases electricity use in region L and amplifies the qualitative effects from introducing growth alone (see figures 5.12 and 5.13). The welfare effect to region L is about 190 billion USD in the low case and 1800 billion USD in the high case.

There are significant gains to be made for both regions by increasing diffusion. I find the welfare effect of diffusion to be between 40 billion and 370 billion USD dollars for the richer region. These effects are only indirect, through lower global temperature and lower climate-related damages. The low-income region has a welfare effect between 190 billion and 1800 billion USD. The energy composition and emissions of the richer region are not decreasing in diffusion, so the welfare effects on the low-income region is strictly local and direct. Next is to do a sensitivity analysis of these results with respect to the elasticities of substitution.

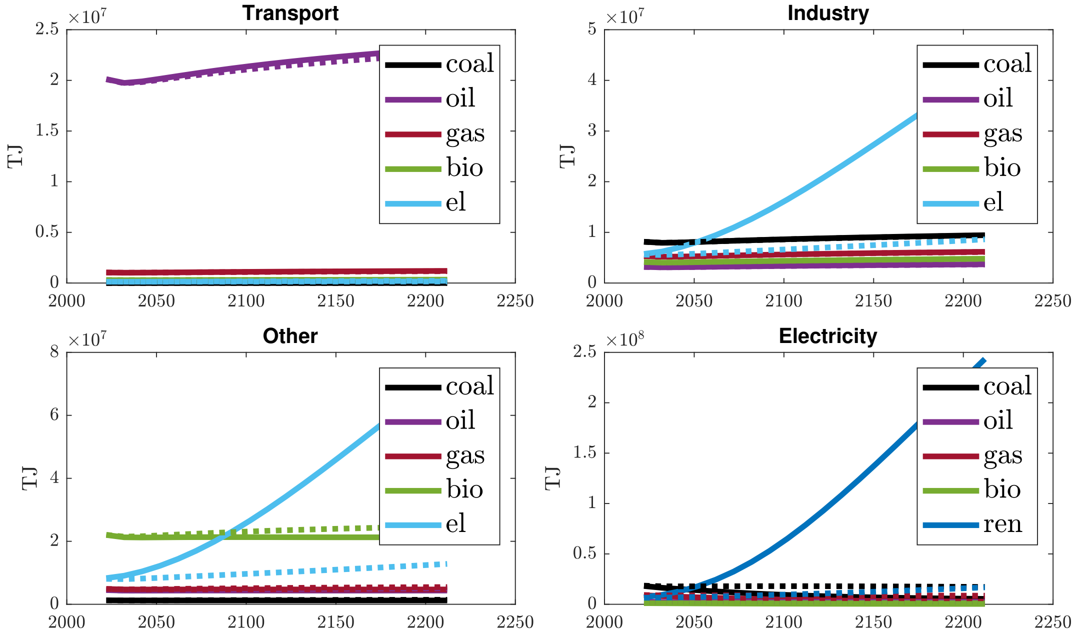

Figure 5.13: Energy by sector in region L. Dotted lines are with no diffusion and solid lines for high diffusion. Note the difference in scales.

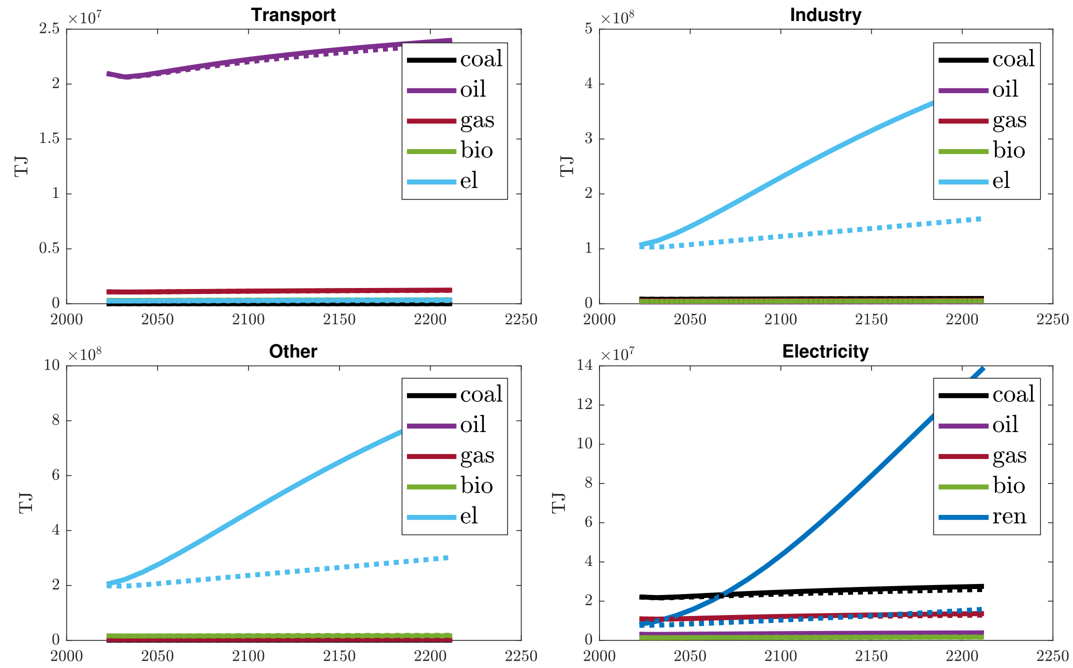

Figure 5.14: Energy by sector in region L, with low substitutability in the electricity sector. Dotted lines are with no diffusion and solid lines for high diffusion. Note the difference in scales.

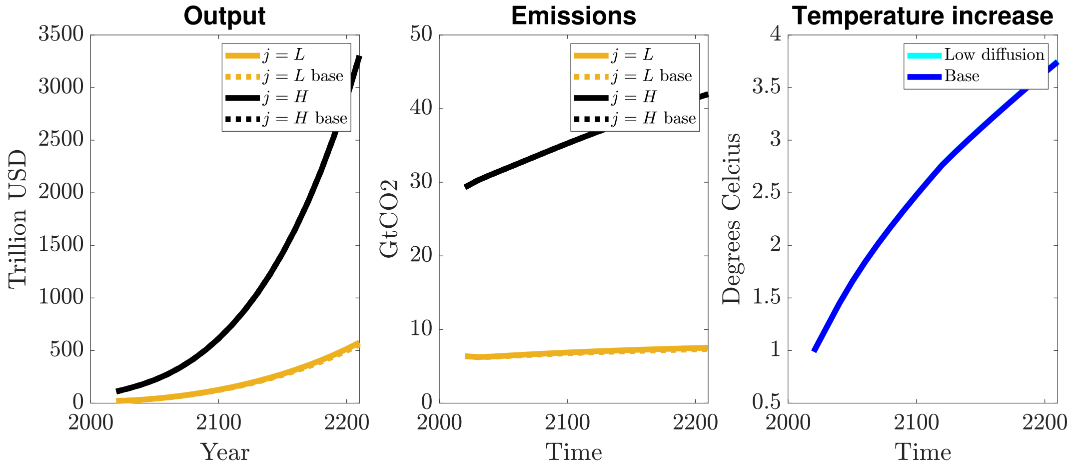

Figure 5.15: Output, emissions and temperature. No vs. high diffusion. Low substitutability.

5.2.3 Sensitivity analysis

In this sensitivity analysis I use the high-diffusion case as the baseline and then vary the elasticities of substitution. In the first scenario I decrease the elasticity of substitution in the electricity sector from 1.8 to just below unity. The results are striking, but maybe expected. For a below-unity substitutability, the inputs in the electricity sector are gross complements. Thus, increasing the use of one factor will increase the use of all other factors to keep output constant. The effects of this is apparent in the bottom right panel of figure 5.14. The implied increase in in fossil fuels increase region L's emissions, thus resulting in a negative welfare effect of diffusion for region H. The net benefit is still positive, but I expect it to decrease in lower inter-fuel substitutability.

This effect also relies on the functional forms imposed by the model. Numerical models often use nested pairs of CES production functions to have a more flexible hierarchy of inputs, and to allow varying degrees of substitutability between inputs. The present production function has all inputs in one level which preserves notational tractability and readability but that comes at the cost of a more flexible production function.

The second sensitivity analysis I make is to increase the elasticity of substitution in transport from 0.2 to 0.5, capturing the potential for a fast global transition to electric or hydrogen fuel cell based transportation[2] The results can be seen in figures 5.16 and 5.17. The energy mix is not very sensitive to the transportation elasticity. There is a slight decrease in oil use in the transportation sector compared to the base case, but not enough to change welfare effects much. The CES production reproduces value shares given the calibrated share. Since oil has a very large current share (around 95% globally), I do not expect to see large changes in oil until the elasticity of substitution increases above unity.

[2]Green hydrogen is made by electrolysis, a electricity-intensive production process. Thus hydrogen and electricity are equivalent energy carriers in my model.

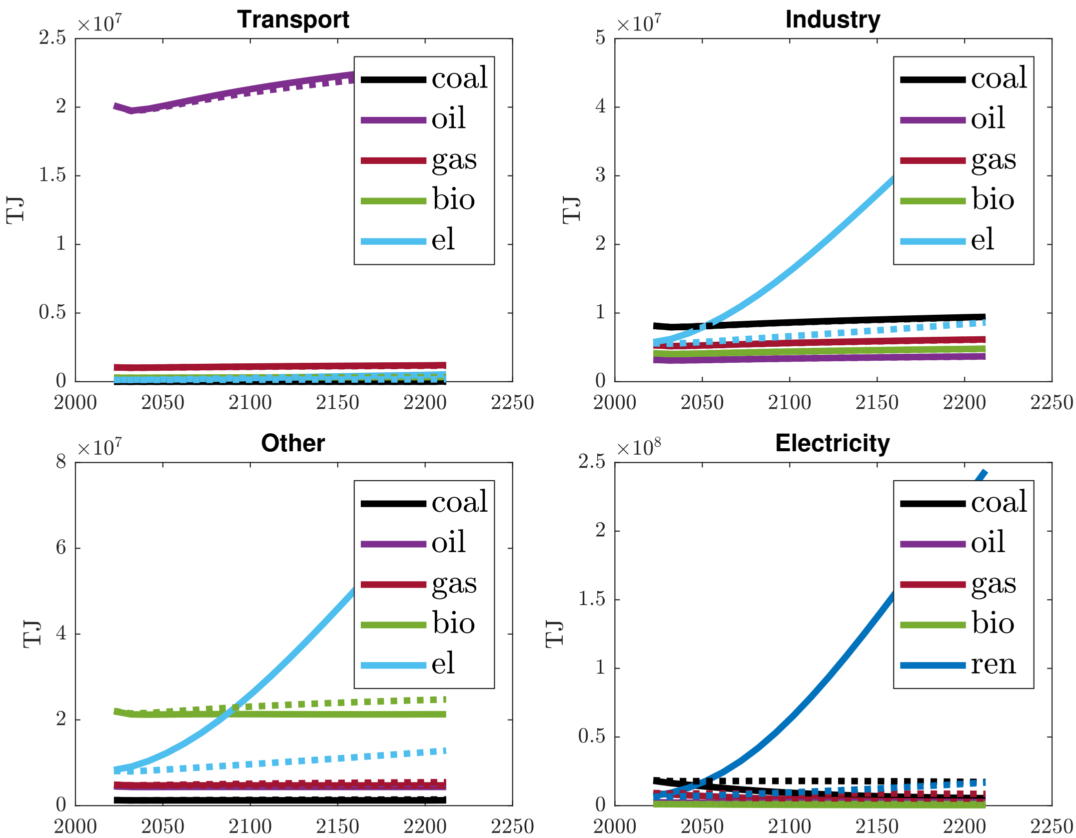

Figure 5.16: Energy by sector in region L, with low substitutability in the electricity sector. Dotted lines are with no diffusion and solid lines for high diffusion. Note the difference in scales.

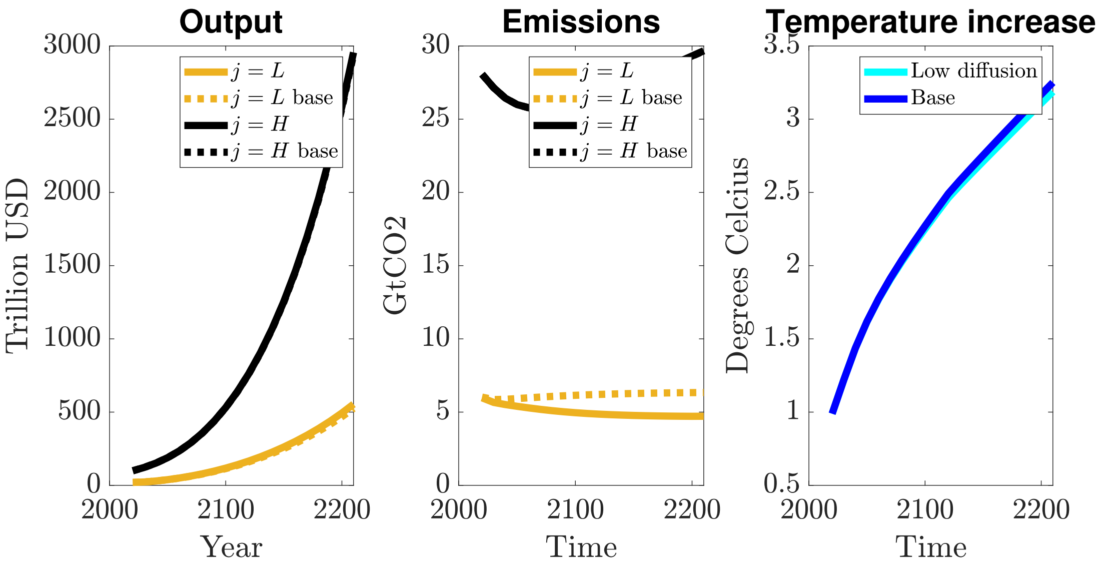

Figure 5.17: Output, emissions and temperature. No vs. high diffusion. Low substitutability.

Chapter 6

Conclusion

In this thesis I have attempted to find the effects on the energy composition and welfare of technological diffusion between regions. To quantify these effects, I calibrated a state-of-the-art analytical integrated assessment model from scratch and introduced a simple technological diffusion mechanism in renewable energy to the base model.

I found that there are significant welfare gains to be made for both regions by increasing technological diffusion. I estimate the welfare effects of diffusion to be between 40 billion and 370 billion US dollars for the richer regionm depending on the degree of diffusion. These effects are indirect to the region, and comes only through lower global temperature and lower climate-related damages. The low-income region has a welfare effect between 190 billion and 1800 billion USD. The energy composition and emissions of the richer region are not decreasing in diffusion, so the welfare effects on the low-income region is strictly local and direct.

These results depend crucially, however, on the inter-fuel elasticity of substitution in the electricity-producing sector in the receiving economy. If renewable energy is a gross complement to fossil fuels in electricity production, emission increases and the welfare effect for the richer region turns negative.

This thesis has made a contribution to the literature on analytical integrated assessment models and I have narrowed the gap between analytic and numerical models. There are several interesting extensions to make in future research. First, one could make the technological diffusion model more realistic either by using other functional forms, such as logistic growth functions, or by endogenizing technology investment. Second, implementing dynamic elasticities of substitution has the potential to capture future transitions in transportation, electricity production and industry.

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Appendix A

Mathematical derivations

In this Appendix I solve the cost minimization problems for the representative firms at each nesting level to obtain their compensated factor demand functions, whose inversions inform the calibration equation I will use[1]. The equations are identical for both regions, so I omit regional indexing. I initially planned to let the elasticities of substitutions in the model be time-dependent, but it turned out to be outside the scope of the thesis as mentioned in the main text. As a result of this path dependency, however, I calculate the inverted compensated demand functions instead of using the more practical and straight-forward calibrated share form equations in Rutherford (2002). The calibrated share form would have permitted a direct interpretation of the CES-parameters as the value shares of the inputs in the calibration year, instead of the more abstract parameters below that depend on the elasticity of substitution[2]. But it is not clear that it is possible to use this form when substitutability itself is changing over time. In the following, I approximately follow the approach laid out in the appendix to Traeger (2022b).

A.1 Final goods aggregation

The representative firm has the following problem:

$$\min_{c_{l,t}\ ,\forall l\in N_c} \sum_{l\in N_c} p_{l,t}c_{l,t} \quad \text{s.t.} \quad A_t\Big(\sum_{l\in N_c} a_{l,t}c_{l,t}^s\Big)^{\frac{1}{s}} = Y_t \quad \text{and} \quad \sum_l a_{l,t} = 1.$$

The Lagrangian to this problem is

$$\mathcal{L} = \sum_{l\in N_c} p_{l,t}c_{l,t} + \lambda\left[Y_t - A_t\Big(\sum_{l\in N_c} a_{l,t}c_{l,t}^s\Big)^{\frac{1}{s}}\right]$$

where λ is the shadow value and where I have omitted the second constraint which holds trivially. The constraints hold for given right-hand-sides, but I omit special notation. The first order

[1] I invoke the second fundamental theorem of welfare economics, which states that any Pareto-optimal allocation could be realized as a decentralized equilibrium. This model is nicely behaved with the normal convexity and has a logarithmic utility function, with interior solutions to the maximization problem. There are no externalities *within each* social planner's domain (although the *global* problem does not have a Pareto optimal decentralized solution).

[2] See e.g. Klump et al. (2011) for a thorough explanation.

condition for final good l is

$$p_{l,t} = \lambda A_t \Big(\sum_{l \in N_c} a_{l,t} c_{l,t}^s \Big)^{\frac{1}{s}-1} a_{l_t} c_{l,t}^{s-1},$$

which solved for $c_{l,t}$ gives

$$c_{l,t} = \left[\frac{\lambda A_t a_{l,t}}{p_{l,t}} \Big(\sum_l a_{l,t} c_{l,t}^s \Big)^{\frac{1}{s}-1} \right]^{\frac{1}{1-s}}, \tag{A.1}$$

still a function of the shadow price. Multiply both sides by $p_{l,t}$, sum over all goods and divide by output to get the average final goods unit costs

$$UC_t \equiv \frac{\sum_l p_{l,t} c_{l,t}}{Y_t} = \frac{1}{Y_t} \lambda A_t \Big(\sum_l a_{l,t} c_{l,t}^s \Big) \Big(\sum_l a_{l,t} c_{l,t}^s \Big)^{\frac{1}{s}-1} = \lambda,$$

which shows that the average unit costs equal the shadow price. Since the production functions exhibit constant returns to scale, the marginal cost will equal units costs. And since the representative firm is a price-taker, marginal costs equal marginal prices. Thus, $\lambda = p_t$. I insert this into (A.1) and solve for $a_{l,t}$ to get

$$a_{l,t} = A_t^{1/s} \frac{p_{l,t}}{p_t} \left(\frac{c_{l,t}}{Y_t} \right)^{1-s}.$$

All goods are measured in calibration-period USD, so I set the final good prices to unity. I do the same for p_t. Furthermore, I want the aggregate good to be measured in USD and not in 'utils'. Therefore, I make the following transformation and get the final calibration expression

$$a_{l,t}^* = \left(\frac{c_{l,t}}{Y_t} \right)^{1-s} \quad \text{with} \quad A_t = \Big(\sum_{l \in N_c} a_{l,t}^* \Big)^{\frac{1}{s}} \quad \text{and} \quad a_{l,t} = \frac{a_{l,t}^*}{\sum_{l \in N_c} a_{l,t}^*}. \tag{A.2}$$

A.2 Final consumption good production

The representative firm production good l has the following problem:

$$\min_{K_{l,t}, N_{l,t}, d_{l,t}} \; p_t^K K_{l,t} + p_t^N N_{l,t} + p_{l,t}^d d_{l,t} \quad \text{s.t.} \quad A_{l,t} K_{l,t}^{\alpha_l} N_{l,t}^{1-\alpha_l-\nu_i} d_{l,t}^{\nu_i} = c_{l,t}.$$

Note that the prices of capital and labor are sector-invariant, which is a result of efficient allocation of these resources. Setting up the Lagrangian and solving the first order equations provides the first order conditions below. Furthermore, since there is constant returns to scale and the firms are price takers, $\lambda = p_{l,t}$. Inserting for this gives the compensated demand functions

$$K_{l,t} = p_{l,t} \frac{\alpha_l}{p_t^K} c_{l,t}, \quad N_{l,t} = p_{l,t} \frac{1-\alpha_l-\nu_l}{p_t^N} c_{l,t}, \quad d_{l,t} = p_{l,t} \frac{\nu_l}{p_{l,t}^d} c_{l,t}. \tag{A.3}$$

The parameter ν_l is sector specific, and I calibrate it according to

$$\nu_i = \frac{p_{l,t}^d d_{l,t}}{p_{l,t} c_{l,t}}. \tag{A.4}$$

As explained in chapter 3, α_l must be sector-independent. Therefore, I use $K_t = \sum_l K_{l,t}$ and Y_t to calibrate it:

$$\alpha_l \equiv \alpha = \frac{p_t^K K_t}{p_t Y_t} = \frac{K_t}{Y_t}, \tag{A.5}$$

where I have set the prices to unity since I measure capital and output both in calibration-period consumption units. Finally, I calibrate $A_{l,t}$ to match total sector output

$$A_{l,t} = \frac{c_{l,t}}{K_{l,t}^{\alpha} N_{l,t}^{1-\alpha-\nu_i} d_{l,t}^{\nu_l}},$$

which is a function of the endogenous control variables $K_{l,t}$, $N_{l,t}$ and $d_{l,t}$. Since these are measured in calibration-period USD, I set the prices in (A.3) to 1 and insert equation (A.3) to get

$$\begin{aligned} A_{l,t} &= \frac{c_{l,t}}{c_{l,t}^{1-\nu_l}\ \alpha^{\alpha} \left(\frac{1-\alpha-\nu_i}{p_t^N}\right)^{1-\alpha-\nu_l} d_{l,t}^{\nu_l}} \\ &= \alpha^{-\alpha} \left(\frac{p_t^N}{1-\alpha-\nu_i}\right)^{1-\alpha-\nu_l} \left(\frac{c_{l,t}}{d_{l,t}}\right)^{\nu_l} \\ &= \alpha^{-\alpha} \nu_l^{-\nu_l} \left(\frac{p_t^N}{1-\alpha-\nu_i}\right)^{1-\alpha-\nu_l}. \end{aligned} \tag{A.6}$$

A.3 Intermediate energy and electricity producers

The firms producing the intermediate energy goods solve the following problem:

$$\min_{e_{l,i,t}\,,\, i \in N_d} \sum_{i \in N_d} p_{i,t}^e e_{l,i,t} \quad \text{s.t.} \quad \tilde{A}_{l,t}\Big(\sum_{i \in N_d} \tilde{a}_{l,i,t} e_{l,i,t}{}^{\tilde{s}_l}\Big)^{\frac{1}{\tilde{s}_l}} = d_{l,t},$$

and the electricity producing firm solves

$$\min_{e_{0,i,t}\,,\, i \in N_e} \sum_{i \in N_e} p_{i,t}^e e_{0,i,t} \quad \text{s.t.} \quad \tilde{A}_{0,t}\Big(\sum_{i \in N_e} \tilde{a}_{0,i,t} e_{0,i,t}{}^{\tilde{s}_l}\Big)^{\frac{1}{\tilde{s}_l}} = e_{0,t}.$$

Using the same methods as above, I get compensated demand solved for the CES parameters in the intermediate energy producing sectors as

$$\begin{aligned} &\tilde{a}_{l,i,t}^* = \tilde{A}_{l,t}^{\frac{1}{\tilde{s}_l}} \frac{p_{i,t}^e}{p_{l,t}^d} \left(\frac{e_{l,i,t}}{d_{l,t}}\right)^{1-\tilde{s}_l} \quad \forall l \in N_c \\ \text{with} \quad &\tilde{A}_{l,t} = \left(\sum_{i \in N_d} \tilde{a}_{l,i,t}^*\right)^{\frac{1}{\tilde{s}_l}} \quad \text{and} \quad \tilde{a}_{l,i,t} = \frac{\tilde{a}_{l,i,t}^*}{\sum_{i \in N_d} \tilde{a}_{l,i,t}^*}. \end{aligned} \tag{A.7}$$

For the electricity sector, I get

$$\begin{aligned} &\tilde{a}_{0,i,t}^* = \tilde{A}_{0,t}^{1/\tilde{s}_l} \frac{p_{i,t}^e}{p_{0,t}^e} \left(\frac{e_{0,i,t}}{e_{0,t}}\right)^{1-\tilde{s}_{0,t}} \\ \text{with} \quad &\tilde{A}_{0,t} = \left(\sum_{i \in N_e} \tilde{a}_{0,i,t}^*\right)^{\frac{1}{\tilde{s}_{0,t}}} \quad \text{and} \quad \tilde{a}_{0,i,t} = \frac{\tilde{a}_{0,i,t}^*}{\sum_{i \in N_e} \tilde{a}_{0,i,t}^*}. \end{aligned} \tag{A.8}$$

A.4 Refined energy production

The producers of refined energy face the following cost-minimization problem:

$$\min_{\bar{K}_{i,t},\bar{N}_{i,t},E_{i,t}} p_t^K \bar{K}_{i,t} + p_t^N \bar{N}_{i,t} + p_{i,t}^E E_{i,t} \quad \text{s.t.} \quad \bar{A}_{i,t}\bar{K}_{i,t}^{\bar{\alpha}_i} \min\{\bar{N}_{i,t}, \bar{a}_{i,t}E_{i,t}\}^{1-\bar{\alpha}_i} = e_{i,t}.$$

The optimal factor demand for a Leontief production function has the factors in equal proportions. Using this, I rewrite the problem to

$$\min_{\bar{K}_{i,t},\bar{N}_{i,t},E_{i,t}} p_t^K \bar{K}_{i,t} + p_t^N \bar{N}_{i,t} + p_{i,t}^E E_{i,t} \quad \text{s.t.} \quad \bar{A}_{i,t}\bar{K}_{i,t}^{\bar{\alpha}_i} \bar{N}_{i,t}^{1-\bar{\alpha}_i} = e_{i,t} \text{ and } \bar{a}_{i,t}E_{i,t} = \bar{N}_{i,t}.$$

The Lagrangian is

$$\mathcal{L} = p_t^K \bar{K}_{i,t} + p_t^N \bar{N}_{i,t} + p_{i,t}^E E_{i,t} + \lambda\left(e_{i,t} - \bar{A}_{i,t}\bar{K}_{i,t}^{\bar{\alpha}_i}\bar{N}_{i,t}^{1-\bar{\alpha}_i}\right) + \mu\left(\bar{N}_{i,t} - \bar{a}_{i,t}E_{i,t}\right),$$

which has the first order conditions

$$\begin{aligned}
\text{(i)} \quad & p_t^K = \lambda\bar{\alpha}_i\bar{A}_{i,t}\bar{K}_{i,t}^{\bar{\alpha}_i-1}\bar{N}_{i,t}^{1-\bar{\alpha}_i} \Rightarrow p_t^K\bar{K}_{i,t} = \lambda\bar{\alpha}_i e_{i,t} \\
\text{(ii)} \quad & p_t^N = \lambda(1-\bar{\alpha}_i)\frac{e_{i,t}}{\bar{N}_{i,t}} - \mu \Rightarrow (p_t^N + \mu)\bar{N}_{i,t} = \lambda(1-\bar{\alpha}_i)e_{i,t} \\
\text{(iii)} \quad & p_{i,t}^E = \bar{a}\mu.
\end{aligned}$$

I insert (iii) into (ii) to eliminate μ and assume that price equals marginal and average costs which eliminates λ to get

$$\bar{K}_{i,t} = \bar{\alpha}_i \frac{p_{i,t}^e}{p_t^K} e_{i,t} \tag{A.9}$$

$$\bar{N}_{i,t} = \frac{(1-\bar{\alpha}_i)p_{i,t}^e e_{i,t}}{p_t^N + \frac{p_{i,t}^E}{\bar{a}_{i,t}}} \quad \text{and} \tag{A.10}$$

$$E_{i,t} = \frac{\bar{N}_{i,t}}{\bar{a}_{i,t}} = \frac{1}{\bar{a}_{i,t}} \frac{(1-\bar{\alpha}_i)p_{i,t}^e e_{i,t}}{p_t^N + \frac{p_{i,t}^E}{\bar{a}_{i,t}}} = \frac{(1-\bar{\alpha}_i)p_{i,t}^e}{\bar{a}_{i,t}p_t^N + p_{i,t}^E}\, e_{i,t},$$

where I used equation (A.10) to eliminate the endogenous $\bar{N}_{i,t}$, and which solved for $\bar{a}_{i,t}$ gives the calibration equations

$$\bar{a}_{i,t} = \frac{\bar{N}_{i,t}}{E_{i,t}} = (1-\bar{\alpha}_i)\frac{p_{i,t}^e}{p_t^N}\frac{e_{i,t}}{E_{i,t}} - \frac{p_{i,t}^E}{p_t^N} \quad \forall i \in I^d. \tag{A.11}$$

Remember that capital's share $\bar{\alpha}_i$ must be equal across the producers at this level in the nested production function. I therefore calibrate $\bar{\alpha} \equiv \bar{\alpha}_i$ using equation (A.9), $\bar{K}_t \equiv \sum_{i\in N_e}\bar{K}_{i,t}$ and $p_t^e e_t \equiv \sum_{i\in N_e} p_{i,t}^e e_{i,t}$ to get the 'mean' capital share of the refined energy sector

$$\bar{\alpha} = \frac{\bar{K}_{,t}}{p_t^e e_t}, \tag{A.12}$$

where I used the normalization $p_t^K = 1$.

Next is to calibrate the $\bar{A}_{i,t}$'s to match output. Rewriting the production function, and using the sector-independent $\bar{\alpha}$, I get

$$\bar{A}_{i,t} = \frac{e_{i,t}}{\bar{K}_{i,t}^{\bar{\alpha}} \bar{N}_{i,t}^{1-\bar{\alpha}}}.$$

I use equations (A.9) and (A.10) to eliminate the endogenous $\bar{K}_{i,t}$ and $\bar{N}_{i,t}$

$$\begin{aligned}
\bar{A}_{i,t} &= \frac{e_{i,t} \left(p_t^N + \frac{p_{i,t}^E}{\bar{a}_{i,t}} \right)^{1-\bar{\alpha}} {p_t^K}^{\bar{\alpha}}}{\left(\bar{\alpha} p_{i,t}^e e_{i,t}\right)^{\bar{\alpha}} \left((1-\bar{\alpha}) p_{i,t}^e e_{i,t}\right)^{1-\bar{\alpha}}} \\
&= {p_{i,t}^e}^{-1} \, \upsilon \left(p_t^N + \frac{p_{i,t}^E}{\bar{a}_{i,t}} \right)^{1-\bar{\alpha}}, \qquad \text{(A.13)}
\end{aligned}$$

where I used the normalization $p_t^K = 1$ and $\upsilon \equiv \left(\bar{\alpha}^{\bar{\alpha}} (1-\bar{\alpha})^{1-\bar{\alpha}}\right)^{-1}$.

Appendix B

A more general diffusion model

Recall equation (3.4)

$$d_{l,t} = \tilde{A}_{l,t}\Big(\sum_{i\in N_d} \tilde{a}_{l,i,t} e_{l,i,t}^{\tilde{s}_{l,t}}\Big)^{\frac{1}{\tilde{s}_{l,t}}}$$

which for each region gives the production of the intermediate energy input in sector l as a function of electricity $e_{l,0,t}$ and other refined energy inputs. Let $B_{l,i,t}$ be the exogenous factor augmenting technology for energy input i in sector l in a given region. Then

$$d_{l,t} = \tilde{A}_{l,t}\Big(\sum_{i\in N_d} \tilde{a}_{l,i,t} (B_{l,i,t} e_{l,i,t})^{\tilde{s}_{l,t}}\Big)^{\frac{1}{\tilde{s}_{l,t}}} \tag{B.1}$$

makes factor-augmenting technological growth in the energy sector explicit.

Let

$$g_{l,i,t} \equiv \frac{\Delta A_{l,i,t}}{A_{l,i,t}} \tag{B.2}$$

be the growth rate of technology for input i in sector l at time t, with $A_{l,i,0} > 0$. Collect all the entries $A_{l,i,t}$ for region j in the $l \times i$ matrix $\boldsymbol{A}_{j,t}$, and let $\boldsymbol{g}_{j,t}$ be a $l \times i$ matrix with the corresponding technology growth rates from (B.2) for region j in period t. The world technology frontier is represented by $\boldsymbol{A}_t$ with growth rates $\boldsymbol{g}_t$. The technological diffusion equation[1] of motion for each region j is

$$\boldsymbol{A}_{j,t+1} = \boldsymbol{\theta}_j * (\boldsymbol{A}_t - \boldsymbol{A}_{j,t}) + (\boldsymbol{1} + \boldsymbol{\lambda}_j) * \boldsymbol{A}_{j,t}, \tag{B.3}$$

where $*$ is the element-wise matrix multiplication operator and $\boldsymbol{1}$ is a matrix of ones. The time-constant and exogenous diffusion parameters has elements $\theta_{j,l,i} \in [0,1]$and $\lambda_{j,l,i} \in [0, g_{l,i}]$[2]. The technology absorption rate $\boldsymbol{\theta}_j$ captures the varying degrees with which regions are able to import various technologies given their policies, institutions and other economic and social factors. This rate is exogenous in the current model, but it is possible to endogenize it as a function of e.g. human capital (see Acemoglu (2009)). The absorption rate captures the delay or imperfectness

[1] The following is based on the continuous time single-good model in Acemoglu (2009), chapter 18.2.1.

[2] The original single-good law of motion in Acemoglu (2009) has $\theta_j \in (0, \infty)$. I think that there is a typo here. Having $\theta_j > 1$ implies that a region could absorb more than the difference between the world frontier and its own technology level, which is hard to argue. That is why I have closed the interval at an upper boundary of 1.

with which technology becomes available across the world. For $\boldsymbol{\theta}_j = \mathbf{0}$, there is no diffusion. For $\boldsymbol{\theta}_j = \mathbf{1}$ all sectors catch up to the World frontier without delay. If the country is the World leader in any technology, $A_{l,i} = A_{j,l,i}$, and there is no diffusion. The local innovation parameter $\boldsymbol{\lambda}_j$ determines the locally sourced growth rate in technology. It captures how fast a region uses it existing knowledge $\boldsymbol{A}_j$ to improve technology. At the boundaries of the permitted interval, a region can either have no local innovation or innovate at the World frontier growth rate.

Equation (B.3) can be rearranged to get the technology growth rates directly for each sector l and energy input i

$$g_{j,t} = \theta_j \tilde{A}_{j,t} + \lambda_j \tag{B.4}$$

where $\tilde{A}_{j,t} \equiv \frac{A_t - A_{j,t}}{A_{j,t}} \in [0, \infty)$ is the rate of difference in technology levels between the World frontier and region j. For a positive diffusion rate, a region with a high local innovation rate can have a higher technological growth rate than regions on the World frontier. This captures the catching-up effect.

The discrete-time model used in this thesis allow discontinuous paths of development, which encapsulates the potential for leap-frogging, where a region does not necessarily visit all the same 'stops' along the technological growth path of the World frontier.

Appendix C

Supplementary figures

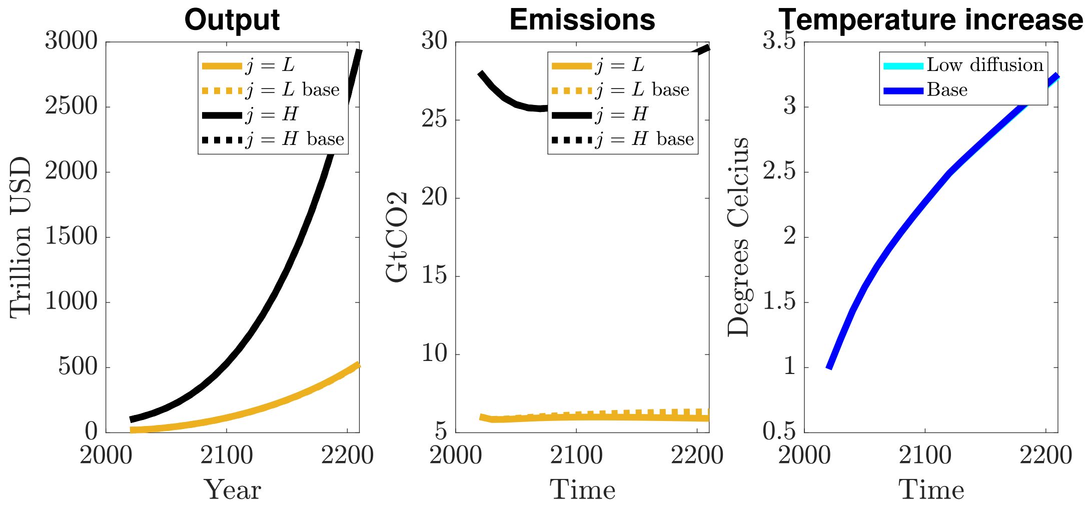

Figure C.1: Output, emissions and temperature. No vs. low diffusion.

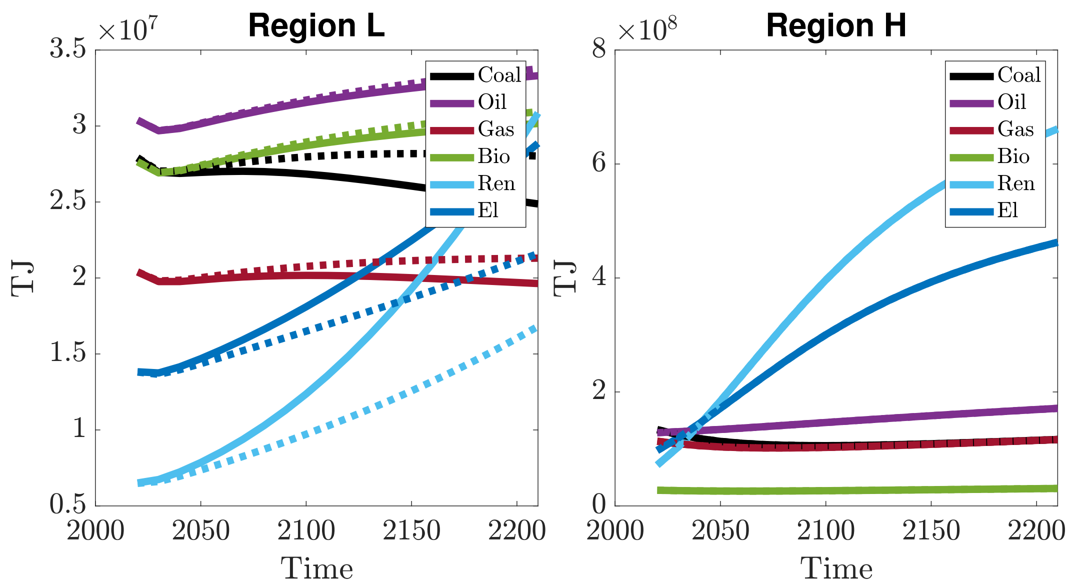

Figure C.2: Energy by source with growth in renewable energy. Dotted lines are with no diffusion and solid lines for low diffusion. Note the difference in scales.

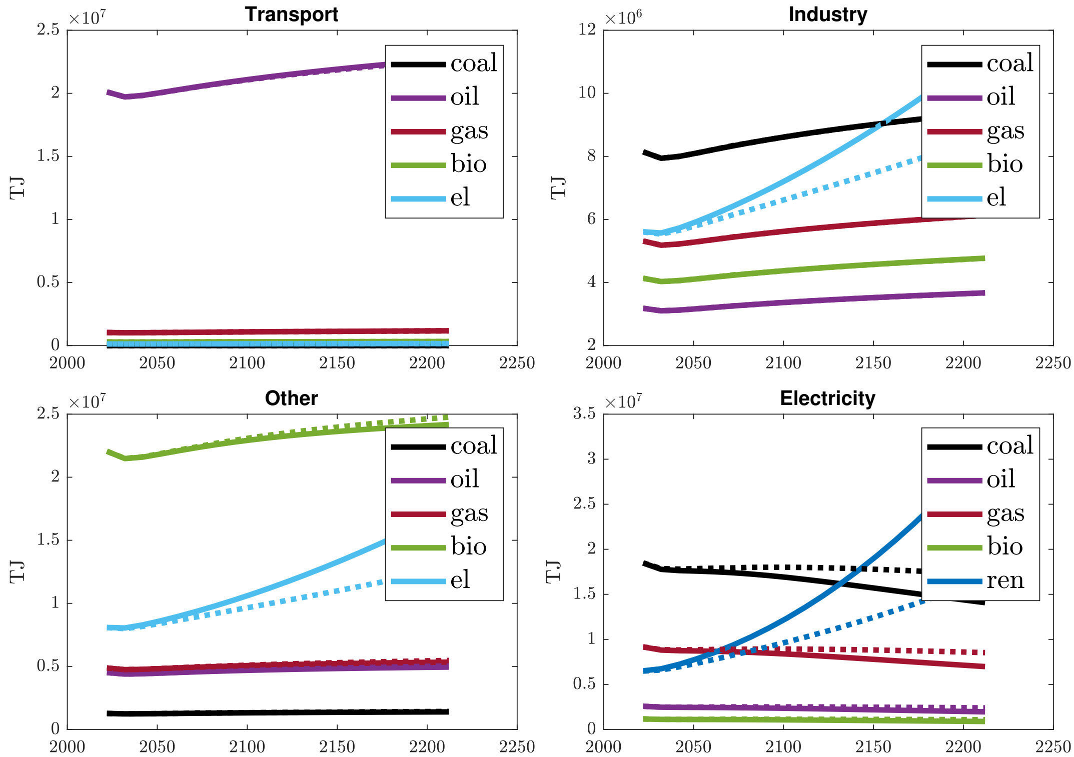

Figure C.3: Energy by sector in region L. Dotted lines are with no diffusion and solid lines for low diffusion. Note the difference in scales.

Appendix D

Supplementary tables

Table D.1: List of countries in each region

1	Region L	Region H
1	Albania	Anguilla
2	Algeria	Antigua and Barbuda
3	Angola	Argentina
4	Bangladesh	Armenia
5	Barbados	Aruba
6	Belize	Australia
7	Benin	Austria
8	Bhutan	Azerbaijan
9	Bolivia (Plurinational State of)	Bahamas
10	Bosnia and Herzegovina	Bahrain
11	Burkina Faso	Belarus
12	Burundi	Belgium
13	Cabo Verde	Bermuda
14	Cambodia	Botswana
15	Cameroon	Brazil
16	Central African Republic	British Virgin Islands
17	Chad	Brunei Darussalam
18	Colombia	Bulgaria
19	Comoros	Canada
20	Congo	Cayman Islands
21	Côte d'Ivoire	Chile
22	D.R. of the Congo	China
23	Djibouti	China, Hong Kong SAR
24	Dominica	China, Macao SAR
25	Ecuador	Costa Rica
26	Egypt	Croatia
27	El Salvador	Curaçao
28	Eswatini	Cyprus
29	Ethiopia	Czech Republic
30	Fiji	Denmark

31	Gambia	Dominican Republic
32	Ghana	Equatorial Guinea
33	Guatemala	Estonia
34	Guinea	Finland
35	Guinea-Bissau	France
36	Guyana	Gabon
37	Haiti	Georgia
38	Honduras	Germany
39	India	Greece
40	Indonesia	Grenada
41	Iran (Islamic Republic of)	Hungary
42	Iraq	Iceland
43	Jamaica	Ireland
44	Jordan	Israel
45	Kenya	Italy
46	Kyrgyzstan	Japan
47	Lao People's DR	Kazakhstan
48	Lesotho	Kuwait
49	Liberia	Latvia
50	Madagascar	Lebanon
51	Malawi	Lithuania
52	Mali	Luxembourg
53	Mauritania	Malaysia
54	Mongolia	Maldives
55	Morocco	Malta
56	Mozambique	Mauritius
57	Myanmar	Mexico
58	Namibia	Montenegro
59	Nepal	Montserrat
60	Nicaragua	Netherlands
61	Niger	New Zealand
62	Nigeria	North Macedonia
63	Pakistan	Norway
64	Paraguay	Oman
65	Peru	Panama
66	Philippines	Poland
67	Republic of Moldova	Portugal
68	Rwanda	Qatar
69	Sao Tome and Principe	Republic of Korea
70	Senegal	Romania
71	Sierra Leone	Russian Federation
72	South Africa	Saint Kitts and Nevis
73	Sri Lanka	Saint Lucia
74	St. Vincent and the Grenadines	Saudi Arabia
75	State of Palestine	Serbia
76	Sudan	Seychelles
77	Syrian Arab Republic	Singapore
78	Tajikistan	Sint Maarten (Dutch part)
79	Togo	Slovakia

80	Tunisia	Slovenia
81	U.R. of Tanzania: Mainland	Spain
82	Uganda	Suriname
83	Ukraine	Sweden
84	Uzbekistan	Switzerland
85	Venezuela (Bolivarian Republic of)	Taiwan
86	Viet Nam	Thailand
87	Yemen	Trinidad and Tobago
88	Zambia	Turkey
89	Zimbabwe	Turkmenistan
90		Turks and Caicos Islands
91		United Arab Emirates
92		United Kingdom
93		United States
94		Uruguay

Appendix E

Wrangling script

Table of Contents

Data Wrangling for ACE %

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Initial setup

```
clear all
clc

% Wrangle these:
wrangle.RICE        = 1; % List of RICE codes and region names
wrangle.PWT         = 1; % Time series of country-level macro data
wrangle.UN          = 1; % Sector output data (2019 mostly, some 2018)
wrangle.WIOD        = 1; % Sector output data missing from UN (2014)
wrangle.ILOSTAT     = 1; % Sector labor data
wrangle.IEA         = 1; % Sector energy volumes
wrangle.OECD        = 1; % Sector capital data
wrangle.USBLS       = 1; % Fine sector capital data (for fuels)
wrangle.sectors     = 1; % Dataset merging for export
wrangle.energy      = 1; % Energy data merging for export
```

PART 1: READ IN RAW DATA AND BASIC CLEANING: %%

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

RICE REGIONS

```
if wrangle.RICE == 1

    % This is a cleaned list to match the available PWT data.
    % There are more countries in RICE, but these are the ones for which we
 have PWT data
    raw.RICE_regions = readtable("raw_data\our_regions_clean.csv");
    RICE_regions = renamevars(raw.RICE_regions,
 ["country_name" "country_code"], ["country" "countrycode"]);
    RICE_regions.short_name =  [];
    % Converting variables to categories (more functionality, less
    % memory required)
    RICE_regions = categorizer(RICE_regions, width(RICE_regions));

    % Merging RICE list with ISO list. Keeping RICE names.
    RICE_regions =
 outerjoin(RICE_regions,isoCountryList,"LeftKeys","countrycode","RightKeys","alpha_3");

    % Keeping only RICE countries (because of PWT data limitations)
    RICE_regions(isundefined(RICE_regions.country),:) = [];
    RICE_regions(:,[5 6 7 9 12 13 14 15]) = [];

    %     % Saving
    wranglingFile.RICE_regions = RICE_regions;

    save("calibData.mat", "RICE_regions", "-append");
    %save("rawData.mat", "raw");
else
    load("calibData.mat", "RICE_regions");
    %load("rawData.mat", "raw");
end


% END RICE REGIONS
```

```
Error using readtable
Unable to find or open 'raw_data\our_regions_clean.csv'. Check the path and
filename or file permissions.

Error in wranglingScript (line 31)
    raw.RICE_regions = readtable("raw_data\our_regions_clean.csv");
```

PWT 2019 (Aggregate macro GDP, capital, labor, growth rates etc. Country level.)

```
if wrangle.PWT == 1


    raw.PWT = readtable("raw_data\pwt100.xlsx", "Sheet", "Data");
```

```
PWT = categorizer(raw.PWT, 2);

% Adding developed/developing regional codes
% NOTE: PWT data is in millions of people. I just want people.
% NOTE: PWT data is in millions of USD. I want just USD.
PWT.cgdpo = 1000000.*PWT.cgdpo;
PWT.cn =    1000000.*PWT.cn;
PWT.emp =   1000000.*PWT.emp;
PWT.pop =   1000000.*PWT.pop;
PWT.gdpPerCap = PWT.cgdpo ./ PWT.pop; % USD per capita

PWT.thesisCode = ~(PWT.gdpPerCap < 14031 | isnan(PWT.gdpPerCap)); %
GdpPerEmp lower than China is defined as developing.


% Getting labsh as extensive variable
PWT.labshExt = PWT.labsh .* PWT.cgdpo;


% Converting the logical to categorical for future use
% Note: The normal way was buggy, so had to use workaround.
PWT = convertvars(PWT, "thesisCode", 'categorical'); % Logical to double
PWT.thesisCode = renamecats(PWT.thesisCode, ["true" "false"], ["2" "1"]);

% JOINING PWT WITH RICE REGIONS (easy, both has three letter abbr. code)
PWT = join(PWT, RICE_regions, Keys="countrycode");
PWT(:, "country_RICE_regions") = [];

% Saving dynamic PWT data for growth rate calculations
PWT2019 = PWT(PWT.year == 2019,:);
countries2019 = unique(PWT2019.countrycode);


pwtDynamic = PWT(PWT.year > 2009,:);



PWT = PWT(PWT.year == 2019,:);
thesis1 = unique(PWT(PWT.thesisCode =="1", "countrycode"));

idl = pwtDynamic.year == 2019 & pwtDynamic.thesisCode == "1";
lowCountries = pwtDynamic.countrycode(idl);
idl = pwtDynamic.year == 2019 & pwtDynamic.thesisCode == "2";
highCountries = pwtDynamic.countrycode(idl);

for k = 1:numel(lowCountries)
    id = pwtDynamic.year ~= 2019 & pwtDynamic.countrycode ==
lowCountries(k);
    pwtDynamic.thesisCode(id) = "1";
end

for k = 1:numel(highCountries)
    id = pwtDynamic.year ~= 2019 & pwtDynamic.countrycode ==
highCountries(k);
```

```
        pwtDynamic.thesisCode(id) = "2";
    end

    PWTsanity1 = PWT;

    G = findgroups(PWT.thesisCode);
    UWplPPP = splitapply(@mean, PWT.pl_gdpo, G);

    % Sum of GDP per thesis region
    G = findgroups(PWT.thesisCode);
    sumGDP = splitapply(@sum, PWT.cgdpo, G);

    % Sum of GDP
    sumGDPWorld = sum(PWT.cgdpo);


    PWT.GDPweight = ones(183,1);
    PWT.GDPweightWorld = ones(183,1);
    %Low income
    PWT{PWT.thesisCode == "1", "GDPweight"} = PWT.cgdpo(PWT.thesisCode
 == "1") / sumGDP(1);
    %High income
    PWT{PWT.thesisCode == "2", "GDPweight"} = PWT.cgdpo(PWT.thesisCode
 == "2") / sumGDP(2);
    %World
    PWT{:, "GDPweightWorld"} = PWT.cgdpo / sumGDPWorld;

    % Sanity check, each group should sum to 1
    G = findgroups(PWT.thesisCode);
    sumWeights = splitapply(@sum, PWT.GDPweight, G);
    %Passed

    PWT.weighedPL = PWT.GDPweight .* PWT.pl_gdpo;
    PWT.weighedPLWorld = PWT.GDPweightWorld .* PWT.pl_gdpo;

    % Finding the weighted average PPP adjusted price levels.
    G = findgroups(PWT.thesisCode);
    wPriceLevel = splitapply(@sum, PWT.weighedPL, G);
    wPriceLevelWorld = sum(PWT.weighedPLWorld);

    wPriceLevel = [wPriceLevelWorld; wPriceLevel];


    % Removing year variable for easy merging with non-2019 data later
    PWT(:, "year") = [];

    save("calibData.mat", "PWT", "-append"); % A full-data 2019 version for
 calibration code
    save("calibData.mat", "pwtDynamic" , "-append"); % A full-data 2010-2019
 for growth rates
    save("calibData.mat", "wPriceLevel", "-append");
    %save("rawData.mat", "raw", "-append");
else
    load("calibData.mat", "PWT", "pwtDynamic", "wPriceLevel");
```

```
    %load("rawData.mat", "raw");

end

% END PWT
```

MAKING A TABLE WITH MODEL COUNTRY NAMES, 3-LETTER CODES, RICECODES AND RICE REGIONS.

Subsetting FROM PWT only the country list and codes

```
countriesPWTRICE = unique([PWT(:,"countrycode"), PWT(:,"country_PWT"),
 PWT(:,"rice_code"), PWT(:,"rice_region"), PWT(:, "country_code"),
 PWT(:,"thesisCode"),PWT(:, "region")]);
countriesPWTRICE = renamevars(countriesPWTRICE, ["country_PWT"], ["country"]);

% IEA data lacks fine level data for some African, Asian and American
 countries.
% Must add these regions manually to country list and assign regions
tabOthAf ={"OAF", "Other Africa", "9", "Africa", "99999", "1", "Africa"};
tabOthAm ={"OAM", "Other non-OECD
 Americas", "10", "LatAm", "88888", "1", "Americas"};
tabOthAs ={"OAS", "Other non-OECD Asia", "12", "OthAs", "77777", "1", "Asia"};

countriesPWTRICE = [countriesPWTRICE; tabOthAf; tabOthAm; tabOthAs];

% END SPECIAL COUNTRYCODES TABLE
```

UN Data. (FOR SECTOR DATA)

```
if wrangle.UN == 1

    % First, I must read in the two tables and separately combine the sectors
    % whithin each system because ofdifferent naming and grouping of sectors.
    % (See:
    % https://ilostat.ilo.org/resources/concepts-and-definitions/
classification-economic-activities/)

    % Second, I must join the two tables to get all the countries in one
 table.

    % Third, I must update the country list to match the PWT list.

    % Fourth, I must decide on which sectors to put in which aggregate. What
 to
    % do with electricity and mining? They should go "below" my three sectors,
    % which is an argument of using the output method. But then, however, many
    % other things go "below" mu three sectors as well (such as vehicle
    % manufacturing, which messes up the energy intermediate interpretation).
```

```
    % Fifth, I must find the proper sectoral shares.

    % Sixth, I must split the table in three -- one for each sector. These
    % tables become the foundation on which to add further calibration
    % variables.

    % These are the variables I need from the UN data
    unVars =
["country" "year" "sector" "accountingType" "currency" "series" "isic" "value"];

    % READING IN AND COMBINING TABLES
    raw.UN_ISIC4 = readtable("raw_data\UN output gva current prices
ISIC4.txt");
    isic = ones(height(raw.UN_ISIC4),1);
    raw.UN_ISIC4.isic = 4.*isic;         % Assigning ISIC version number for
later identification
    raw.UN_ISIC3 = readtable("raw_data\UN_output_sectors.txt");
    isic = ones(height(raw.UN_ISIC3),1);
    raw.UN_ISIC3.isic = 3.*isic;
    raw.UN = [raw.UN_ISIC4;raw.UN_ISIC3];        % Vertical append

    unData = renamevars(raw.UN,
["CountryOrArea" "Year" "SubItem" "Item" "Currency" "Series" "isic" "Value"],
unVars);
    unData = unData(:, unVars);
    unData = categorizer(unData,5);
    % Keeping value added (GDP) and output. NOTE: A MISTAKE TO KEEP VA.
    % BUG.
    %     unData = unData(unData.accountingType == "Equals: VALUE ADDED,
GROSS, at basic prices" | ...
    %                     unData.accountingType == "Output, at basic
prices",:);
    unData = unData(unData.accountingType == "Output, at basic prices",:);
    unData(:,"accountingType") = [];

    % Listing all sectors to see which are redundant
    sectorsAndIsicTab = unData(:,["sector" "isic"]);
    [~, sectorsAndIsic] = findgroups(sectorsAndIsicTab);

    % Removing pre-aggregated sectors and subsectors that could cause issues
in summation
    unData((unData.sector == "Agriculture, hunting and related service
activities (01)" | ...
        unData.sector == "Agriculture, hunting, forestry; fishing (A+B)" | ...
        unData.sector == "Crop and animal production, hunting and related
service activities (01)" | ...
        unData.sector == "Education; health and social work; other community,
social and personal services (M+N+O)" | ...
        unData.sector == "Financial intermediation; real estate, renting and
business activities (J+K)" | ...
        unData.sector == "Fishing and aquaculture (03)" | ...
        unData.sector == "Forestry and logging (02)" | ...
        unData.sector == "Forestry, logging and related service activities
(02)" | ...
```

```
        unData.sector == "Manufacturing, mining and quarrying and other
industrial activities (B+C+D+E)" | ...
        unData.sector == "Other service activities (R+S+T)" | ...
        unData.sector == "Professional, scientific, technical, administrative
and support service activities (M+N)" | ...
        unData.sector == "Public administration and defence, education, human
health and social work activities (O+P+Q)" | ...
        unData.sector == "Wholesale and retail trade, transportation and
storage, accommodation and food service activities (G+H+I)" | ...
        unData.sector == "Wholesale retail trade, repair of motor vehicles,
motorcycles, etc.; hotels and restaurants (G+H)"), ...
        :) = [];

    % Finding the remanding list of sectors, for merging
    sectorsAndIsicTab = unData(:,["sector" "isic"]);
    [~, sectorsAndIsic] = findgroups(sectorsAndIsicTab);
    % Defining model sectors (see sectorsAndIsic for list of all sectors)
    electricitySector = [{'Electricity, gas and water supply (E)'}
        {'Electricity, gas, steam and air conditioning supply (D)'}];
    miningSector = [{'Mining and quarrying (B)' }
        {'Mining and quarrying (C)'}];

    transportSector = [{'Transportation and storage (H)'}
        {'Transport, storage and communications (I)'}];
    industrySector = [{'Construction (F)'}
        {'Manufacturing (C)' }
        {'Manufacturing (D)'}];
    otherSector = [{'Accommodation and food service activities (I)'}
        {'Administrative and support service activities (N)'}
        {'Agriculture, forestry and fishing (A)'}
        {'Arts, entertainment and recreation (R)'}
        {'Education (P)'}
        {'Financial and insurance activities (K)'}
        {'Fishing (B)'}
        {'Human health and social work activities (Q)'}
        {'Information and communication (J)'}
        {'Other service activities (S)'}
        {'Private households with employed persons (P)'}
        {'Private households with employed persons (T)'}
        {'Professional, scientific and technical activities (M)'}
        {'Public administration and defence; compulsory social security (O)'}
        {'Public administration and defense; compulsory social security (L)'}
        {'Real estate activities (L)'}
        {'Water supply; sewerage, waste management and remediation activities
(E)'}
        {'Wholesale and retail trade; repair of motor vehicles and motorcycles
(G)'}];
    industrySector = [industrySector;electricitySector;miningSector];


    % Merging detailed sectors into model sectors
    unData.sector = mergecats(unData.sector, transportSector, "Transport (and
storage)");
```

```
   unData.sector = mergecats(unData.sector, industrySector, "Industry
(manufacturing and construction)");
   unData.sector = mergecats(unData.sector, otherSector, "Other");
   %unData.sector = mergecats(unData.sector, electricitySector,
"Electricity");
   %unData.sector = mergecats(unData.sector, miningSector, "Mining");

   % Fixing name differences between UN and PWT. There are 147 countries in
the UN data and
   % 183 in PWT. Sorting out spelling differences.

   countriesUN = unique(unData.country);
   countriesPWT = unique(countriesPWTRICE.country);
   inUNnotinPWT = setdiff(countriesUN, countriesPWT);
   inPWTnotinUN = setdiff(countriesPWT,countriesUN);
   unData.country = renamecats(unData.country, ...
       ["China, Hong Kong Special Administrative Region" ...
       "China, Macao Special Administrative Region" ...
       "Czechia" ...
       "Tanzania - Mainland" ...
       "Saint Vincent and the Grenadines"], ...
       [string(countriesPWT(countriesPWT == "China, Hong Kong SAR")) ...
       string(countriesPWT(countriesPWT == "China, Macao SAR")) ...
       string(countriesPWT(countriesPWT == "Czech Republic")) ...
       string(countriesPWT(countriesPWT == "U.R. of Tanzania: Mainland")) ...
       string(countriesPWT(countriesPWT == "St. Vincent and the
Grenadines"))]);
   countriesUNcheck = unique(unData.country);

   % Merging some sub-countries into mother country to better mix with
   % other datasets
   unData.country = mergecats(unData.country,
["Denmark" "Greenland"], "Denmark");

   % Collecting sectors
   unData = varfun(@sum, unData, ...
       GroupingVariables=["country" "year" "sector"], ...
       InputVariables="value");

   % Merging territories into mother country
   unData.country = mergecats(unData.country,
["Denmark" "Greenland"], "Denmark");

   % ADDING COUNTRY CODES TO UN DATA

   % Note: The joining key is the 3-letter country code because of spelling
differences in full country names.

   % JOINING UNDATA TO THE COUNTRYLISTS AND 3-LETTER CODE FROM RICE AND PWT
   % Joining tables
   unData = outerjoin(unData,countriesPWTRICE); % XXX ONLY 130 COUNTRIES.
NEED TO FIX NAMING BEFORE THIS.
   unCountriesAfterJoin = unique(unData.country_unData); %now 193 countries
   % If the country is not in UN data, I copy the name from PWT data.
```

```
    notInUnData = isundefined(unData.country_unData);
    countriesNotInUnData = unData(notInUnData,
["country_countriesPWTRICE" "countrycode"]);
    unData.country_unData(notInUnData) =
 unData.country_countriesPWTRICE(notInUnData);
    % Assigning year and sector gategory to missing data vars (PWT
    % countries not in UN)
    isUndefined = isundefined(unData.year);
    unData.year(isUndefined) = "9999";      % Just a missing data marker
    isUndefined = isundefined(unData.sector);
    unData.sector(isUndefined) = "Missing Data";
    % For now I am just dropping the 10 small countries with UN data and no
 PWT
    % % data. (XXX Figure out if some can be used)
    %unData(isundefined(unData.country_countryLists),:) = [];
    % Keeping only needed vars
    unData = unData(:,
["country_unData" "year" "sector" "sum_value" "countrycode" "rice_code" "rice_region"]);

    % END OF ADDING COUNTRY CODES TO UN DATA

    %unData = unData(unData.year == "2019", :); % 130 countries for 2019, 144
 for 2018, 148 for 2017
    %unData = unData((unData.sector == "Total Economy" | unData.sector ==
 "Missing Data"),:);

    save("wrangling.mat", "unData", "-append");
    %save("rawData.mat", "raw", "-append");
else
    load("wrangling.mat", "unData");
    %load("rawData.mat", "raw");
end

% END UN DATA WRANGLING
```

WORLD INPUT-OUTPUT DATABASE (FOR MISSING COUNTRIES IN UN)

WIOD is a smaller but more detailed database. It has data for 4 of the large regions missing in UN data: China, Indonesia, Russia, Taiwan. Only smaller countries are missing in UN, to whom I extrapolate shares when done.

```
if wrangle.WIOD == 1

    % Reading in raw data (XXX automate somehow?)
    raw.WIOD_CHN = readtable("raw_data\WIOD\CHN_NIOT_nov16.xlsx",
 Sheet="National IO-tables", VariableNamesRange="A2", DataRange="A3");
    %raw.WIOD_CZE = readtable("raw_data\WIOD\CZE_NIOT_nov16.xlsx",
 Sheet="National IO-tables", VariableNamesRange="A2", DataRange="A3");
    raw.WIOD_IDN = readtable("raw_data\WIOD\IDN_NIOT_nov16.xlsx",
 Sheet="National IO-tables", VariableNamesRange="A2", DataRange="A3");
    raw.WIOD_RUS = readtable("raw_data\WIOD\RUS_NIOT_nov16.xlsx",
 Sheet="National IO-tables", VariableNamesRange="A2", DataRange="A3");
```

```
    raw.WIOD_TWN = readtable("raw_data\WIOD\TWN_NIOT_nov16.xlsx",
Sheet="National IO-tables", VariableNamesRange="A2", DataRange="A3");

    % Manually adding countrycodes (XXX could automate from regexp on
filename)
    raw.WIOD_CHN.countrycode(:) = "CHN";
    %raw_WIOD_CZE.countrycode(:) = "CZE"; Found CZE data in UN under
    %different name
    raw.WIOD_IDN.countrycode(:) = "IDN";
    raw.WIOD_RUS.countrycode(:) = "RUS";
    raw.WIOD_TWN.countrycode(:) = "TWN";

    % Vertical concat. of each country into one big table for all five
    % countries
    wiodData = [raw.WIOD_CHN;raw.WIOD_IDN;raw.WIOD_RUS;raw.WIOD_TWN]; % Add
raw.WIOD_CZE if needed later


    wiodVars = ["countrycode" "year" "code" "sector" "origin" "value"];
    wiodData = renamevars(wiodData,
["countrycode" "Var1" "Var2" "Var3" "Var4" "TotalOutput"], wiodVars);
    wiodData(wiodData.year ~= 2014,:) = [];
    wiodData = wiodData(:,wiodVars);
    wiodData(wiodData.origin ~= "Domestic",:) = [];
    wiodData = categorizer(wiodData, 5);


    electricitySector = {'Electricity, gas, steam and air conditioning
supply'};
    miningSector = {'Mining and quarrying'};
    transportSector = [{'Land transport and transport via pipelines'}
        {'Water transport'}
        {'Air transport'}
        {'Warehousing and support activities for transportation'}
        {'Postal and courier activities'}];
    industrySector = [{'Construction'}
        {'Manufacture of food products, beverages and tobacco products'}
        {'Manufacture of textiles, wearing apparel and leather products'}
        {'Manufacture of wood and of products of wood and cork, except
furniture; manufacture of articles of straw and plaiting materials'}
        {'Manufacture of paper and paper products'}
        {'Printing and reproduction of recorded media'}
        {'Manufacture of coke and refined petroleum products'}
        {'Manufacture of chemicals and chemical products'}
        {'Manufacture of basic pharmaceutical products and pharmaceutical
preparations'}
        {'Manufacture of rubber and plastic products'}
        {'Manufacture of other non-metallic mineral products'}
        {'Manufacture of basic metals'}
        {'Manufacture of fabricated metal products, except machinery and
equipment'}
        {'Manufacture of computer, electronic and optical products'}
        {'Manufacture of electrical equipment'}
        {'Manufacture of machinery and equipment n.e.c.'}
```

```
        {'Manufacture of motor vehicles, trailers and semi-trailers'}
        {'Manufacture of other transport equipment'}
        {'Manufacture of furniture; other manufacturing'}
        {'Repair and installation of machinery and equipment'}
        electricitySector
        miningSector
        ];
    otherSector = [{'Crop and animal production, hunting and related service
activities'}
        {'Forestry and logging'}
        {'Fishing and aquaculture'}
        {'Water collection, treatment and supply'}
        {'Sewerage; waste collection, treatment and disposal activities;
materials recovery; remediation activities and other waste management
services'}
        {'Wholesale and retail trade and repair of motor vehicles and
motorcycles'}
        {'Wholesale trade, except of motor vehicles and motorcycles'}
        {'Retail trade, except of motor vehicles and motorcycles'}
        {'Accommodation and food service activities'}
        {'Publishing activities'}
        {'Motion picture, video and television programme production, sound
recording and music publishing activities; programming and broadcasting
activities'}
        {'Telecommunications'}
        {'Computer programming, consultancy and related activities;
information service activities'}
        {'Financial service activities, except insurance and pension funding'}
        {'Insurance, reinsurance and pension funding, except compulsory social
security'}
        {'Activities auxiliary to financial services and insurance
activities'}
        {'Real estate activities'}
        {'Legal and accounting activities; activities of head offices;
management consultancy activities'}
        {'Architectural and engineering activities; technical testing and
analysis'}
        {'Scientific research and development'}
        {'Advertising and market research'}
        {'Other professional, scientific and technical activities; veterinary
activities'}
        {'Administrative and support service activities'}
        {'Public administration and defence; compulsory social security'}
        {'Education'}
        {'Human health and social work activities'}
        {'Other service activities'}
        {'Activities of households as employers; undifferentiated goods- and
services-producing activities of households for own use'}
        {'Activities of extraterritorial organizations and bodies'}
        ];

    % NOTE: Can get electricity and so on as separate sectors. Here they are
    % merged into other.
```

```
    wiodData.sector = mergecats(wiodData.sector, transportSector, "Transport
(and storage)");
    wiodData.sector = mergecats(wiodData.sector, industrySector, "Industry
(manufacturing and construction)");
    wiodData.sector = mergecats(wiodData.sector, otherSector, "Other");

    % Collecting sectors
    wiodData = varfun(@sum, wiodData, ...
        GroupingVariables=["countrycode" "year" "sector"], ...
        InputVariables="value");

    % Creating Total Economy sector
    wiodDataTotal = varfun(@sum, wiodData, ...
        GroupingVariables=["countrycode" "year"], ...
        InputVariables="sum_value");
    wiodDataTotal = renamevars(wiodDataTotal, ["GroupCount" "sum_sum_value"],
["sector" "sum_value"]);
    wiodDataTotal =
convertvars(wiodDataTotal,wiodDataTotal.Properties.VariableNames{"sector"},'categorical')
    wiodDataTotal.sector = renamecats(wiodDataTotal.sector, "3", "Total
Economy");

    % Merging Total Economy category and data into main wiod table
    wiodData(:,"GroupCount") = [];
    wiodData = [wiodData; wiodDataTotal];
    wiodData = sortrows(wiodData, "countrycode");

    save("wrangling.mat", "wiodData", "-append");
    %save("rawData.mat", "raw", "-append");
else
    load("wrangling.mat", "wiodData");
    %load("rawData.mat", "raw");
end

% END WIOD WRANGLING
```

ILOSTAT LABOR DATA

```
if wrangle.ILOSTAT == 1

    % Basic read-ins and preprocessing
    raw.ILOSTAT = readtable("raw_data\ilostat labor data sector shares (189C
with SECTOR SHARES).csv");
    ilostatVars = ["country", "sector", "secLabSh"];
    ilostatData = renamevars(raw.ILOSTAT,
["ReferenceArea" "EconomicActivity" "Value"], ilostatVars);
    ilostatData = ilostatData(:,ilostatVars);
    ilostatData = categorizer(ilostatData, 2);


    electricitySector = {'Detailed: Utilities ~ISIC rev.4 D; E'}; % Note:
Utilities contain more than just electricity production
    miningSector = {'Detailed: Mining and quarrying ~ISIC rev.4 B'};
```

```
   transportSector = [{'Detailed: Transport; storage and communication ~ISIC
rev.4 H; J'}];
   industrySector = [{'Detailed: Manufacturing ~ISIC rev.4 C'}
       {'Detailed: Construction ~ISIC rev.4 F'}
       electricitySector
       miningSector];
   otherSector = [{'Detailed: Agriculture; forestry and fishing ~ISIC rev.4
A'}
       {'Detailed: Wholesale and retail trade; repair of motor vehicles and
motorcycles ~ISIC rev.4 G'}
       {'Detailed: Accommodation and food service activities ~ISIC rev.4 I'}
       {'Detailed: Financial and insurance activities ~ISIC rev.4 K'}
       {'Detailed: Real estate; business and administrative activities ~ISIC
rev.4 L; M; N'}
       {'Detailed: Public administration and defence; compulsory social
security ~ISIC rev.4 O'}
       {'Detailed: Education ~ISIC rev.4 P'}
       {'Detailed: Human health and social work activities ~ISIC rev.4 Q'}
       {'Detailed: Other services ~ISIC rev.4 R; S; T; U'}
       ];

   ilostatData.sector = mergecats(ilostatData.sector,
transportSector, "Transport (and storage)");
   ilostatData.sector = mergecats(ilostatData.sector,
industrySector, "Industry (manufacturing and construction)");
   ilostatData.sector = mergecats(ilostatData.sector, otherSector, "Other");

   ilostatData = ilostatData( ...
       (ilostatData.sector == "Transport (and storage)" | ...
       ilostatData.sector == "Industry (manufacturing and construction)"
| ...
       ilostatData.sector == "Electricity" | ...
       ilostatData.sector == "Mining" | ...
       ilostatData.sector == "Other"),:);

   % Collecting sectors
   ilostatData = varfun(@sum, ilostatData, ...
       GroupingVariables=["country" "sector"], ...
       InputVariables="secLabSh");

   % Cleaning
   ilostatData = renamevars(ilostatData,"sum_secLabSh", "secLabSh");
   ilostatData = ilostatData(:,["country" "sector" "secLabSh"]);

   % Unstacking to get a variable per sector (a wider table, one country per
row)
   ilostatData = unstack(ilostatData,"secLabSh","sector",...
       "VariableNamingRule","preserve");
   ilostatData = renamevars(ilostatData, ...
       ["Transport (and storage)" "Industry (manufacturing and
construction)" "Other"], ...
       ["transportLabSh" "industryLabSh" "otherLabSh"]);
```

```
% Removing ILOSTAT regions
dropIlostat = {'ASEAN'
    'Africa'
    'Africa: High income'
    'Africa: Low income'
    'Africa: Lower-middle income'
    'Africa: Upper-middle income'
    'Americas'
    'Americas: High income'
    'Americas: Low income'
    'Americas: Lower-middle income'
    'Americas: Upper-middle income'
    'Arab League'
    'Arab States'
    'Arab States: High income'
    'Arab States: Low income'
    'Arab States: Lower-middle income'
    'Arab States: Upper-middle income'
    'Asia and the Pacific'
    'Asia and the Pacific: High income'
    'Asia and the Pacific: Low income'
    'Asia and the Pacific: Lower-middle income'
    'Asia and the Pacific: Upper-middle income'
    'BRICS'
    'Caribbean'
    'CARICOM'
    'Central Africa'
    'Central America'
    'Central Asia'
    'Central and Western Asia'
    'Central and Western Asia: High income'
    'Central and Western Asia: Low income'
    'Central and Western Asia: Lower-middle income'
    'Central and Western Asia: Upper-middle income'
    'Eastern Africa'
    'Eastern Asia'
    'Eastern Asia: High income'
    'Eastern Asia: Low income'
    'Eastern Asia: Lower-middle income'
    'Eastern Asia: Upper-middle income'
    'Eastern Europe'
    'Eastern Europe: High income'
    'Eastern Europe: Lower-middle income'
    'Eastern Europe: Upper-middle income'
    'Europe and Central Asia'
    'Europe and Central Asia: High income'
    'Europe and Central Asia: Low income'
    'Europe and Central Asia: Lower-middle income'
    'Europe and Central Asia: Upper-middle income'
    'European Union 27'
    'European Union 28'
    'G20'
    'G7'
    'Latin America and the Caribbean'
```

```
    'Latin America and the Caribbean: High income'
    'Latin America and the Caribbean: Low income'
    'Latin America and the Caribbean: Lower-middle income'
    'Latin America and the Caribbean: Upper-middle income'
    'MENA'
    'Northern Africa'
    'Northern Africa: Lower-middle income'
    'Northern Africa: Upper-middle income'
    'Northern America'
    'Northern America: High income'
    'Northern Europe'
    'Northern, Southern and Western Europe'
    'Northern, Southern and Western Europe: High income'
    'Northern, Southern and Western Europe: Upper-middle income'
    'Pacific Islands'
    'South-Eastern Asia'
    'South-Eastern Asia and the Pacific'
    'South-Eastern Asia and the Pacific: High income'
    'South-Eastern Asia and the Pacific: Lower-middle income'
    'South-Eastern Asia and the Pacific: Upper-middle income'
    'Southern Africa'
    'South America'
    'Southern Asia'
    'Southern Asia: Low income'
    'Southern Asia: Lower-middle income'
    'Southern Asia: Upper-middle income'
    'Southern Europe'
    'Sub-Saharan Africa'
    'Sub-Saharan Africa: High income'
    'Sub-Saharan Africa: Low income'
    'Sub-Saharan Africa: Lower-middle income'
    'Sub-Saharan Africa: Upper-middle income'
    'Western Africa'
    'Western Asia'
    'Western Europe'
    'World'
    'World excluding BRICS'
    'World: High income'
    'World: Low income'
    'World: Lower-middle income'
    'World: Upper-middle income'};

ilostatData(ismember(ilostatData.country, dropIlostat),:) = [];

% Sorting out naming differences.
countriesILO = unique(ilostatData.country);
countriesPWT = unique(countriesPWTRICE.country);
inILOnotPWT = setdiff(countriesILO, countriesPWT);
inPWTnotinILO = setdiff(countriesPWT,countriesILO);
ilostatData.country = renamecats(ilostatData.country, ...
    ["Bolivia" ...
    "Cape Verde" ...
    "Congo, Democratic Republic of the" ...
    "Czechia" ...
```

```
        "Hong Kong, China" ...
        "Iran, Islamic Republic of" ...
        "Korea, Republic of" ...
        "Lao People's Democratic Republic" ...
        "Macau, China" ...
        "Moldova, Republic of" ...
        "Occupied Palestinian Territory" ...
        "Saint Vincent and the Grenadines" ...
        "Taiwan, China" ...
        "Tanzania, United Republic of" ...
        "Venezuela, Bolivarian Republic of"], ...
        [string(countriesPWT(countriesPWT == "Bolivia (Plurinational State
 of)")), ...
        string(countriesPWT(countriesPWT == "Cabo Verde")), ...
        string(countriesPWT(countriesPWT == "D.R. of the Congo")), ...
        string(countriesPWT(countriesPWT == "Czech Republic")), ...
        string(countriesPWT(countriesPWT == "China, Hong Kong SAR")), ...
        string(countriesPWT(countriesPWT == "Iran (Islamic Republic
 of)")), ...
        string(countriesPWT(countriesPWT == "Republic of Korea")), ...
        string(countriesPWT(countriesPWT == "Lao People's DR")), ...
        string(countriesPWT(countriesPWT == "China, Macao SAR")), ...
        string(countriesPWT(countriesPWT == "Republic of Moldova")), ...
        string(countriesPWT(countriesPWT == "State of Palestine")), ...
        string(countriesPWT(countriesPWT == "St. Vincent and the
 Grenadines")), ...
        string(countriesPWT(countriesPWT == "Taiwan")), ...
        string(countriesPWT(countriesPWT == "U.R. of Tanzania:
 Mainland")), ...
        string(countriesPWT(countriesPWT == "Venezuela (Bolivarian Republic
 of)"))]);
    countriesILOcheck = unique(ilostatData.country);

    save("wrangling.mat", "ilostatData", "-append");
    %save("rawData.mat", "raw", "-append");
else
    load("wrangling.mat", "ilostatData");
    %load("rawData.mat", "raw");
end

% END ILOSTAT WRANGLING
```

IEA VOLUME BALANCES

```
if wrangle.IEA == 1
    raw_IEA = readtable("raw_data\IEA energy volumes.xlsx", Sheet="Data",
 VariableNamesRange="A4", DataRange="A6");
    raw_IEA_Other = readtable("raw_data\WBAL_Extract-Sharing_V2.xlsx",
 Sheet="Data_Add", VariableNamesRange="A4", DataRange="A5");
    % Cleaning to merge the two datasets.
    ieaDataOther = renamevars(raw_IEA_Other, "Var2", "PRODUCT");
    ieaDataOther = movevars(ieaDataOther, 'Coal', 'Before', 'Coal_1');
    ieaDataOther = movevars(ieaDataOther, 'Coal_1', 'Before', 'Coal_2');
```

```
    ieaDataOther = movevars(ieaDataOther, 'Coal_2', 'After', 'Total_2');
    ieaDataRawMerged = [raw_IEA;ieaDataOther];

    % We have 2015, 2018, 2019 data. Keeping only 2019 data.
    ieaData = removevars(ieaDataRawMerged,3:24);

    % Taking absolute values of everything
    % Negative values were transformation. Not needed.
    %ieaData = abs(ieaData)

    % Combining fuels to our aggregated fuels
    ieaData.oil = ieaData.CrudeOil_2 + ieaData.OilProducts_2; % Crude oil and
 oil products
    ieaData.renewables = ieaData.Nuclear_2 + ieaData.Hydro_2 +
 ieaData.Solar_Wind_Etc__2;
    ieaData.elAndHeat = ieaData.Electricity_2 + ieaData.Heat_2;
    ieaVars = ["sector" "country" "natGas" "bio" "total" "coal"];
    ieaData = renamevars(ieaData,
 ["Var1" "PRODUCT" "NaturalGas_2" "BiofuelsAndWaste_2" "Total_2" "Coal_2"],
 ieaVars);
    ieaData = ieaData(:,
["country" "sector" "coal" "oil" "natGas" "bio" "renewables" "elAndHeat"]);
    ieaData = categorizer(ieaData, 2);
    %     % Removing IEA regions
    %     ieaData((ieaData.country == "Africa" | ...
    %         ieaData.country == 'Memo: European Union-27' | ...
    %         ieaData.country == 'Memo: European Union-28' | ...
    %         ieaData.country == 'Memo: FSU 15' | ...
    %         ieaData.country == 'Memo: IEA Total' | ...
    %         ieaData.country == 'Memo: Non-OECD Total' | ...
    %         ieaData.country == 'Memo: OECD Total' | ...
    %         ieaData.country == 'Non-OECD Americas' | ...
    %         ieaData.country == 'Non-OECD Asia (excluding China)' | ...
    %         ieaData.country == 'Non-OECD Europe and Eurasia' | ...
    %         ieaData.country == 'OECD Americas' | ...
    %         ieaData.country == 'OECD Asia Oceania' | ...
    %         ieaData.country == 'OECD Europe' | ...
    %         ieaData.country == 'World'), :) = [];

    ieaDataSanity = ieaData;

    % Sorting out naming differences.
    countriesIEA = unique(ieaData.country);
    countriesPWT = unique(countriesPWTRICE.country);
    inIEAnotPWT = setdiff(countriesIEA, countriesPWT);
    inPWTnotinIEA = setdiff(countriesPWT,countriesIEA);
    ieaData.country = renamecats(ieaData.country, ...
        ["Bolivarian Republic of Venezuela" ...
        "Chinese Taipei" ...
        "Curaçao/Netherlands Antilles" ...
        "Democratic Republic of the Congo" ...
        "Hong Kong (China)" ...
        "Islamic Republic of Iran" ...
        "Korea" ...
```

```
        "Lao People's Democratic Republic" ...
        "People's Republic of China" ...
        "Plurinational State of Bolivia" ...
        "Republic of North Macedonia" ...
        "Republic of the Congo" ...
        "Slovak Republic" ...
        "United Republic of Tanzania"], ...
        [string(countriesPWT(countriesPWT == "Venezuela (Bolivarian Republic
of)")), ...
        string(countriesPWT(countriesPWT == "Taiwan")), ...
        string(countriesPWT(countriesPWT == "Curaçao")), ...
        string(countriesPWT(countriesPWT == "D.R. of the Congo")), ...
        string(countriesPWT(countriesPWT == "China, Hong Kong SAR")), ...
        string(countriesPWT(countriesPWT == "Iran (Islamic Republic
of)")), ...
        string(countriesPWT(countriesPWT == "Republic of Korea")), ...
        string(countriesPWT(countriesPWT == "Lao People's DR")), ...
        string(countriesPWT(countriesPWT == "China")), ...
        string(countriesPWT(countriesPWT == "Bolivia (Plurinational State
of)")), ...
        string(countriesPWT(countriesPWT == "North Macedonia")), ...
        string(countriesPWT(countriesPWT == "Congo")), ...
        string(countriesPWT(countriesPWT == "Slovakia")), ...
        string(countriesPWT(countriesPWT == "U.R. of Tanzania: Mainland"))]);
    countriesIEAcheck = unique(ieaData.country);


    ieaDataSanity2 = ieaData;

    % Merging these three input-output types into electricity production
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'Electricity Plants'}
        {'CHP Plants'}
        ], "4 electricity");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'Residential'}
        {'Commercial and public services'}
        {'Agriculture/forestry'}
        {'Fishing'}], "3 other");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'Industry'}], "2 industry");
    ieaData.sector = renamecats(ieaData.sector, ...
        ["Transport"], ...
        ["1 transport"]);


    ieaDataSanity2b = ieaData;



    % Summing over grouped categories
    % Taking aboslute value to get rid of negative entries (transformation in
raw data)
```

```
    ieaData = varfun(@(x) sum(abs(x)), ieaData , "GroupingVariables",
["country" "sector"], ...
        "InputVariables",3:8);

    ieaDataSanity3 = ieaData;

    % The following for-loop is based on help from mathworks.com forum
    % https://se.mathworks.com/matlabcentral/answers/1710975-how-to-
conditionally-and-by-groups-subtract-one-row-from-another-in-table
    % Find the available countries
    countries = unique(ieaData.country);



    ieaData = removevars(ieaData, ["GroupCount" ]);
    ieaData = renamevars(ieaData, 3:8,
 ["coal" "oil" "natGas" "bio" "renew" "elAndHeat"]);

    % Loop through the available countries computing the net consumption for
    % each
    endRow = size(ieaData,1); % current ending row number
    for k = 1:numel(countries)
        % sum the supplies and consumption
        idl = ieaData.sector == "Total energy supply" & ieaData.country ==
 countries(k);
        totalSupply = sum(ieaData{idl,3:end},1);
        idl = ieaData.sector == "Total final consumption" & ieaData.country ==
 countries(k);
        totalConsumption = sum(ieaData{idl,3:end},1);
        idl = ieaData.sector == "4 electricity" & ieaData.country ==
 countries(k);
        totalElectricity = sum(ieaData{idl,3:end},1);

        % compute net
        misc = totalSupply -totalConsumption - totalElectricity;
        % and add row
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
 rows
        newRow.sector = "misc";
        newRow{1,3:end} = misc;
        ieaData(endRow,:) = newRow;
    end


    % Does not make sense to perform misc. operation on electricity and total
    ieaData{ieaData.sector == "misc", ["elAndHeat"]} = 0;

    ieaData = sortrows(ieaData,'country','ascend');
    ieaDataSanity4 = ieaData;

    % For each country, add misc to the sectors according to fuel shares
    endRow = size(ieaData,1); % current ending row number
    for k = 1:numel(countries)
```

```
        % take out vectors for each sector
        idl = ieaData.sector == "1 transport" & ieaData.country ==
countries(k);
        transport = ieaData{idl,3:end};
        idl = ieaData.sector == "2 industry" & ieaData.country ==
countries(k);
        industry = ieaData{idl,3:end};
        idl = ieaData.sector == "3 other" & ieaData.country == countries(k);
        other = ieaData{idl,3:end};
        idl = ieaData.sector == "Total final consumption" & ieaData.country ==
countries(k);
        totalConsumption = ieaData{idl,3:end};
        idl = ieaData.sector == "misc" & ieaData.country == countries(k);
        misc = ieaData{idl,3:end};

        % calculate shares (5x1) each
        trSh = transport ./ totalConsumption;
        inSh = industry ./ totalConsumption;
        otSh = other ./ totalConsumption;

        % stack to get (3x5) to use dot product
        sh = [trSh;inSh;otSh];
        miscMatrix = repmat(misc, 3, 1);

        % matrix of misc split across sectors and fuels
        miscSectors = sh .* miscMatrix;

        % and add row for transport
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
rows
        newRow.sector = "misc tr";
        newRow{1,3:end} = miscSectors(1,:);
        ieaData(endRow,:) = newRow;

        % industry
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
rows
        newRow.sector = "misc in";
        newRow{1,3:end} = miscSectors(2,:);
        ieaData(endRow,:) = newRow;

        % and other
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
rows
        newRow.sector = "misc ot";
        newRow{1,3:end} = miscSectors(3,:);
        ieaData(endRow,:) = newRow;

    end
```

```
    ieaDataSanity5 = ieaData;

    % Merging misc. with corresponding sectors and summing again
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'1 transport' 'misc tr'}], "1 transport");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'2 industry' 'misc in'}], "2 industry");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'3 other' 'misc ot'}], "3 other");

    % omitnan is important since previous step gave 0/0 for some fuels in some
 regions
    ieaData = varfun(@(x) sum(x, "omitnan"), ieaData , "GroupingVariables",
["country" "sector"], ...
        "InputVariables",3:8);
    ieaData = removevars(ieaData, ["GroupCount" ]);
    ieaData = renamevars(ieaData, 3:8,
 ["coal" "oil" "natGas" "bio" "renew" "elAndHeat"]);

    ieaDataSanity6 = ieaData;

    % For each country, add energy own use and losses in electricity to
 sectors
    endRow = size(ieaData,1); % current ending row number
    for k = 1:numel(countries)

        % take out vectors for each sector

        idl = ieaData.sector == "4 electricity" & ieaData.country ==
 countries(k);
        el = ieaData{idl,"elAndHeat"};
        idl = ieaData.sector == "1 transport" & ieaData.country ==
 countries(k);
        transport = ieaData{idl,"elAndHeat"};
        idl = ieaData.sector == "2 industry" & ieaData.country ==
 countries(k);
        industry = ieaData{idl,"elAndHeat"};
        idl = ieaData.sector == "3 other" & ieaData.country == countries(k);
        other = ieaData{idl,"elAndHeat"};
        idl = ieaData.sector == "Total final consumption" & ieaData.country ==
 countries(k);
        totalConsumption = ieaData{idl,"elAndHeat"};

        % eiou is Energy industry own use + Losses = Elec - cons
        eiou = el - totalConsumption;
        % calculate shares (1x1) each
        trSh = transport / totalConsumption;
        inSh = industry / totalConsumption;
        otSh = other / totalConsumption;

        % stack to get (3x1) to use dot product
        sh = [trSh;inSh;otSh];
        eiouVector = repmat(eiou, 3,1);
```

```
        % matrix of electricity energy own use split across sectors
        eiouSectors = sh .* eiouVector;
        eiouRow = zeros(3,6);
        eiouRow(:,6) = eiouSectors;


        % and add row for transport
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
 rows
        newRow.sector = "eiou tr";
        newRow{1,3:end} = eiouRow(1,:);
        ieaData(endRow,:) = newRow;

        % industry
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
 rows
        newRow.sector = "eiou in";
        newRow{1,3:end} = eiouRow(2,:);
        ieaData(endRow,:) = newRow;

        % and other
        endRow = endRow + 1;
        newRow = ieaData(find(idl),:); % base on any of the current matching
 rows
        newRow.sector = "eiou ot";
        newRow{1,3:end} = eiouRow(3,:);
        ieaData(endRow,:) = newRow;

    end

    ieaDataSanity7 = ieaData;

    % Merging misc. with corresponding sectors and summing again
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'1 transport' 'eiou tr'}], "1 transport");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'2 industry' 'eiou in'}], "2 industry");
    ieaData.sector = mergecats(ieaData.sector, ...
        [{'3 other' 'eiou ot'}], "3 other");

    % omitnan is important since previous step gave 0/0 for some fuels in some
 regions
    ieaData = varfun(@(x) sum(x, "omitnan"), ieaData , "GroupingVariables",
["country" "sector"], ...
        "InputVariables",3:8);
    ieaData = removevars(ieaData, ["GroupCount" ]);
    ieaData = renamevars(ieaData, 3:8,
 ["coal" "oil" "natGas" "bio" "renew" "elAndHeat"]);

    ieaDataSanity8 = ieaData;

    %     Cleaning and deleting
```

```
    ieaData(ieaData.sector == "Total energy supply",:) = [];
    ieaData(ieaData.sector == "Total final consumption",:) = [];
    ieaData(ieaData.sector == "Energy industry own use",:) = [];
    ieaData(ieaData.sector == "misc",:) = [];
    ieaData.sector = removecats(ieaData.sector, ["Total energy supply" ...
        "Total final consumption" ...
        "Energy industry own use" ...
        "misc"]);

    % Unstacking to get sector-wise usage of each fuel (incl. electricity
    % as sector)
    ieaDataUnstacked = unstack(ieaData,
 ["coal" "oil" "natGas" "renew" "bio" "elAndHeat"], "sector");


    % Summing over fuel use in sectors to get total fuel use per country
    coalVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "coal", "IgnoreCase",true);
    oilVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "oil", "IgnoreCase",true);
    natGasVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "natGas", "IgnoreCase",true);
    bioVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "bio", "IgnoreCase",true);
    renewVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "renew", "IgnoreCase",true);
    elAndHeatVars =
 contains(ieaDataUnstacked.Properties.VariableNames(:), "elAndHeat", "IgnoreCase",true);

    ieaDataUnstacked.coal = sum(ieaDataUnstacked{:,coalVars},2);
    ieaDataUnstacked.oil = sum(ieaDataUnstacked{:,oilVars},2);
    ieaDataUnstacked.natGas = sum(ieaDataUnstacked{:,natGasVars},2);
    ieaDataUnstacked.bio = sum(ieaDataUnstacked{:,bioVars},2);
    ieaDataUnstacked.renew = sum(ieaDataUnstacked{:,renewVars},2);
    ieaDataUnstacked.elAndHeat = sum(ieaDataUnstacked{:,elAndHeatVars},2);


    save("wrangling.mat", "ieaData", "-append");
    save("wrangling.mat", "ieaDataUnstacked", "-append");
    %save("rawData.mat", "raw", "-append");
else
    load("wrangling.mat", "ieaData");
    load("wrangling.mat", "ieaDataUnstacked");
    %load("rawData.mat", "raw");
end

% END IEA WRANGLING
```

PWT TRANSPORT CAPITAL DETAIL DATA

```
% PWT data is only for transport equipent, while OECD has for the whole
% sector. I think we are better off extrapolating OECD data than using
% negatively biased PWT data.
```

```
% raw.pwtTransData = readtable("raw_data\pwt100-capital-detail.xlsx",
 Sheet="Data");
% pwtTransData = raw.pwtTransData(raw.pwtTransData.year == 2019,["countrycode"
 "Nc_Mach" "Nc_Struc" "Nc_TraEq" "Nc_Other"]);
% pwtTransData = categorizer(pwtTransData, 1);
% pwtTransData.capStock = pwtTransData.Nc_Mach + pwtTransData.Nc_Struc +
 pwtTransData.Nc_TraEq + pwtTransData.Nc_Other;
% pwtTransData.transCapShPWT = pwtTransData.Nc_TraEq ./ pwtTransData.capStock;
% pwtTransData = pwtTransData(:, ["countrycode" "transCapShPWT"]);

% END PWT TRANSPORT SHARE WRANGLING
```

OECD CAPITAL DETAILS DATA ()

```
if wrangle.OECD == 1

    raw.OECD = readtable("raw_data\oecd capital data.csv");
    oecdDataAll = raw.OECD(:,
["LOCATION" "Country" "Variable" "Industry" "Time" "Value"]);
    oecdDataAll = categorizer(oecdDataAll, 4);
    oecdDataAll = oecdDataAll(oecdDataAll.Variable == 'Net capital stock,
 volumes',:);



    % For sectors
    keep = [{'TOTAL'
        'Agriculture, hunting, forestry and fishing [A]'
        'Mining and quarrying [B]'
        'Manufacturing [C]'
        'Electricity, gas, steam and air conditioning supply [D]'
        'Water supply; sewerage, waste management and remediation activities
 [E]'
        'Construction [F]'
        'Wholesale and retail trade, repair of motor vehicles and motorcycles
 [G]'
        'Transportation and storage [H]'
        'Accommodation and food service activities [I]'
        'Information and communication [J]'
        'Financial and insurance activities [K]'
        'Real estate activities [L]'
        'Professional, scientific and technical activities [M]'
        'Administrative and support service activities [N]'
        'Public administration and defence; compulsory social security [O]'
        'Education [P]'
        'Human health and social work activities [Q]'
        'Arts, entertainment and recreation [R]'
        'Other service activities [S]'}];
    oecdData = oecdDataAll(ismember(oecdDataAll.Industry, keep),:);
    oecdData = renamevars(oecdData, ...
        ["LOCATION" "Country" "Industry" "Time"], ...
```

```
        ["countrycode" "country" "sector" "year"]);

    transportSector = [{'Transportation and storage [H]'}];
    industrySector = [{'Manufacturing [C]'}
        {'Construction [F]'}
        {'Mining and quarrying [B]'}
        {'Electricity, gas, steam and air conditioning supply [D]'}];
    otherSector = [{'Agriculture, hunting, forestry and fishing [A]'}
        {'Water supply; sewerage, waste management and remediation activities
[E]'}
        {'Wholesale and retail trade, repair of motor vehicles and motorcycles
[G]'}
        {'Accommodation and food service activities [I]'}
        {'Information and communication [J]'}
        {'Financial and insurance activities [K]'}
        {'Real estate activities [L]'}
        {'Professional, scientific and technical activities [M]'}
        {'Administrative and support service activities [N]'}
        {'Public administration and defence; compulsory social security [O]'}
        {'Education [P]'}
        {'Human health and social work activities [Q]'}
        {'Arts, entertainment and recreation [R]'}
        {'Other service activities [S]'}];

    oecdData.sector = mergecats(oecdData.sector, transportSector, "Transport
(and storage)");
    oecdData.sector = mergecats(oecdData.sector, industrySector, "Industry
(manufacturing and construction)");
    oecdData.sector = mergecats(oecdData.sector, otherSector, "Other");

    % Unstacking to get a variable per sector (a wider table, one country per
row)
    oecdData = unstack(oecdData,"Value","sector",...
        "VariableNamingRule","preserve");
    oecdData = renamevars(oecdData, ...
        ["Transport (and storage)" "Industry (manufacturing and
construction)" "Other" "TOTAL"], ...
        ["transCap" "indCap" "othCap" "totalCap"]);

    oecdData.transCapSh = oecdData.transCap ./ oecdData.totalCap;
    oecdData.indCapSh = oecdData.indCap ./ oecdData.totalCap;
    oecdData.othCapSh = 1 - oecdData.transCapSh - oecdData.indCapSh;
    oecdData.sanity = oecdData.transCapSh + oecdData.indCapSh +
oecdData.othCapSh;
    % Sanity check failed for several countries
    % Some are just missing "other" categories --> now using reciprocal
    % Delete Ireland and Israel. They are missing manufacturing.
    oecdData((oecdData.country == "Ireland" | oecdData.country == "Israel"),:)
= [];
    oecdData(isnan(oecdData.transCap),:) = [];

    % Manually keeping most recent data [XXX Automate]
    oecdData = oecdData([2 4 6 7 9 11 13 15 16 18 20 22 23 25 27 28 30 32 33
34 35 37 38 40 42 44 47 50 55],:);
```

```
    oecdData = oecdData(:,["countrycode" "transCapSh" "indCapSh" "othCapSh"]);

    save("wrangling.mat", "oecdData", "-append");
    %save("rawData.mat", "raw.OECD", "-append");
else
    load("wrangling.mat", "oecdData");
    %load("rawData.mat", "raw.OECD");
end
```

US BLS DETAILED CAPITAL DATA FOR FUEL CAPITAL USE

```
% Getting total capital in US coal/oil/gas production and refinement.

% if wrangle.USBLS == 1

raw_USBLS = readtable("raw_data\USBLS cap_details.xlsx", Sheet="Data",
 VariableNamesRange="A1", DataRange="A2");
usblsVars = ["sector" "type" "category" "unit" "value"];
usblsDataAll = renamevars(raw_USBLS,
 ["NAICSTitle" "MeasureTitle" "AssetCategory" "DurationTitle" "x2019"],
 usblsVars);
usblsDataAll = usblsDataAll(:,usblsVars);
usblsDataAll = categorizer(usblsDataAll,4);
% Note: Convert to 2017 dollars (PWT uses 2017)
usblsDataAll = usblsDataAll(usblsDataAll.type == "Productive capital stock
 (direct aggregate-billions of 2012 dollars)", :);
usblsDataAll = usblsDataAll(usblsDataAll.category == "All assets", :);
usblsDataAll = usblsDataAll(usblsDataAll.unit == "Levels", :);
usblsData = usblsDataAll( ...
    (usblsDataAll.sector == "Oil and gas extraction" | ...
    usblsDataAll.sector == "Mining, except oil and gas" | ...
    usblsDataAll.sector == "Petroleum and coal products" | ...
    usblsDataAll.sector == "Pipeline transportation"), :);

% The direct capital stock
% NOTE: This used PWT in millions, which is later changed to just ones.
usblsFossilCapSum = sum(usblsData.value); % In billions 2012 USD
usblsFossilCap = 1.0676 * usblsFossilCapSum; % In billions 2017 USD using
 https://www.in2013dollars.com/us/inflation/2012
usblsFossilCap = 1000 * usblsFossilCap; % PWT uses millions 2017 USD.
PWTcapUS = 69059088;
usblsFCsh = usblsFossilCap / PWTcapUS;
% About 5,8% of total US capital stock share of PWT. Seems high?

% Capital stock as share of total
usblsTotCap = sum([2620.40700000000;2913.24600000000; ...
    3198.02200000000;840.280000000000;6422.82200000000; ...
    5284.94200000000;1949.82800000000;3703.83500000000; ...
    2097.87400000000;7141.95100000000;1033.88200000000; ...
    753.843000000000;519.944000000000;908.600000000000; ...
    1886.45500000000;300.480000000000]);
```

```
usblsTotCap = usblsTotCap * 1067,6;
usblsGovCap = 18739.076 * 1067,6;

usblsCapSh = usblsFossilCap / (usblsTotCap+usblsGovCap);
% This method gave 9% of total capital share. Maybe this data only
% has private sector?
% Added government, now it is 6,2% of total capital.
% Average of 5,8% and 6,2% is 6%. Six percent of total capital
% should go to fossil fuel extraction. This gives \bar(K), which
% must be subtracted from capital in indstry to avoid double
% counting


%     save("calibData.mat", "usblsFossilCap", "-append");
% else
%     load("calibData.mat", "usblsFossilCap");
% end
```

CHINA CAPITAL DETAILS

Manually extracted 2019 capital data from China Statistical Yearbook 2020 The following sectors: 'Mining and Washing of Coal' 'Extraction of Petroleum and Natural Gas' 'Professional and Support Activities for Mining' 'Processing of Petroleum, Coal and Other Fuels'

```
raw_ChinaCapDetails = readtable("raw_data\china capital details.csv");
chinaCapData = categorizer(raw_ChinaCapDetails, 1);
chinaCapData.capStock = chinaCapData.totalAssets - chinaCapData.currentAssets;
chinaCapIndTotal = chinaCapData{1,"capStock"}; % 100 million 2019 Yuan
chinaCapFossil = sum(chinaCapData{2:5, "capStock"}); % 100 million 2019 Yuan
chinaCapFossil = chinaCapFossil * 100; % To million 2019 Yuan
chinaCapFossil = chinaCapFossil / PWT{PWT.countrycode == "CHN", "xr"} ; %
 Converted from million 2019 Yuan to million 2019 USD
chinaCapFossil = 0.96 * chinaCapFossil; % To 2017 USD
chinaCapFossilSh = chinaCapFossil / PWT{PWT.countrycode == "CHN", "cn"};
% constists of 1% of total capital.

% Total assets method
chinaTotalAssetsFossil = sum(chinaCapData.totalAssets(2:5));
chinaTotalAssetsFossil = (chinaTotalAssetsFossil * 100  * 0.96) /
 PWT{PWT.countrycode == "CHN", "xr"};
chinaCapShTotAsSh = chinaTotalAssetsFossil / PWT{PWT.countrycode
 == "CHN", "cn"};
% this method gives 1.55% --> I use this one.
% Implies Russia 3%


% RUSSIA:
% https://www.investopedia.com/articles/markets/082615/5-biggest-russian-
natural-gas-companies.asp
% Got total assets from there
```

PART 2: COMBINING PRE-PROCESSED DATA INTO USABLE SPREADSHEETS FOR CALIBRATION %%

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%
```

MERGING FOR FINAL GOOD SECTORS CALIBRATION

Combining data: PWT, UN, WIOD, ILOSTAT, OECD

```
if wrangle.sectors == 1

   % WIOD/UN MERGE
   finalGoodSectors = outerjoin(wiodData, unData, Keys="countrycode",
 MergeKeys=true);

   % Manually merging variables (XXX Could automate or shorten?)
   % Year variables
   isUndefined = isundefined(finalGoodSectors.year_wiodData);
   finalGoodSectors.year_wiodData(isUndefined) =
 finalGoodSectors.year_unData(isUndefined);
   finalGoodSectors(:,"year_unData") = [];
   % Sector variables
   isUndefined = isundefined(finalGoodSectors.sector_wiodData);
   finalGoodSectors.sector_wiodData(isUndefined) =
 finalGoodSectors.sector_unData(isUndefined);
   finalGoodSectors(:,"sector_unData") = [];
   % Value variables
   isUndefined = isnan(finalGoodSectors.sum_value_wiodData); % Numbers use
 NAN, categories <undefined>
   finalGoodSectors.sum_value_wiodData(isUndefined) =
 finalGoodSectors.sum_value_unData(isUndefined);
   finalGoodSectors(:,"sum_value_unData") = [];
   % Renaming variables to tidy up
   finalGoodSectors = renamevars(finalGoodSectors,
["country_unData" "year_wiodData" "sector_wiodData" "sum_value_wiodData"], ...
        ["country" "year" "sector" "output"]);



   % Exporting list of countries with missing sector data
   countriesWithoutSectors =
 [finalGoodSectors.country(isnan(finalGoodSectors.output))
 finalGoodSectors.countrycode(isnan(finalGoodSectors.output))];

   % For now, I 'm just dropping the small countries for which there is no
   % PWT data.
```

```
   finalGoodSectors(isundefined(finalGoodSectors.countrycode),:) = [];

   % Unstacking sectorData to get a variable per sector (a wider table)
   finalGoodSectors = unstack(finalGoodSectors,"output","sector",...

 "AggregationFunction",@(x)x(~isempty(x)),"VariableNamingRule","preserve");


   % Getting sectors as shares of output
   finalGoodSectors.totalShare = finalGoodSectors{:,"Total Economy"} ./
finalGoodSectors{:,"Total Economy"};
   finalGoodSectors.transportShare = finalGoodSectors{:,"Transport (and
storage)"} ./ finalGoodSectors{:,"Total Economy"};
   finalGoodSectors.industryShare = finalGoodSectors{:,"Industry
(manufacturing and construction)"} ./ finalGoodSectors{:,"Total Economy"};
   finalGoodSectors.otherShare = finalGoodSectors.totalShare -
finalGoodSectors.transportShare - finalGoodSectors.industryShare; % As
reciprocial because poor data
   finalGoodSectors.sanityShare = finalGoodSectors.industryShare +
finalGoodSectors.transportShare + finalGoodSectors.otherShare;
   %              % Some countries do not sum to unity if reciprocal method
isn't
   %              % used
   %              poorDataCountries = sectorData(sectorData.sanityShare <
0.9,:);
   %              goodDataCountries = sectorData(sectorData.sanityShare >
0.99,:);
   %              poorDataSum = summary(poorDataCountries);
   %              goodDataSum = summary(goodDataCountries);


   % Doing single year to use 2019 only (and 2014 for those few WIOD
   % countries). Full data: 2019 has 114 countries, 2018 125, 2017 130.
   % NOTABLE missing shares from 2019:
   %   Canada, Egypt, Japan, Korea, Philippines, UK
   % Missing shares if 2018:
   %   Canada, Egypt, Phillipines
   % If 2017:
   %   Egypt, Phillipines (non-recoverable
   % I choose 2019 as base year, but use older data for those with no
   % 2019 data. NOTE: Year 9999 are missing countries from UN, but kept for
   % regional extrapolation.
   finalGoodSectors = finalGoodSectors( ...
       (finalGoodSectors.year == "2014" | ...
       finalGoodSectors.year == "2019" | ...
       finalGoodSectors.year == "9999" | ...
       finalGoodSectors.country == "Japan" | ...
       finalGoodSectors.country == "Canada" | ...
       finalGoodSectors.country == "United Kingdom" | ...
       finalGoodSectors.country == "Republic of Korea" | ...
       finalGoodSectors.country == "Yemen"),:);
   finalGoodSectors((finalGoodSectors.country == "Japan" &
(finalGoodSectors.year == "2017" | isnan(finalGoodSectors.otherShare))), :) =
[];
```

```
    finalGoodSectors((finalGoodSectors.country == "Republic of Korea" &
 (finalGoodSectors.year == "2017" | isnan(finalGoodSectors.otherShare))), :) =
 [];
    finalGoodSectors((finalGoodSectors.country == "United Kingdom" &
 (finalGoodSectors.year == "2017" | isnan(finalGoodSectors.otherShare))), :) =
 [];
    finalGoodSectors((finalGoodSectors.country == "Canada" &
 isnan(finalGoodSectors.otherShare)),:) = [];
    finalGoodSectors((finalGoodSectors.country == "Yemen" &
 isnan(finalGoodSectors.otherShare)),:) = [];

    %sectorData = sectorData((sectorData.year == "2014" | sectorData.year ==
 "2018"),:);
    %sectorData = sectorData(sectorData.sector == 'Total Economy',:);

    % Keeping only needed vars (dropping year, even if not all ==2019.
    % See previous point).
    finalGoodSectors = finalGoodSectors(:,
["countrycode" "country" "rice_code" "rice_region" "transportShare" "industryShare" "other

    % GDP, CAPITAL, EMPLOYMENT MERGE FROM PWT
    finalGoodSectors =
 outerjoin(finalGoodSectors,PWT,"Keys","countrycode","MergeKeys",true);
    finalGoodSectors = finalGoodSectors(:,
["country_PWT" "countrycode" "rice_code_PWT" "rice_region_PWT"  ...

  "thesisCode" "cgdpo" "cn" "emp" "transportShare" "industryShare" "otherShare" "labsh" "l
    finalGoodSectors = renamevars(finalGoodSectors,
 ["country_PWT" "rice_code_PWT" "rice_region_PWT"],
 ["country" "rice_code" "rice_region"]);

    % MERGING WITH ILOSTAT ALSO
    finalGoodSectors = outerjoin(finalGoodSectors, ilostatData);
    %sectorLabor.Sanity = sectorLabor.otherLabSh + sectorLabor.industryLabSh +
 sectorLabor.transportLabSh;
    % sanity check passed

    finalGoodSectorsSanity = finalGoodSectors;

    % Deleting small countries without PWT data

 finalGoodSectors(isundefined(finalGoodSectors.country_finalGoodSectors), :) =
 [];

    %sectorData = removevars(sectorData, "country_ilostatData");

    % MERGING WITH OECD CAPITAL SHARE DATA
    finalGoodSectors = outerjoin(finalGoodSectors,oecdData);
    finalGoodSectors = renamevars(finalGoodSectors, ...
        ["country_finalGoodSectors" "countrycode_finalGoodSectors"], ...
        ["country" "countrycode"]);
```

```
    % MERGING WITH PWT CAPITAL IN TRANSPORT DATA
    %     sectorData = outerjoin(sectorData,pwtTransData);
    %     sectorData = renamevars(sectorData, "countrycode_sectorData",
 "countrycode");
    %     sectorData.tranSanity = sectorData.transCapSh -
 sectorData.transCapShPWT;
    % Sanity check failed. OECD >> PWT. Off by up to 10 percetage points.
    % PWT data is only for 'transport equipment', OECD has all capital in
    % the sector which could include more than just the equipment.
    % Conclusion: Dropping PWT data.

    %     % MERGING WITH IEA VOLUME DATA
    %     sectorDataWithIEA = outerjoin(sectorData, ieaDataUnstacked);
    %
    % MERGING WITH REGION CODES
    finalGoodSectors = outerjoin(finalGoodSectors, countriesPWTRICE,
 Keys="countrycode", MergeKeys=true);


    % Deleting small countries without PWT data
    %sectorData(isundefined(sectorData.country_sectorData), :) = [];

    %sectorData = removevars(sectorData, ["country"]);
    finalGoodSectors = renamevars(finalGoodSectors,  ...

 ["country_finalGoodSectors" "rice_code_finalGoodSectors" "rice_region_finalGoodSectors" "
        ["country" "rice_code" "rice_region" "thesisCode"]);
    finalGoodSectors = sortrows(finalGoodSectors, "countrycode");

    finalGoodSectors = sortrows(finalGoodSectors, "countrycode", "ascend");

    sectorDataPreInterpol = finalGoodSectors;


    save("calibData.mat", "sectorDataPreInterpol", "-append");
else
    load("calibData.mat", "sectorDataPreInterpol");

end
```

MERGING AND PREPARING INTERMEDIATE AND REFINED ENERGY SECTORS

Data: IEA

```
if wrangle.energy == 1
    valueset = 1:4;
    catnames = {'transport','industry','other', 'electricity'};

    energyData = outerjoin(countriesPWTRICE, ieaData);

    energyDataSanity = energyData;
```

```
    energyData(isundefined(energyData.countrycode),:) = [];
    energyData(isnan(energyData.coal),:) = [];
    energyData.sector = string(energyData.sector);
    energyData = sortrows(energyData, ["countrycode" "sector"], "ascend");

    %sizes2 = categorical(A2,valueset,catnames,'Ordinal',true)

    energyDataUnstacked = outerjoin(countriesPWTRICE, ieaDataUnstacked);
    energyDataUnstacked(isundefined(energyDataUnstacked.countrycode),:) = [];
  % Countries with no PWT data.
    energyDataUnstacked =
 sortrows(energyDataUnstacked, "countrycode", "ascend");
    energyDataUnstacked(isnan(energyDataUnstacked.coal),:) = []; % Countries
 with no IEA data

    save("calibData.mat", "energyData", "-append");
    save("calibData.mat", "energyDataUnstacked", "-append");
else
    load("calibData.mat", "energyData", "energyDataUnstacked");

end
```

MERGING INTO ONE BIG SHEET

```
wrangledData = outerjoin(finalGoodSectors, energyDataUnstacked,
 Keys="countrycode");
```

Functions %%

```
%%%%%%%%%%%%%%%

% Changes table variables to category-type. Easier to work with.
function tab = categorizer(tabInput, numOfVars)
for i = 1:numOfVars
    tabInput =
 convertvars(tabInput,tabInput.Properties.VariableNames{i},'categorical');
end
tab = tabInput;
end
```

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Appendix F

Calibration script

Table of Contents


```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% ACE native production system
%
% last edited 05/24/22
% ANDREAS SYNC CHECK 16:22 CT 5:01
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% README %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%
% - Required add-ons: Statistical and Machine learning package (for regress
 function) %
% - Pick correct region before running code, at first headline in SETUP.
        %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%

% MATRIX ORDERS %%%
%
% a) Sectors are ALWAYS ordered (1) Transport (2) Industry (3) Other
%
% b) Fuels are ordered
% EITHER
% Coal, oil, natgas, bio, renew [into elec]
% OR
% Coal, oil, natgas, bio, elect [into int (d)]
% so it is the fifth input that changes.
%
% c) *Regions* are always columns, while *sectors* or *fuels* are rows.

% Table of contents
% 1. Setup (load data, set code logicals, pick region and substitutabilities)
```

```
% 2. Growth rate calculations
% 3. Missing data interpolations
% 4. Regional aggregation
% 5. Calibration input data read-in
% 6. Calibration calculations
% 7. Production calculations

% LOADED DATASETS
% pwtDynamic: Used for growth rates. PWT 2010-2019.
% finalGoods Data: Final good sectors. PWT, UN, WIOD, OECD, ILOSTAT.
% energyData: IEA energy data (matrix form, 4 rows per country)
% energyDataUnstacked: IEA energy data (one row per country, wider)
% wPriceLevel: Vector of regional price levels for thesis

% CALIBRATION INPUT TABLE NAMES (Interpolated and regionalized)
% growthRates = Regional growth rates [XXX and World coming]
% finalGoods = Regional final good sector
% energyMatrix & energy = energy data in matrix and one-row form, resp.

% UNITS (after conversions)
% Final good sector: Real GDP (in PPP 2017USD) -- NOTE: Original PWT is in
 millions. This is just in ones.
% Energy: Terajoules (can consider Megajoules instead)
% Emissions: kg CO2
% Price of energy: USD/TJ (PPP)
% Price of emissions: USD/kg

% Notes:
% - all production parameters are in the prod structure, e.g.: prod.a_fin,
 prod.alpha_fin
% - all calibration inputs are in the calib structure.
% - initial state values are initial.

% Code is called by RegionalACE, requiring calibrate_calculate being defined:
% = 1 : calibration
% = 2 : calculation
% = 3 : both (if using file as stand-alone, uncomment next line)
%clear all; calibrate_calculate = 3; recycle_mat_files = 0;

% NOTE CT:
%
%  Overwritten alpha in the main code by hand for the moment subracting
 nu*alpha_bar
%


if calibrate_calculate == 1 | 3
```

1. SETUP

```
    %clear all
    %clc
```

```
    if recycle_mat_files == 0

        load('calibData.mat'); % Data import from wrangling.m

        prod.structure = 'ACE native';
        production.gr = 1;
        production.interpolate = 1;
        production.regionalize = 1;
        production.calibration_input=1; % Initialize parameters and variables
with data input
        production.coefficients=1; % to calibrate the production system
        %production.calculation=1; % to use the file for simulating production

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Remove comment for selected region %
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        regionSelected = "thesisCode"; % 0 is WORLD, 1 is LOW, 2 is HIGH
        %regionSelected = "rice_code"; % NOTE: Will be biased until alpha bar
and prices are RICE-regionalized
        %regionSelected = "country_code"; % NOTE: Will not work until
correspondance between IEA data and rest is sorted.

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Substitutabiity parameters in different sectors: %
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % World parameters
        prod.agg_s = -1; % Subst. at aggregation level
        prod.agg_sbar = 1; % Returns to scale
        prod.int_s = [-4 -.0001 .1667]';  % Subst. energy intermediate sectors
        prod.int_s_0 = .444; % Subst. in electricity production


        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Avg. Fossil industry capital share of total capital %
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Used to get alpha bars, which are extrapolated
        fossilCapShareUS = 0.055; % Source USBLS (2019 data), China, Russia
        fossilCapShareCHN = 0.0155; % Source Chn. stat. yearbook 2020.
        fossilCapShareRUS = 0.03; % Source various.

        %%%%%%%%%%%%%
        % Alpha bar %
        %%%%%%%%%%%%%
        % US alpha bar: 0.7723 (based on 5.5% capital)
        % Chinese: 0.283 (1.55%)
        % Russian: 0.469 (3%)
        alphaBarH = 0.712 % 80/20 avg of US and Russia
        alphaBarL = 0.283 % Chinese data.
        alphaBarH = 0.1
        alphaBarL = 0.05
        alphaBarW = 0.8*alphaBarH + 0.2*alphaBarL; % Weighed by share of total
fossil.
```

```
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % CO2 coefficients per fuel type %
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % CO2 emissions should be in kg per TJ
        % [Coal, oil, gas, bio, renew]'
        co2Factors = [90762.95;
            69247.51;
            50148.00;
            3462.38;
            0];

        % Observed emissions correction (IEA = 33.2 Gt)
        co2Factors = co2Factors .* 1.0463;

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Average world refined energy prices %
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Original units %%%
        % Coal:               83.16 USD per million tonne
        % Oil prodcuts:       71.64 USD per barrel
        % Nat. gas:           3.13 USD per million Btu
        % Bio (ethanol):      1.25 USD per gallon
        % Bio (biodiesel):    800 USD per ton
        % Bio (wood pell):    166.25 per ton
        % Renew:              0,055 USD/kWh

        % 1 short ton = 0.90718474 tonne

        % Conversion factors (https://www.justintools.com/unit-conversion/
energy.php)
        % COAL
        % 1 Tonne of coal equivalent =  0.029288 TJ
        % OIL PRODUCTS
        % Barrel to tonnes (oil products basket) = 0.124.       BP Conversion
 factors
        % Tonne to gigajoule (oil products basket) = 43.076     BP Conversion
 factors
        % Gigajoule to terajoule = 0.001
        % ===> 1 barrel = 0.005341424 TJ
        % NATURAL GAS
        % 1 000 000 Btu = 0.00105505585 TJ
        % BIO
        % Ethanol: 80000 Btu per gallon whivh gives 8.440448E-5 TJ
        % Biodiesel: 1 t biodiesel = 0,86 toe which is 0.03600648 TJ
        % Pellets: 1 t pellets = 5 MWh = 0.018 TJ
        % RENEW:
        % 1 kWh = 3.6E-6 TJ


        % Converting idiosyncratic units to USD/TJ
        price.coal = 83.16/0.029288;
        price.oil = 71.64/0.005341424;
        price.natGas = 3.13/0.00105505585;
        %price.bioE = 1.3/8.440448E-5;
```

```
        %price.bioD = 850 / 0.03600648;
        price.bioW = 166.25 / 0.018;
        price.renew = 0.055 / 3.6E-6;

        % Vector of refined energy prices
        enePricesWorld = [
            price.coal;
            price.oil;
            price.natGas;
            price.bioW;
            price.renew
            ];

        % Electricity = price of renewables
        elPriceWorld = price.renew;

        % Setting prices for the two thesis regions
        enePricesHigh = enePricesWorld;
        elPriceHigh = elPriceWorld;
        % bioenergy price half in low-income countries
        enePricesLow = enePricesHigh .* [1 1 1 .5 1]';
        elPriceLow = elPriceHigh;

        % Merging, converting from 2019 to 2017 and adjusting for PPP
        % Energy
        enePrices = [enePricesWorld enePricesLow enePricesHigh]; % regional
matrix
        enePrices = enePrices .* 0.9588; % Inflation adjustment
        enePrices = enePrices ./ wPriceLevel'; % PPP correction
        % Electricity
        elPrices = [elPriceWorld elPriceLow  elPriceHigh]; % Nominal 2019 USD.
Row, one price for each region.
        elPrices = elPrices .* 0.9588 ; % Inflation adjusted. Row, one price
for each region.
        elPrices = elPrices ./ wPriceLevel'; % PPP adjusted 2017 USD.

        %%%%%%%%%%%%%%%%%%%%
        % Emissions prices %
        %%%%%%%%%%%%%%%%%%%%

        % Finding world average emissions price
        emCoverage = 0.145; % World Bank estimate coverage rate
        emPriceCovered = 2.74887 % Weighted avg price of covered emissions, in
2017USD per TONNE co2
        emPriceCovered = emPriceCovered / 1000; % to per kg co2 (emissions
factors are in kg per TJ)
        emPriceWorld = emCoverage * emPriceCovered; % Avg world emissions
price.

        % Setting emissions prices for two-region model
        emPriceL = 0; % No price initiatives in these countries
        emPriceH = emPriceWorld / 0.807; % 80.7 percent of tot. emissions are
in H.
```

```
        % Collecting and adjusting for PPP
        emPrices = [emPriceWorld emPriceL emPriceH;] % In USD/tCO2 - row
 vector
        emPricesKG = emPrices .* wPriceLevel'; % PPP adjusted (kg CO2)
        % Need same units as ene prices, for additivity.
        % This is a matrix: rows are fuels, columns are regions
        %emPricesTJ = co2Factors * emPrices;  % In nom USD/TJ, for PPP
 sensitivity check
        emPricesTJ =  co2Factors * emPricesKG; % in PPP USD/TJ


        % end setup
```

GROWTH RATES

(1) Takes pwtDynamic as input (2) Groups data into regions (3) Calculates growth rates for GDP and capital per region (4) Adds world growth rate on top of table (5) "growthRates" is output table (region 0 is World)

```
        if production.gr == 1
            % Aggregates GDP and capital over regions for each year and takes
 log transformations.
            % Runs a regression of logvars on constant and year to get avg.
 yearly growth rates.

            pwtDynamicRegional = varfun(@(x) sum(x, "omitnan"),
 pwtDynamic, 'InputVariables' , ...
                ["cgdpo" "cn"] , 'GroupingVariables' ,
 [regionSelected "year"]);
            logs = varfun(@log, pwtDynamicRegional,"InputVariables",
["Fun_cgdpo" "Fun_cn"]);
            pwtDynamicRegional = [pwtDynamicRegional logs];
            reg_gdp = varfun(@(x) regress(x, [ones(10,1)
 unique(pwtDynamicRegional.year)]), ...
                pwtDynamicRegional, 'InputVariables' , 'log_Fun_cgdpo'
 , 'GroupingVariables' , regionSelected);
            %       pwtDynamicRegional, InputVariables="log_Fun_cgdpo",
 GroupingVariables=regionSelected);
            reg_cap =varfun(@(x) regress(x, [ones(10,1)
 unique(pwtDynamicRegional.year)]), ...
                pwtDynamicRegional, 'InputVariables' , 'log_Fun_cn'
 , 'GroupingVariables' , regionSelected);
            %       pwtDynamicRegional, InputVariables="log_Fun_cn",
 GroupingVariables=regionSelected);
            gr_gdp = reg_gdp(2:2:end, :);
            gr_cap = reg_cap(2:2:end, :);
            growthRates = join(gr_gdp,gr_cap);

            % World
            %    pwtDynamicWorld = varfun(@(x) sum(x, "omitnan"), pwtDynamic,
 InputVariables=["cgdpo" "cn"], GroupingVariables="year");
            pwtDynamicWorld = varfun(@(x) sum(x, "omitnan"),
 pwtDynamic, 'InputVariables' , ["cgdpo" "cn"] , 'GroupingVariables'
 , 'year');
```

```
            logs = varfun(@log, pwtDynamicWorld,"InputVariables",
["Fun_cgdpo" "Fun_cn"]);
            pwtDynamicWorld = [pwtDynamicWorld logs];
            reg_gdpW = regress(pwtDynamicWorld.log_Fun_cgdpo, [ones(10,1)
 unique(pwtDynamicWorld.year)]);
            reg_capW = regress(pwtDynamicWorld.log_Fun_cn, [ones(10,1)
 unique(pwtDynamicWorld.year)])
            growthRatesWorld = [reg_gdpW(2) reg_capW(2)];

            newRow = growthRates(1,:);
            newRow{1,regionSelected} = categorical(0);
            newRow{1,3:4} = growthRatesWorld;

            growthRates = [newRow; growthRates];

        end % growth rate calculations
```

MISSING DATA INTERPOLATION IN FINAL GOOD SECTOR DATA

I use the regional averages to interpolate missing country-level data. This code interpolates over RICE regions, but it is possible to use other regions (after some cumbersome re-coding)

```
        if production.interpolate == 1

            % Saving an untouched version
            finalGoodsData = sectorDataPreInterpol;

            % Finding GDP per capital stock and GDP per worker to use for
            % extrapolation
            finalGoodsData.capPerGdp = finalGoodsData{:,"cn"} ./
 finalGoodsData{:,"cgdpo"};
            finalGoodsData.empPerGdp = finalGoodsData{:,"emp"} ./
 finalGoodsData{:,"cgdpo"};

            % Finding mean of sectors in each region
            sectorDataRegionsMean = varfun(@(x) mean(x,'omitnan'),
 finalGoodsData, ...
                'GroupingVariables' , ["rice_region" "rice_code"], ...
                'InputVariables' , [ ...
                "cgdpo" ...
                "cn" ...
                "emp" ...
                "capPerGdp" ...
                "empPerGdp" ...
                "transportShare" ...
                "industryShare" ...
                "otherShare" ...
                "transportLabSh" ...
                "industryLabSh" ...
                "otherLabSh" ...
                "transCapSh" ...
```

```
                "indCapSh" ...
                "othCapSh" ...
                "labsh"]);
            %       "othCapSh"]);  and above:
            %        GroupingVariables=["rice_region" "rice_code"], ...
            %        InputVariables=[ ...

            % Applying regional mean shares to countries without sectoral data

            % Missing GDP shares
            for i = 1:12
                if ~isempty(finalGoodsData((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.transportShare)),:))
                    % Filling in missing GDP shares from regional mean
                    finalGoodsData.transportShare((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.transportShare))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_transportShare"};
                    finalGoodsData.industryShare((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.industryShare))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_industryShare"};
                    finalGoodsData.otherShare((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.otherShare))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_otherShare"};
                else
                    disp(i)
                end
            end

            % Missing capital data
            for i = 1:12
                if ~isempty(finalGoodsData((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.cn)),:))
                    % Filling in missing capital data from cap/gdp mean
                    % extrapolation of regional mean
                    finalGoodsData.capPerGdp((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.capPerGdp))) = ...
                        ectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_capPerGdp"};
                    % Getting capital and labor from gdp*(x/gdp) [last
fraction is regional mean]
                    finalGoodsData.cn((finalGoodsData.rice_code == string(i) &
isnan(finalGoodsData.cn))) = ...
                        finalGoodsData.cgdpo((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.cn))) .* ...
                    finalGoodsData.capPerGdp((finalGoodsData.rice_code ==
string(i) & ...
                        isnan(finalGoodsData.cn)));
                else
                    disp(i)
                end
            end
```

```
            % Missing emp data
            for i = 1:12
                if ~isempty(finalGoodsData((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.emp)),:))
                    % Filling in missing labor data from emp/gdp mean
                    % extrapolation of regional mean
                    finalGoodsData.empPerGdp((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.empPerGdp))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_empPerGdp"};
                    % Getting capital and labor from gdp*(x/gdp) [last
fraction is regional mean]
                    finalGoodsData.emp((finalGoodsData.rice_code == string(i)
& isnan(finalGoodsData.emp))) = ...
                        finalGoodsData.cgdpo((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.emp))) .*...
                    finalGoodsData.empPerGdp((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.emp)));
                else
                    disp(i)
                end
            end

            % Missing labor share in sectors data
            for i = 1:12
                if ~isempty(finalGoodsData((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.transportLabSh)),:))
                    % Filling in missing labor shares from regional mean
                    finalGoodsData.transportLabSh((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.transportLabSh))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_transportLabSh"};
                    finalGoodsData.industryLabSh((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.industryLabSh))) = ...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_industryLabSh"};
                    finalGoodsData.otherLabSh((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.otherLabSh))) =...
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_otherLabSh"};
                else
                    disp(i)
                end
            end

            % Missing labor share of GDP data
            for i = 1:12
                if ~isempty(finalGoodsData((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.labsh)),:))
                    % Filling in missing labor shares from regional mean
                    finalGoodsData.labsh((finalGoodsData.rice_code ==
string(i) & isnan(finalGoodsData.labsh))) =...
```

```
                        sectorDataRegionsMean{sectorDataRegionsMean.rice_code
== string(i),"Fun_labsh"};
                else
                    disp(i)
                end
            end

            % Getting capital share of GDP as extensive variable preparing for
regional aggregation
            finalGoodsData.capPropExtPWT = finalGoodsData.cgdpo .* (1 -
finalGoodsData.labsh);

            % Missing capital share data. For now, all NaNs get the OECD
average, irrespective of region
            finalGoodsData.transCapSh(isnan(finalGoodsData.transCapSh)) =
mean(finalGoodsData.transCapSh, "omitnan");
            finalGoodsData.indCapSh(isnan(finalGoodsData.indCapSh)) =
mean(finalGoodsData.indCapSh, "omitnan");
            finalGoodsData.othCapSh(isnan(finalGoodsData.othCapSh)) =
mean(finalGoodsData.othCapSh, "omitnan");

            finalGoodsData = sortrows(finalGoodsData,'rice_code','ascend');

            % Getting nominal value added instead of shares of output
            finalGoodsData.transVA = finalGoodsData{:,"transportShare"} .*
finalGoodsData{:,"cgdpo"};
            finalGoodsData.indVA = finalGoodsData{:,"industryShare"} .*
finalGoodsData{:,"cgdpo"};
            finalGoodsData.othVA = finalGoodsData{:,"otherShare"} .*
finalGoodsData{:,"cgdpo"};
            %sectorData.sanity = sectorData.transVA + sectorData.indVA +
sectorData.othVA - sectorData.cgdpo;
            %  sanity check passed
            %sectorData.Sanity = sectorData.otherLabSh +
sectorData.industryLabSh + sectorData.transportLabSh;
            % sanity check passed

            % Getting number employed in sector instead of fraction
            finalGoodsData.transLab = finalGoodsData{:,"transportLabSh"} .*
finalGoodsData{:,"emp"} / 100;
            finalGoodsData.indLab = finalGoodsData{:,"industryLabSh"} .*
finalGoodsData{:,"emp"} / 100;
            finalGoodsData.othLab = finalGoodsData{:,"otherLabSh"} .*
finalGoodsData{:,"emp"} / 100;
            %sectorData.sanityLab = sectorData.emp -sectorData.transLab -
sectorData.indLab - sectorData.othLab;
            % sanity check passed

            % Getting capital value instead of shares
            finalGoodsData.transCap = finalGoodsData{:,"transCapSh"} .*
finalGoodsData{:,"cn"};
            finalGoodsData.indCap = finalGoodsData{:,"indCapSh"} .*
finalGoodsData{:,"cn"};
```

```
            finalGoodsData.othCap = finalGoodsData{:,"othCapSh"} .*
finalGoodsData{:,"cn"};
            %sectorData.sanityLab = sectorData.cn - sectorData.transCap -
sectorData.indCap - sectorData.othCap;
            % sanity check passed

        end %interpolation
```

REGIONAL AGGREGATION (of levels)

This section takes country level macro and energy data and aggregates it into regions. Region 0 is World. For thesis, region 1 is Poor and 2 is Rich.

```
        if production.regionalize == 1

            % For pre-aggregation deletion of share variables
            notShareVars =
~contains(finalGoodsData.Properties.VariableNames(:), "Sh");

            %%%%%%%%%
            % WORLD %
            %%%%%%%%%

            regionCode = categorical("0");
            GroupCount = 1;

            % Final good sectors
            finalGoodsWorld = finalGoodsData(:,notShareVars);
            finalGoodsWorld = varfun(@(x) sum(x, "omitnan"),
finalGoodsWorld, ...
                "InputVariables", @isnumeric);
            finalGoodsWorld = addvars(finalGoodsWorld, regionCode,
GroupCount, 'Before', 1);

            % Energy unstacked (Whole region in one row)
            energyWorld = varfun(@(x) sum(x, "omitnan"),
energyDataUnstacked, ...
                "InputVariables", @isnumeric);
            energyWorld = addvars(energyWorld, regionCode,
GroupCount, 'Before', 1);

            % Energy stacked (Four rows per region)
            energyWorldStacked = varfun(@(x) sum(x, 'omitnan'),
energyData, ...
                "InputVariables",@isnumeric, "GroupingVariables",["sector"]);
            energyWorldStacked.regionCode(:) = regionCode;
            energyWorldStacked.GroupCount(:) = GroupCount;
            energyWorldStacked = movevars(energyWorldStacked, ...
                ["regionCode" "GroupCount"], 'Before', 1);

            %%%%%%%%%%%
            % REGIONS %
            %%%%%%%%%%%
```

```
            % Final good sectors
            finalGoodsRegional = finalGoodsData(:,notShareVars);
            finalGoodsRegional = varfun(@(x) sum(x, "omitnan"),
 finalGoodsRegional, ...
                "InputVariables", @isnumeric, 'GroupingVariables' ,
 [regionSelected]);
            %"InputVariables", @isnumeric,
 GroupingVariables=[regionSelected]);
            finalGoodsRegional.Properties.VariableNames(1) = "regionCode";

            % Energy unstacked (Whole region in one row)
            energyRegional = varfun(@(x) sum(x, "omitnan"),
 energyDataUnstacked, ...
                "InputVariables", @isnumeric, "GroupingVariables",
[regionSelected]);
            energyRegional.Properties.VariableNames(1) = "regionCode";

            % Energy stacked (Four rows per region)
            energyRegionalStacked = varfun(@(x) sum(x, 'omitnan'),
 energyData, ...
                "InputVariables",@isnumeric, "GroupingVariables",
[regionSelected "sector"]);
            energyRegionalStacked.Properties.VariableNames(1) = "regionCode";


            finalGoods = [finalGoodsWorld;finalGoodsRegional];
            finalGoods.capShPWT = finalGoods.Fun_capPropExtPWT ./
 finalGoods.Fun_cgdpo;




            energy = [energyWorld;energyRegional];
            energyMatrix = [energyWorldStacked;energyRegionalStacked];

            % Adding total fuel use
            energy.totalFossil = energy.Fun_coal + energy.Fun_oil +
 energy.Fun_natGas;
            energy.totalPrimary = energy.Fun_coal + energy.Fun_oil +
 energy.Fun_natGas + ...
                energy.Fun_bio + energy.Fun_renew;

            if regionSelected == "thesisCode"
                % Manually appending bunkers to thesis emissions, since this
 data was made available right before the deadline.
                energy.Fun_oil_x1Transport = energy.Fun_oil_x1Transport +
 [1.8E+07; 0.3E+07; 1.5E+07];
                energy.Fun_oil = energy.Fun_oil + [1.8E+07; 0.3E+07; 1.5E+07];
            end

        end % region making
```

Calibration read-ins (bottom-->top)

This section takes cleaned and regionalized data and reads it into vectors used for parameter calibration and model initialization

```
        if production.calibration_input == 1

            % Loops over all regions
            numOfRegions = size(finalGoods, 1);
            for i = 1:numOfRegions

                % CO2Factors
                prod.co2Factors(:,i) = co2Factors;

                % REFINED ENERGY SECTOR: prices and energy volumes
                % Rows: Energy sector. Column: Region.
                if regionSelected == "thesisCode"
                    % (p^e) (5x1) vector [coal; oil; natGas; bio; renew]
                    calib.price_ene_e(:,i) = enePrices(:,i) +
 emPricesTJ(:,i); % PPP USD/TJ
                elseif regionSelected == "rice_code"
                    calib.price_ene_e(:,i) = enePricesWorld +
 emPricesTJ(:,1); % TJ
                end
                % (e_i) (5x1) vector [coal; oil; natGas; bio; renew]
                calib.quant_ene_e(:,i) = energy{i,
["Fun_coal"; "Fun_oil"; "Fun_natGas"; "Fun_bio"; "Fun_renew"]}; % TJ

                % REFINED ENERGY SECTOR: emissions
                % Emissions are in kg, to match real emission data.
                % Rows: Energy sector. Column: Region.
                if regionSelected == "thesisCode"
                    % (p^E) Emission prices. (5x1) vector, one per fuel.
                    calib.price_ene_E(i) = emPricesKG(i); % PPP USD/kgCO2
                    % (E) Emissions per fuel. (5x1) vector, one per fuel
                    calib.quant_ene_E(:,i) = co2Factors .*
 calib.quant_ene_e(:,i); % kg CO2
                elseif regionSelected == "rice_code"
                    % (p^E) Emission prices. (5x1) vector, one per fuel.
                    calib.price_ene_E(i) = emPricesKG(1); % PPP USD/kgCO2
 (World avg for all regions)
                    % (E) Emissions per fuel. (5x1) vector, one per fuel
                    calib.quant_ene_E(:,i) = co2Factors .*
 calib.quant_ene_e(:,i); % kg CO2
                end


                % ELECTRICITY SECTOR
                % Rows: Fuel inputs to electricity. Column: Region.
                if regionSelected == "thesisCode"
                    calib.price_int_0(i) = elPrices(i) +
 emPricesTJ(i); %(p^e_0) electricity price scalar
                elseif regionSelected == "rice_code"
```

```
                calib.price_int_0(i) = elPrices(1) + emPricesTJ(1);
            end
            %calib.quant_ene_0 = energyMatrix{28,

            calib.quant_ene_0(:,i) = ...
                energy{i,
["Fun_coal_x4Electricity"; "Fun_oil_x4Electricity"; "Fun_natGas_x4Electricity"; "Fun_bio_
            calib.quant_ene_0_inputSum(i) = sum(calib.quant_ene_0(:,i)); %
(e_0)(sum of inputs before losses)
            calib.quant_int_0Test(i) = energy{i, ["Fun_elAndHeat"]}; %
(e_0) the total produced electricity (read-in of output from data)


            % INTERMEDIATE SECTOR
            % Rows: Inputs and outputs. Column: Region.
            calib.price_int_d(i) = 1; % (p_l^d) Intermediate good prices
(unity by normalization)
            calib.price_int_e(:,i) = [calib.price_ene_e(1:4,i);
calib.price_int_0(i)]; % (N/A) Vector of prices of inputs to intermediate
production [c o g b el]'
            %calib.quant_int_e = energyMatrix{25:27, ["Fun_coal" "Fun_oil"
"Fun_natGas" "Fun_bio" "Fun_elAndHeat"]}; % (N/A) (3x5)
            calib.quant_int_e_tr(:,i) = energy{i,
["Fun_coal_x1Transport"; "Fun_oil_x1Transport"; "Fun_natGas_x1Transport"; "Fun_bio_x1Tran
            calib.quant_int_e_in(:,i) = energy{i,
["Fun_coal_x2Industry"; "Fun_oil_x2Industry"; "Fun_natGas_x2Industry"; "Fun_bio_x2Industr
            calib.quant_int_e_ot(:,i) = energy{i,
["Fun_coal_x3Other"; "Fun_oil_x3Other"; "Fun_natGas_x3Other"; "Fun_bio_x3Other"; "Fun_elA
            % Stacking sectors to get matrix for easier calc. in next
step. Remember, happens for each country so matrix is ok.
            calib.quant_int_e = [calib.quant_int_e_tr(:,i)';
calib.quant_int_e_in(:,i)'; calib.quant_int_e_ot(:,i)'];
            calib.quant_int_d_val(:,i) = calib.quant_int_e *
calib.price_int_e(:,i); % Matrix multiplication (3x5)(5x1) = (3x1) vector of
value of intermediate by sector
            %calib.quant_int_d_test = sum(calib.quant_int_e,2);
            calib.quant_int_0(i) = calib.quant_int_e_tr(5,i) +
calib.quant_int_e_in(5,i) + calib.quant_int_e_ot(5,i);

            % FINAL GOODS AND AGGREGATION
            % Rows: Inputs and outputs. Column: Region.
            calib.price_fin_c(i) = 1;   % (p_l) Sector prices (column
vector)
            calib.price_K(i) = 1; % (p^K) (economy-wide)
            %calib.price_N(i) = 1; % (omega) (economy-wide

            calib.quant_fin_c(:,i) = [finalGoods{i, "Fun_transVA"};
                finalGoods{i, "Fun_indVA"};
                finalGoods{i, "Fun_othVA"}]; % (c) (3x1) Sector
quantities.
            calib.quant_fin_K(:,i) = finalGoods{i, "Fun_cn"}; % (K)
Scalar. Total capital in region, used to calibrate alpha.
            calib.quant_fin_K_sectors(:,i) = finalGoods{i,
["Fun_transCap"; "Fun_indCap"; "Fun_othCap"]};
```

```
                calib.quant_fin_N(:,i) = finalGoods{i, "Fun_emp"}; % (N)
 Scalar.Total labor in region (not vector!)
                calib.quant_fin_N_sectors(:,i) = finalGoods{i,
 ["Fun_transLab"; "Fun_indLab"; "Fun_othLab"]};

                calib.price_agg_Y(i) = 1;     % (p) Aggregate price level
 (scalar)
                calib.quant_agg_Y(:,i) = finalGoods{i, "Fun_cgdpo"};

                calib.gr_Y(i) = growthRates{i, "Fun_log_Fun_cgdpo"};
                calib.gr_K(i) = growthRates{i, "Fun_log_Fun_cn"};

                % end calibration read-ins
```

Calibration coefficient equations

Each set of sectors has a matrix containing varieties in columns and production coefficients on different inputs in a row

```
                % Alpha bar is extrapolated from only 3 countries.
                % High is 80/20 split of US and Russia.
                % Low is China
                % I use world average if RICE regions are used
                if regionSelected == "thesisCode"
                    if i == 1
                        prod.ene_alpha(i) = alphaBarW;
                    elseif i == 2
                        prod.ene_alpha(i) = alphaBarL;
                    elseif i == 3
                        prod.ene_alpha(i) = alphaBarH;
                    end
                elseif regionSelected == "rice_code"
                    prod.ene_alpha(i) = alphaBarW;
                end



                % (a_{1,i}^tilde) Intermediate energy good CES shares (NOTE:
 col 5 is electricity. Does not include renew) (B.14)
                % % Rows: Fuel-specific parameters. Column: Region.
                % NOTE: currently manually selecting substitutability
 parameter. Should be automated to have dynamic number of sectors.
                prod.int_atildestar_tr(:,i) = (calib.price_int_e(:,i) /
 calib.price_int_d(i)) .* (calib.quant_int_e_tr(:,i) ./ ...
                    calib.quant_int_d_val(1,i)).^(1-prod.int_s(1));
                prod.int_asum_tr(i) = sum(prod.int_atildestar_tr(:,i));
                prod.int_Atilde_tr(i) = prod.int_asum_tr(i).^(1./
prod.int_s(1));
                prod.int_atilde_tr(:,i) = prod.int_atildestar_tr(:,i) ./
 prod.int_asum_tr(i);

                prod.int_atildestar_in(:,i) = (calib.price_int_e(:,i) /
 calib.price_int_d(i)) .* (calib.quant_int_e_in(:,i) ./ ...
                    calib.quant_int_d_val(2,i)).^(1-prod.int_s(2));
```

```
                prod.int_asum_in(i) = sum(prod.int_atildestar_in(:,i));
                prod.int_Atilde_in(i) = prod.int_asum_in(i).^(1./
prod.int_s(2));
                prod.int_atilde_in(:,i) = prod.int_atildestar_in(:,i) ./
 prod.int_asum_in(i);

                prod.int_atildestar_ot(:,i) = (calib.price_int_e(:,i) /
 calib.price_int_d(i)) .* (calib.quant_int_e_ot(:,i) ./ ...
                    calib.quant_int_d_val(3,i)).^(1-prod.int_s(3));
                prod.int_asum_ot(i) = sum(prod.int_atildestar_ot(:,i));
                prod.int_Atilde_ot(i) = prod.int_asum_ot(i).^(1./
prod.int_s(3));
                prod.int_atilde_ot(:,i) = prod.int_atildestar_ot(:,i) ./
 prod.int_asum_ot(i);

                % (a_{0,i}^tilde) Electricity sector CES share on fuel inputs
 (incl. renew) (missing in theory, from B.19)
                % % Rows: Fuel-specific parameters. Column: Region.
                % Note:
                prod.int_atildestar_0(:,i) = (calib.price_ene_e(:,i) ./
 calib.price_int_0(i)) .* (calib.quant_ene_0(:,i) ./ ...
                    calib.quant_int_0(i)).^(1-prod.int_s_0); % (1x5) vector.
 Electricity sector. idx 5 is RENEW, not ELECTRICITY
                prod.int_asum_0(i) = sum(prod.int_atildestar_0(:,i));
                prod.int_Atilde_0(i) = prod.int_asum_0(i).^(1./prod.int_s_0);
                prod.int_atilde_0(:,i) = prod.int_atildestar_0(:,i) ./
 prod.int_asum_0(i);

                % (alpha, nu) Final consumption good CD function share
 calibration (B.12)
                % alpha is sector INdependent. CHECK: Should be (3x1)
 identical entries or scalar.
                % NOTE: I multiply the FLOW Y by 10 to get decadal timestep
                prod.fin_alpha(i)  = (calib.price_K(i) ./
 calib.price_fin_c(i)) .* (calib.quant_fin_K(i) ./ ...
                    (10*calib.quant_agg_Y(i))); % Scalar or (3x1) vector with
 identical entries.


                % nu is sector DEpendent
                prod.fin_nu(:,i)  = (calib.price_int_d(i) ./
 calib.price_fin_c(i)) .* (calib.quant_int_d_val(:,i) ./ ...
                    calib.quant_fin_c(:,i)); % Should be a (3x1) vector.
 Originally 0.1.

                % getting the overall nu for wage calibration
                prod.fin_nuOverAll(i) = sum(calib.quant_int_d_val(:,i)) ./
 sum(calib.quant_fin_c(:,i));
                prod.fin_nuOverAll(i) = mean(prod.fin_nu(:,i));
                %prod.fin_nuOverAll(i) = 3 * prod.fin_nuOverAll(i);
                prod.fin_alpha(i) = prod.fin_alpha(i) - prod.fin_nuOverAll(i);

                %Debug
                %prod.fin_alpha(i) = alphaTest(i);
```

```
                calib.shareN(i) = 1 - prod.fin_alpha(i)-
 prod.fin_nuOverAll(i);
                calib.GDPtoN(i)=calib.quant_agg_Y(i) / calib.quant_fin_N(i);
                calib.price_N(i) = (1 - prod.fin_alpha(i)-
 prod.fin_nuOverAll(i)) .* (calib.quant_agg_Y(i) / ...
                    calib.quant_fin_N(i));




                % (a^bar) The coefficient on E inside the min() function
                % Rows: Fuel-specific parameters. Column: Region.
                prod.ene_abar(:,i) = ((1-prod.ene_alpha(i)).*
 (calib.price_ene_e(:,i) .* calib.quant_ene_e(:,i)) ./ ...
                    (calib.price_N(i) .* calib.quant_ene_E(:,i))) - ...
                    (calib.price_ene_E(i) ./ calib.price_N(i)); % (5x1) vector
 of Leontief coefficients, one for each fuel.


                % (a) Final aggregation CES function share calibration (B.11)
                prod.agg_astar(:,i) =  (calib.quant_fin_c(:,i) ./
 calib.quant_agg_Y(i)).^(1-prod.agg_s);
                prod.agg_asum(:,i) = sum(prod.agg_astar(:,i))
                prod.agg_A(i) = prod.agg_asum(i).^(1/prod.agg_s);
                % This is the important output
                prod.agg_a(:,i) = prod.agg_astar(:,i) / prod.agg_asum(i); %
 Should sum to one
```

Initialization of other coefficients

(A^bar) TFP in refined energy production % Rows: Fuel-specific parameters. Column: Region.

```
                prod.ene_Abar(:,i) = ((calib.price_N(i)
 + (calib.price_ene_E(:,i) ./ prod.ene_abar(:,i))).^(1-
prod.ene_alpha(i))) ./ ...
                    (calib.price_ene_e(:,i) .*
 (prod.ene_alpha(i)^prod.ene_alpha(i))*((1-prod.ene_alpha(i))^(1-
 prod.ene_alpha(i))));

                % With co2factors
                prod.ene_Abar(:,i) = ((calib.price_N(i)
 + (calib.price_ene_E(:,i) .* prod.co2Factors(:,i))).^(1-
prod.ene_alpha(i))) ./ ...
                    (calib.price_ene_e(:,i) .*
 (prod.ene_alpha(i)^prod.ene_alpha(i))*((1-prod.ene_alpha(i))^(1-
 prod.ene_alpha(i))));

                % No alpha version
                %prod.ene_Abar(:,i) = (calib.price_N(i) +
 (calib.price_ene_E(:,i) ./ prod.ene_abar(:,i))) ./ calib.price_ene_e(:,i);
```

```
                %     prod.fin_A(:,i) = calib.quant_fin_c(:,i) ./ ...
                %         (calib.quant_fin_c(:,i).^(1-
prod.fin_nuOverAll(:,i)) .* prod.fin_alpha(i).^prod.fin_alpha(i) .* ...
                %         ((1 - prod.fin_alpha(i) - prod.fin_nu(:,i))/
calib.price_N(i)).^(1-prod.fin_alpha(i) - prod.fin_nu(i)) .* ...
                %         calib.quant_int_d_val(:,i).^prod.fin_nu(:,i));   %
 TFP final good production (column vector)

                %     % A version 2
                %     prod.fin_A2(:,i) = prod.fin_alpha(i).^(-
prod.fin_alpha(i)) .* ...
                %         ((calib.price_N(i) ./ (1-
prod.fin_alpha(i) - prod.fin_nuOverAll(i))).^(1-prod.fin_alpha(i) -
 prod.fin_nuOverAll(i))) .* ...
                %         (calib.quant_fin_c(:,i) ./
 calib.quant_int_d_val(:,i)).^(prod.fin_nuOverAll(i));
                %
                %
                %     % Trying another version of A
                %     prod.fin_A(:,i) = prod.fin_alpha(i).^(-
prod.fin_alpha(i)) .* ...
                %         prod.fin_nuOverAll(:,i).^(-
prod.fin_nuOverAll(:,i)) .* ...
                %     (calib.price_N(i) ./ (1 - prod.fin_alpha(i) -
 prod.fin_nuOverAll(:,i))).^(1 - prod.fin_alpha(i) - prod.fin_nuOverAll(:,i));

                % Trying another version of A (sector wise nu)
                prod.fin_A(:,i) = prod.fin_alpha(i).^(-
prod.fin_alpha(i)) .* ...
                    prod.fin_nu(:,i).^(-prod.fin_nu(:,i)) .* ...
                    (calib.price_N(i) ./ (1 - prod.fin_alpha(i) -
 prod.fin_nu(:,i))).^(1 - prod.fin_alpha(i) - prod.fin_nu(:,i));

                %     prod.fin_A2(:,i) = prod.fin_alpha(i).^(-
prod.fin_alpha(i)) .* ...
                %         ((calib.price_N(i) ./ (1-prod.fin_alpha(i) -
 prod.fin_nu(:,i))).^(1-prod.fin_alpha(i) - prod.fin_nu(:,i))) .* ...
                %         (calib.quant_fin_c(:,i) ./
 calib.quant_int_d_val(:,i)).^(prod.fin_nu(:,i));

            end % for loop
        end

        save Prod_ACEn.mat

    else
        load Prod_ACEn.mat
    end % direct read-in option

end % end of calibrate loop
```

Production calculation

```
if calibrate_calculate == 2 | 3
```

```
%if production.calculation == 1

for i = 1:numOfRegions
```

Need input vectors to carry out calculation:

```
      controltest.K_fin(:,i) = calib.quant_fin_K_sectors(:,i); %(3,1) per
region
      controltest.N_fin(:,i) = calib.quant_fin_N_sectors(:,i); %(3,1) per
region
      controltest.K_ene(:,i) = ones(5,1);
      controltest.N_ene(:,i) = ones(5,1);
      controltest.K_ene(:,i) = calib.quant_fin_K(i) .*
[.0014;.0058;.0012;.0009;.0029];
      controltest.N_ene(:,i) = calib.quant_fin_N(i) .*
[.0068;.0271;.0055;.0041;.0138];
      controltest.E(:,i) = calib.quant_ene_E(:,i); %(5,1) per region
      controltest.sums(:,i) = [calib.quant_ene_e(1:4,i);
calib.quant_int_0(i)]; % Rows: Total energy prod. per fuel (5th is
electricity).
      controltest.el_e_shares(:,i) = calib.quant_ene_0(:,i)       ./
calib.quant_ene_e(:,i);
      controltest.int_e_shares_tr(:,i) =calib.quant_int_e_tr(:,i) ./
controltest.sums(:,i);
      controltest.int_e_shares_in(:,i) =calib.quant_int_e_in(:,i) ./
controltest.sums(:,i);
      controltest.int_e_shares_ot(:,i) =calib.quant_int_e_ot(:,i) ./
controltest.sums(:,i);
      %controltest.int_e_shares = ones(3,5)/5; % Each sector's coefficient
on fuel inputs. Col5 is electricity

      controltest.elTest(i) = controltest.int_e_shares_tr(5,i) +
controltest.int_e_shares_in(5,i) + ...
          controltest.int_e_shares_ot(5,i);
      %controltest.elTest(i) = calib.quant_int_0(i);
      % Each set of sectors has a matrix containing varieties in columns and
production coefficients on different inputs in a row
```

Refined primary energy production:

```
      % Debugging:
      %     prod.ene_Abar(:,i) = 1;


      % column vector of dimenions 'fuels'.
      f_ene(:,i) = min(controltest.N_ene(:,i) , prod.ene_abar(:,i) .*
controltest.E(:,i)); % min of elements in each row, returns (5x1) vector
      %f_ene(5,i) = controltest.N_ene(5,i);
      e_ene(:,i) = prod.ene_Abar(:,i) .*
controltest.K_ene(:,i).^prod.ene_alpha(i) .* f_ene(:,i).^(1 -
prod.ene_alpha(i));
```

Electricity sector

```
        % Debugging:
        %     prod.int_Atilde_0(i) = 1;

        e_ene_0(i) = prod.int_Atilde_0(i) .* sum(prod.int_atilde_0(:,i) .*
 (controltest.el_e_shares(:,i) .* e_ene(:,i)).^prod.int_s_0).^(1./
prod.int_s_0); % Scalar
```

Intermediate sector (sector specific energy composite):

```
        % Debugging:
        %     prod.int_Atilde_tr(i) = 1;
        %     prod.int_Atilde_in(i) = 1;
        %     prod.int_Atilde_ot(i) = 1;
        % ---> Setting to one fixes Rich > World problem for d_int.


        d_int_tr(i) = prod.int_Atilde_tr(i).* (prod.int_atilde_tr(5,i) .*
 (controltest.int_e_shares_tr(5,i) .* e_ene_0(i)).^prod.int_s(1) + ...
            sum(prod.int_atilde_tr(1:4,i) .*
 (controltest.int_e_shares_tr(1:4,i) .* e_ene(1:4,i)).^prod.int_s(1))).^(1./
prod.int_s(1));

        d_int_in(i) =  prod.int_Atilde_in(i).* (prod.int_atilde_in(5,i) .*
 (controltest.int_e_shares_in(5,i) .* e_ene_0(i)).^prod.int_s(2) + ...
            sum(prod.int_atilde_in(1:4,i) .*
 (controltest.int_e_shares_in(1:4,i) .* e_ene(1:4,i)).^prod.int_s(2))).^(1./
prod.int_s(2));

        d_int_ot(i) = prod.int_Atilde_ot(i) .* (prod.int_atilde_ot(5,i) .*
 (controltest.int_e_shares_ot(5,i) .* e_ene_0(i)).^prod.int_s(3) + ...
            sum(prod.int_atilde_ot(1:4,i) .*
 (controltest.int_e_shares_ot(1:4,i) .* e_ene(1:4,i)).^prod.int_s(3))).^(1./
prod.int_s(3));

        d_int(:,i) = [d_int_tr(i); d_int_in(i); d_int_ot(i)];


        % XXX double check that equation above is raising right parts to right
 power...
```

Final good production sector:

column vector 'goods' (e.g. transport, industry, other)

```
        % Debugging:
        %     prod.fin_A(:,i) = 1;

        %Sectorwise nu
```

```
        c_fin(:,i) = (prod.fin_A(:,i) .*
 controltest.K_fin(:,i).^prod.fin_alpha(i) .* ...
            controltest.N_fin(:,i).^(1-prod.fin_alpha(i)-prod.fin_nu(:,i)) .*
 d_int(:,i).^prod.fin_nu(:,i));
```

Final good aggregation sector:

scalar

```
        % Debugging:
        %     prod.agg_A(:,i) = 1;

        c_agg(i) = prod.agg_A(i).*(sum(prod.agg_a(:,i) .*
 c_fin(:,i).^prod.agg_s))^(prod.agg_sbar/prod.agg_s);

        emi(:,i) = e_ene(:,i) ./ prod.ene_abar(:,i);


        compEn(:,i) = e_ene(:,i) ./ (calib.quant_ene_e(:,i));
        compEl(:,i) = e_ene_0(:,i) ./ (calib.quant_int_0(i));
        compInt(:,i) = d_int(:,i) ./ calib.quant_int_d_val(:,i);
        compSec = c_fin(:,i) ./ [finalGoods{:,"Fun_transVA"}
 finalGoods{:,"Fun_indVA"} finalGoods{:,"Fun_othVA"}]';

    end % for loop
    c_agg' ./ finalGoods{:,"Fun_cgdpo"}
    disp(['Aggregate consumption is ' num2str(c_agg)])

    Y_gross_Andreas=c_agg(i)

end  % of calculation loop

countrylist = PWT(:, ["country_PWT" "thesisCode"]);

%writetable(finalGoodsRegional, 'finalGoods.xlsx');
% writetable(energyRegionalStacked, 'energyRegional.xlsx');
writetable(countrylist, 'countries.xlsx');
```

Diffusion model

Diffusion init

```
prod.ene_Abar_dyn(:,i)= prod.ene_Abar(:,i); % initializing vector of TFP in
 energy
g_ren_H= 0.01; % high income renewable growth
g_renDecline = 0.02;
theta_diffu = 0; % diffusion parameter (in 0 1)
lambda_diffu = 0.00; % inherent growth in low income (in >0)
welfare(i) = 0;
L
% Growth in renewable energy TFP
Ahat = (prod.ene_Abar_dyn(5,3) - prod.ene_Abar_dyn(5,2))./
 prod.ene_Abar_dyn(5,2)
```

```
breakcheck =  Ahat > 0.01
if diffusion == 1
    prod.ene_Abar_dyn(5,1) =
 prod.ene_Abar_dyn(5,1).*exp(g_ren_H(t).*timestep);
    if breakcheck
        g_ren_L = theta_diffu .* Ahat + lambda_diffu;
    else
        g_ren_L = 0;
    end
    prod.ene_Abar_dyn(5,2) = prod.ene_Abar_dyn(5,2)*exp(g_ren_L*timestep);
    prod.ene_Abar_dyn(5,3) =
 prod.ene_Abar_dyn(5,3).*exp(g_ren_H(t).*timestep);
end
g_ren_LTime(t) = g_ren_L;
AhatOverTime(t) = Ahat;

E(i,t)=sum(Emi);
E_field(i,:,t)=Emi';
C_fin_field(i,:,t) = c_fin;
C_fin_tr(i,t)=c_fin(1);
C_fin_in(i,t)=c_fin(2);
C_fin_ot(i,t)=c_fin(3);
d_fin_tr(i,t)=d_int(1);
d_fin_in(i,t)=d_int(2);
d_fin_ot(i,t)=d_int(3);
% Total energy use in regions
ene_field(i,:,t) = ene';
e_ene_field(i,:,t) = e_ene;
e_ene_tot(i,t)=sum(e_ene_field(i,:,t),2);
ene_tot(i,t)=sum(ene_field(i,:,t),2);
e_ene_c(i,t) = e_ene(1); % coal
e_ene_o(i,t) = e_ene(2); % oil
e_ene_g(i,t) = e_ene(3); % gas
e_ene_b(i,t) = e_ene(4); % bio
e_ene_r(i,t) = e_ene(5); % renew
e_ene_e(i,t) = e_el(1); % el
% How to find energy use within a sector?
ene_tr(:,i,t) = cont(:,1) .* ene;
ene_in(:,i,t) = cont(:,2) .* ene;
ene_ot(:,i,t) = cont(:,3) .* ene;
ene_el(:,i,t) = [cont(1:4,4) .* ene(1:4); e_ene(5)];
% debug
%ene_sum = ene_tr + ene_in  +ene_ot  + ene_el;

utility(i,t) = log(Y_net(i,t)*x(i)); % utils in that period
if t == 1
    welfare(i,t) =  utility(i,t);
else
    welfare(i,t) = welfare(i,t-1)+beta(i)^t .* utility(i,t); % the final t
 gives the total discounted
end
```

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