Supplementary Material for Clean Growth

Contents

S1 Capitalist Investment Problem

We explicitly separate the problem of the household into a problem of a capitalist (who accumulates assets locally), and workers, who supply labor inelastically and face no dynamic decisions. The problem of the capitalist is

$$U_j = \max_{C_{j,t},\{I^k_{j,t+1}\},a_{j,t+1},M_{j,t},F_{j,t}} \sum_{t=0}^{\infty} \beta^t (\log(C_{j,t}) + \epsilon log(M_{j,t})),$$

subject to

$$P^{\mathcal{C}}_{j,t}C_{j,t} + \sum_{k\in\{\mathcal{R},F,\mathcal{K}\}} P^k_{j,t}I^k_{j,t} + a_{j,t+1} = E^K_{j,t} + R^{\mathcal{A}}_t a_{j,t} + (M_{j,t} - M_{j,t+1}) \tag{S1}$$

$$E^K_{j,t} = R^{\mathcal{K}}_{j,t}K^{\mathcal{K}}_{j,t} + p^E_{j,t}\sum \theta^R_j K^{\mathcal{R}}_{j,t} + p^E_{j,t}(K^{\mathcal{F}}_{j,t})^{\alpha}F^{1-\alpha}_{j,t} - p^{\mathcal{F}}_t F_{j,t}$$

$$K^k_{j,t+1} = (1-\delta)K^k_{j,t} + I^k_{j,t} \quad k = F, \mathcal{K}$$

$$K^{\mathcal{S}}_{j,t+1} = (1-\delta)K^{\mathcal{S}}_{j,t} + \Theta^{\mathcal{S}}_{j,t}I^{\mathcal{R}}_{j,t}$$

$$K^{\mathcal{W}}_{j,t+1} = (1-\delta)K^{\mathcal{W}}_{j,t} + \Theta^{\mathcal{W}}_{j,t}I^{\mathcal{R}}_{j,t}$$

$$I^k_{j,t+1} \geq 0$$

and the no-Ponzi condition

$$\lim_{t\to\infty} \frac{a_t}{\prod_{s=0}^t R^{\mathcal{A}}_{j,t}} \geq 0.$$

We proceed in three stages. First, the choice of fossil fuels inputs in each period is static, and so satisfies

$$F_{j,t} = K_{j,t}\left((1-\alpha)\frac{p^E_{j,t}}{p^{\mathcal{F}}_t}\right)^{\frac{1}{\alpha}}.$$

Net income is then

$$E_{j,t} = r^{\mathcal{K}}_{j,t}K^{\mathcal{K}}_{j,t} + p^E_{j,t}\theta_j K^{\mathcal{R}}_{j,t} + \Omega_{j,t}K^{\mathcal{F}}_{j,t} + w_{j,t}L_{j,t} + \Pi^{\mathcal{T}}_{j,t} + \Pi^{\mathcal{F}}_{j,t},$$

where $\Omega_{j,t} \equiv \left(p^E_{j,t}\right)^{\frac{1+\alpha}{\alpha}} \left(p^{\mathcal{F}}_t\right)^{-\frac{1}{\alpha}} \left((1-\alpha) - (1-\alpha)^{\frac{1}{\alpha}}\right)$. Second, in equilibrium, the return on the riskless bond must be weakly greater than the (net) return on all three types of capital, investment in which is constrained to be non-negative. Otherwise, the agent can achieve unbounded utility by borrowing at a lower rate and financing a capital purchase with a higher return. Moreover, in any period when positive investment in capital is undertaken, the return must be equal to the bond return, which also cannot be negative due to the zero nominal return on money holdings. The return on renewable capital is

$$R^{\mathcal{R}}_{j,t} = (\frac{p^E_{j,t+1}\bar{\theta}_{j,t+1}}{\bar{P}^{\mathcal{R}}_{j,t}} + \frac{\bar{P}^{\mathcal{R}}_{j,t+1}}{\bar{P}^{\mathcal{R}}_{j,t}}(1-\delta)),$$

the return on a unit of fossil fuel capital is

$$R^{\mathcal{F}}_{j,t} = (\frac{\Omega_{j,t+1}}{P^{\mathcal{F}}_{j,t}} + \frac{P^{\mathcal{F}}_{j,t+1}}{P^{\mathcal{F}}_{j,t}}(1-\delta)),$$

and production capital

$$R^{\mathcal{K}}_{j,t} = (\frac{r^{\mathcal{K}}_{j,t+1}}{P^{\mathcal{C}}_{j,t}} + \frac{P^{\mathcal{C}}_{j,t+1}}{P^{\mathcal{C}}_{j,t}}(1-\delta)).$$

In fact, given the lack of uncertainty in any period where the agent holds positive capital of any type, the return must be equal to the bond return. As such, it suffices to consider the problem of the total wealth of the agent,

$$W_{j,t} = P^{\mathcal{C}}_{j,t-1}K^{\mathcal{K}}_{j,t} + P^{\mathcal{R}}_{j,t-1}K^{\mathcal{R}}_{j,t} + P^{\mathcal{F}}_{j,t-1}K^{\mathcal{F}}_{j,t} + a_{j,t},$$

and we can write the simplified problem

$$U_j = \underset{C_{j,t},W_{j,t+1},M_{j,t+1}}{max} \sum_{t=0}^{\infty} \beta^t(\log(C_{j,t}) + \epsilon log(M_{j,t}))$$

subject to

$$P^{\mathcal{C}}_{j,t}C_{j,t} + W_{j,t+1} = R_t W_{j,t} + (M_{j,t} - M_{j,t+1}), \tag{S2}$$

$$\underset{t\to\infty}{lim} \frac{W_{j,t}}{\prod_{s=0}^{t} R_t} \geq 0.$$

We then have the following result:

Proposition 1. *Optimal consumption satisfies*

$$C_{j,t} = X(R_t, P^{\mathcal{C}}_{j,t}, P^{\mathcal{C}}_{j,t+1})W_{j,t} + Y(R_t, P^{\mathcal{C}}_{j,t}, P^{\mathcal{C}}_{j,t+1})M_{j,t}.$$

Moreover, as $\epsilon \to 0$,

$$C_{j,t} \to (1 - \beta\frac{P^{\mathcal{C}}_{j,t}}{P^{\mathcal{C}}_{j,t+1}})R_t W_{j,t}.$$

Proof. The association first order conditions for consumption, wealth and money are

$$\frac{\beta^t}{C_{j,t}} = \lambda_t P^{\mathcal{C}}_{j,t},$$

$$\epsilon\frac{\beta^{t+1}}{M_{t+1}} + \lambda_{t+1} = \lambda_t,$$

$$\lambda_t = R_t \lambda_{t+1},$$

where λ_t is the period budget constraint Lagrange multiplier. From these we can derive optimal money holdings as

$$\epsilon \frac{\beta^{t+1}}{M_{t+1}} = (1 - \frac{1}{R_t}) \frac{\beta^t}{P^C_{j,t} C_{j,t}},$$

$$M_{t+1} = \epsilon \beta \frac{R_t}{R_t - 1} P^C_{j,t} C_{j,t}. \tag{S3}$$

The Euler equation reads

$$\frac{C_{t+1}}{C_t} = \beta \frac{P^C_{j,t}}{P^C_{j,t+1}} R_t.$$

Now conjecture the optimal policy takes the form

$$C_{j,t} = X W_{j,t} + Y M_{j,t}.$$

Then from the Euler equation we have

$$X W_{j,t+1} + Y M_{t+1} = \beta \frac{P^C_{j,t}}{P^C_{j,t+1}} R_t (X W_{j,t} + Y M_{j,t}),$$

and inserting the policy for money in (S3) and the budget constraint from (S2) we get

$$X(R_t W_{j,t} + M_{j,t} - (1 + \epsilon \beta \frac{R_t}{R_t - 1}) P^C_{j,t} (X W_{j,t} + Y M_t)) + Y \epsilon \beta \frac{R_t}{R_t - 1} P^C_{j,t} (X W_{j,t} + Y M_t) = \beta \frac{P^C_{j,t}}{P^C_{j,t+1}} R_t (X W_{j,t} + Y M_{j,t}).$$

Matching coefficients for X we have

$$X(1 + \epsilon \beta \frac{R_t}{R_t - 1}) P^C_{j,t} = (1 - \beta \frac{P^C_{j,t}}{P^C_{j,t+1}}) R_t + Y \epsilon \beta \frac{R_t}{R_t - 1} P^C_{j,t}.$$

Matching the other coefficients

$$X - X(1 + \epsilon \beta \frac{R_t}{R_t - 1} P^C_{j,t}) Y + Y = \beta \frac{P^C_{j,t}}{P^C_{j,t+1}} R_t Y,$$

which we can solve for Yas

$$Y = \frac{X}{\epsilon \beta \frac{P^C_{j,t}}{P^C_{j,t+1}} R_t X + (1 - \beta) R_t - 1}.$$

The solutions to these two equations give two unique coefficients $X(R_t, P^C_{j,t}, P^C_{j,t+1})$ and $Y(R_t, P^C_{j,t}, P^C_{j,t+1})$. This is a familiar result that the policy rule in a consumption-savings problem is independent of future interest rates under log utility (see Steve and Ben Moll), modified only to permit non-negative holdings of money. Note that in the limit X approaches

$$\lim_{\epsilon \to 0} X(R_t, P^{\mathcal{C}}_{j,t}, P^{\mathcal{C}}_{j,t+1}) = (1 - \beta \frac{P^{\mathcal{C}}_{j,t}}{P^{\mathcal{C}}_{j,t+1}}) R_t.$$

□

Third, we determine investment in capital in the following way. The total investment in production capital comes from equation the return to the bond return, as

$$R^{\mathcal{A}}_t = (\frac{r^{\mathcal{K}}_{j,t}}{P^{\mathcal{C}}_{j,t}} + \frac{P^{\mathcal{C}}_{j,t+1}}{P^{\mathcal{C}}_{j,t}}(1-\delta)),$$

which determines a value for $r^{\mathcal{K}}_{j,t}$. Given this, we can determine the total amount of capital services demanded from the local sectoral demands. In particular, the Cobb-Douglass sectoral production function gives

$$\frac{v^L_{js} L_{js,t}}{v^L_{js} K_{js,t}} = \frac{r^{\mathcal{K}}_{j,t}}{w_{j,t}},$$

from which we can derive

$$K^{\mathcal{K}}_{j,t} = \frac{w_{j,t}}{r^{\mathcal{K}}_{j,t}} \sum_s \frac{v^L_{js}}{v^L_{js}} L_{js,t},$$

and investment from the law of motion

$$I^{\mathcal{K}}_{j,t} = K^{\mathcal{K}}_{j,t+1} - (1-\delta) K_{j,t}.$$

Fossil and renewable investment are determined by ensuring

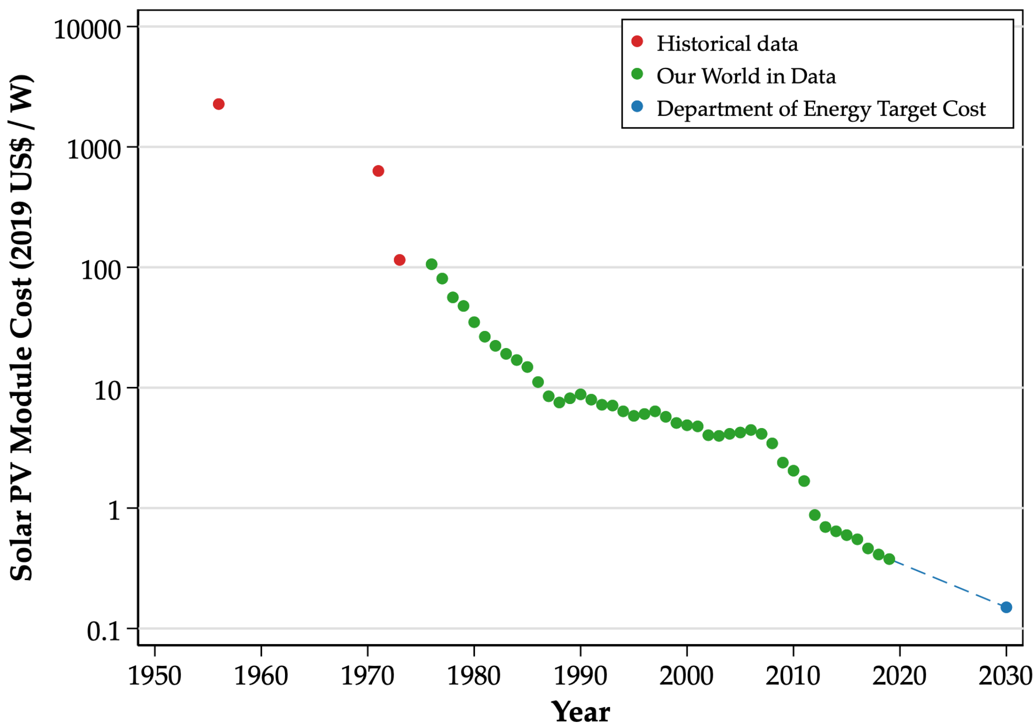
$$R^{\mathcal{A}}_t \geq (\frac{p^E_{j,t+1}\theta_j}{P^{\mathcal{R}}_{j,t}} + \frac{P^{\mathcal{R}}_{j,t+1}}{P^{\mathcal{R}}_{j,t}}(1-\delta)),$$

$$R^{\mathcal{F}}_{j,t} \geq (\frac{\Omega_{j,t}}{P^{\mathcal{F}}_{j,t}} + \frac{P^{\mathcal{F}}_{j,t+1}}{P^{\mathcal{F}}_{j,t}}(1-\delta)),$$

where investment is only positive if these hold with equality. When they hold with equality, we can back out a capital stock of each type, and an associated investment from the law of motion, recalling that the capitalist takes the sequence of fossil fuel capital prices $P^{\mathcal{F}}_{j,t}$ and renewable capital prices $P^{\mathcal{R}}_{j,t+1}$ as given. Lastly, given $C_{j,t}$, $M_{j,t}$ from the policy function, $\{I^k_{j,t}\}_k$ and an initial a_0 and M_0, demand for bonds can be computed from the budget constraint of the capitalist. The policy rule gives

$$C_{j,t} + W_{j,t+1} = R_t W_{j,t} + (M_{j,t} - M_{j,t+1}),$$

Figure S1: Cost per Watt of Solar Photovoltaics



Notes: Prices of Solar Photovoltaic modules for price in U.S. Dollars per Watt. Sources: For historical data, Farmer and Lafond (2016), Perlin (1999) (Chapter 6); for modern data, in LCOE, World in Data; for future projections SETO (2021).

which in the case of small ϵ reduces to

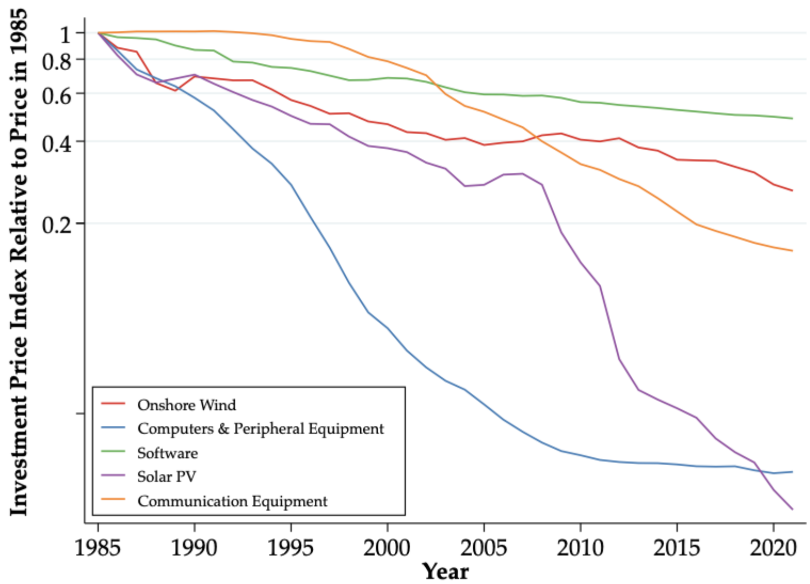
$$W_{j,t+1} = \beta R_t W_{j,t+1}.$$

S2 Data on The Renewable Technological Revolution

Renewable technologies have seen consistent improvements over the past many decades. In this Appendix, we provide evidence that renewable technological improvement is a technological revolution still in the making. For our analysis we focus on photovoltaics (PV) and onshore wind. The history of photovoltaics dates back to 1839 when French scientist Edmond Becquerel discovered the photovoltaic effect. Commercial production of photovoltaics only started in 1954 when the first silicon based photovoltaics were invented by Bell labs with a 4% efficiency in conversion of light to electricity. The first commercial application of this technology in 1956 was priced at $2269 per Watt, in 2013 prices. In Figure S1 we plot the Solar PV efficiency over time with data until 2019 and with recent projections from the Department of Energy. The price per Watt has fallen to $0.38 in 2019 , and the Department of Energy expects that new projects, will cost $0.15 per Watt in 2030.

This extraordinary technological progress rivals any other investment price cost decrease, and

Figure S2: Investment Price Index for Sectors with Fastest Declines and Renewables



Notes: This graph presents the price of investment for the three sectors with the fastest declines from BEA and renewables, with 1985 normalized to 1. Sources: The price of investment data for computers & peripheral equipment and communication equipment are from Bureau of Economic Analysis (BEA), software from FRED, solar PV from Our World in Data and Onshore Wind from IRENA.

matches even that of computers. In Figure S2 we plot the sectors with fastest price declines in investment costs from the Bureau of Economic Analysis Database and Solar PV and Onshore Wind Investment Costs from 1985 to 2021. In this graph we use US dollar per kilowatt for Solar PV and Onshore Wind. We normalize all prices to 1 in 1985 and illustrate relative investments from then to 2021. Our choice of initial year is dictated by the availability of onshore wind data. Computer and Peripheral Equipment prices show the fastest declines for the first two decades but the rapid speedup in Solar PV innovation in the last two decades meant that the PV have now declined more than any other technology and in a trajectory to even larger declines. Onshore wind costs have been consistently falling throughout and decrease a little bit slower than communication equipment during that period, but still faster than software.

To formally compute the cost of investment of these different sectors we measure the user cost of Solar Photovoltaics (PV) and Onshore Wind following Caunedo et al. (2021). In particular, we use the familiar arbitrage condition of Jorgenson (1963) so that User cost = adjusted price of renewable * (Interest rate – (1– depreciation rate) * relative price change). Table **??** depicts the results. Solar PV and Computers user costs drop fastest, at a rate faster than 12%. These declines swamp the other sectors with very rapidly declining costs. However, Onshore wind declines are just a little bit slower than software and communication equipment, the sectors with the slowest declining costs.

The price indices used to compute the change in price of investment are from the BEA for computers and communication equipment U.S. Bureau of Economic Analysis, "Table 5.5.4. Price Indexes for Private Fixed Investment in Equipment by Type", from FRED for software, from Our World in Data for Solar PV and from IRENA for Onshore wind.[1] The depreciation rates used to construct the user cost of capital are from the BEA for computers, communication equipment and software, from Wiser and Bolinger (2019) for onshore wind, and from Jordan and Kurtz (2013) for Solar PV. We use FRED data for the personal consumption expenditure index (PCEP). Solar PV depreciation rates were estimated at 5% per year between 1985 and 2005, and at 4% between 2006 and 2020 as solar PV useful life increased over more recent years (NREL) while onshore wind depreciation rates declined from 5% pre 2010 to 3.3% post 2010.

S3 Data Construction

S3.1 Production and Employment Data

We obtain data on production and employment by region from various sources. In this section we describe the procedure for each one separately, and close the section briefly describing the final dataset.

S3.1.1 OECD Regional Data

Data is sourced from the OECD iLibrary, which provides regional economic data by year at three different territorial levels (TL): TL3 and TL2 and TL1.[2] TL1 regions correspond to countries, with each one composed of large TL2 regions similar to US states. Lastly, TL3 regions are contained within TL2, and are comparable to counties or commuting zones in the US. Among the different economic variables contained in the data, we focus on Gross Value Added (GVA) per worker, and employment levels. Both measures are disaggregated by industry following the High-level SNA/ISIC aggregation (A*10) system, which groups economic activities in 10 different sectors, shown in Table S1.[3] Furthermore, we measure GVA per worker in current USD adjusted by Purchase Power Parity (PPP). Additionally, while the OECD iLibrary has data available from 1995 to 2021, we restrict to data for 2015, as it had the least amount of missing data by industry for most countries. Exceptions to this rule are Poland and Japan, for which we use data for 2016. For Poland, we do this to increase the number of regions with sectoral production and employment. Japan, on the other hand, only has data available every even year. In an final step, we drop regions that are duplicated or consist of mixes of individual regions. This effectively drops 8 regions in Belgium, 14 in Croatia, 2 in Estonia, 4 in Italy, and 9 in Norway.

For several countries in the OECD, we use other data sources with finer spatial resolution (see below).

[1] See BEA https://fred.stlouisfed.org/series/B985RG3A086NBEA.

[2] This data can be found in https://doi.org/10.1787/region-data-en.

[3] The table is a replica of Table 4.1 in https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf

Table S1: High-level SNA/ISIC aggregation (A*10)

ISIC, Rev. 4 sections	Description
A	Agriculture, forestry and fishing
B, C, D, and E	Manufacturing, mining and quarrying and other industrial activities
F	Construction
G,H, and I	Wholesale and retail trade, transportation and storage, accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities*
M and N	Professional, scientific, technical, administrative and support service activities
O, P and Q	Public administration and defence, education, human health and social work activities
R, S,T, and U	Other service activities

* of which imputed rental services of owner-occupied dwellings.

S3.1.2 United States

We obtain data for the US from the 2015 County Business Patterns (CBP), which provides payroll and employment data by industry and county. [4] Industries in the CBP are aggregated using the 2012 North American Industry Classification System (NAICS) and we limit our analysis to the 20 two-digit NAICS industries. We do this for two reasons. First, these closely match the SNA/ISIC sections. Second, for many small counties the information at two-digit industries is the only one available.

As a first step, we impute employment and payroll for county-industry pairs which have withheld data due to privacy concerns. For employment, these observations are flagged indicating in which range the hidden value lies (e.g., flag B indicates the employment in that county-sector is between 20 and 99). Instead of imputing the midpoint of the interval, we proceed as follows. We obtain grand totals for employment and payroll at the county level from the CBP, provided under a unique "NAICS" code within the database. Then, we compute the difference between these grand totals and the computed totals from the available data. For a given county C, we call this difference ΔE_C. The main challenge is that, within a county, missing values could have different ranges. Consequently, it is not possible to split ΔE_C into equal parts. Thus, we proceed as follows. Fix a county C and let $i \in \{1, \ldots, N\}$ be the two-digit industries with withheld employment data in C. Call e_{iC} the employment level of sector i in county C. Then, we want to find $\{e_{iC}\}_i$ such that

[4]This can be obtained at https://www.census.gov/data/datasets/2015/econ/cbp/2015-cbp.html.

$$\sum_i e_{iC} = \Delta E_C \tag{S4}$$

subject to $e_{iC} \in \left\{\underline{e_i}, \overline{e_i}\right\}$. From the possible solutions, we will take the one that evenly places all e_{iC} in the same fraction of their interval. In other words, defining

$$\tilde{e}_{iC} \equiv \frac{e_{iC} - \underline{e_i}}{\overline{e_i} - \underline{e_i}},$$

we assume $\tilde{e}_{iC} = \tilde{e}_{jC} \equiv \tilde{e}_C$ for all i, j. We then can rewrite (S4) as

$$\left(\sum_i \overline{e}_i - \underline{e_i}\right) \tilde{e}_C = \Delta E_C - \sum_i \underline{e_i},$$

and compute $\tilde{e}_C$ and $\tilde{e}_{iC}$ according to the relations above. Finally, for payroll, we start by computing the difference between the grand total and the computed total using the available data. We then split the payroll over the industries with missing values assuming each worker has an identical wage. In other words, we split the difference in annual payroll using weights based on the imputed employment from the previous step.

The second step is to match the CBP sectors with our SNA/ISIC aggregation. Given the similarity between both classifications, we manually assign each of these sectors to their corresponding SNA/ISIC section (from A to U).[5]

Finally, we match each county in the CBP to its correspondent 1990 commuting zone (CZ), such that the final dataset is at the SNA/ISIC group-CZ level.[6] We also multiply the payroll numbers by a constant factor so that the country level payroll per worker value equals the GDP per worker observed in the OECD data.

S3.1.3 Australia

For Australia, we use data on employment by industry provided by the Australian Bureau of Statistics (ABS) at the Statistical Area 4 (SA4) level.[7] These are the largest sub-State regions in Australia, and represent labor markets or groups of labor markets within each State and Territory.[8]

[5]The only exception is Utilities (NAICS sector 22) which contains 3 three-digit sectors: Electric Power Generation, Transmission and Distribution; Natural Gas Distribution; and Water, Sewage and Other Systems. The first two corespond to SNA/ISIC section D, while the third corresponds to section E. Because of this, we split NAICS sector 22 in three parts and assign 2 to section D and the last one to section E.

[6]Crosswalks between counties and CZs are available from different sources. One of these crosswalks can be found at https://healthinequality.org/data/. Given that counties in 1990 have changed over time, we follow the indications from David Dorn, which can be found at https://www.ddorn.net/data.htm. For other counties which are not described in David Dorn's instructions, we manually assign their corresponding CZ when possible.

[7]Specifically, employment data by industry comes from the Labour Force Survey and can be found in https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release.

[8]More information about Statistical Area 4 regions can be found in https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/

As with our previous sources, we are able to map each industry to its corresponding SNA/ISIC group. Employment data is available every three months, starting in August 1999. For our purposes, we use employment for November 2015.

We also obtain regional GDP figures for all SA4 regions from the "Industry Insights" report, published by the Office of the Chief Economist of the Department of Industry, Science and Resources of Australia.[9] Numbers are provided every five years, starting in 2001, and we use those for 2016. As we lack detailed industry data by region, to translate the regional GDP to region-industry levels we assume an equal productivity across all sectors.

S3.1.4 Brazil

For Brazil, we use data from two sources: Instituto Brasileiro de Geografia e Estatística (IBGE), and DataViva. Employment data by sector and region are provided by DataViva.[10] The website offers data for different years, aggregated at different geographic levels, and by SNA/ISIC groups sectors. We employ the 137 "mesoregions", which are the first sub-State regional aggregation. Shapefiles for these regions are provided by IBGE.[11]

GVA data by state and sector is provided by IBGE as a time series from 2002 to 2019.[12] Sectors are, or can be directly matched to, the SNA/ISIC (A*10) aggregation. To translate state level data into the mesoregions, we compute GVA per worker at the state-sector level, and assume this value is constant among mesoregion-sector pairs belonging to the same state. Finally, we use data only for 2015 to match the OECD data.

S3.1.5 China

For China, we obtain 2015 GDP at the province level from EPS China Data.[13] We also obtain gross value added by industry and province in 2015 from Zheng et al. (2021).[14] Additionally, we complement these two data sources with employment by industry-region in 2015 from the 2016 China Statistical Yearbook.[15] The yearbooks do not have data by industry-region for all types of employment. To overcome this hurdle, we obtain the non-private urban employment by industry-sector, and rescale these values such that the total employment for China is equal to the published figure. In terms of regions, all datasets contain 31 China provinces (which do not include

main-structure-and-greater-capital-city-statistical-areas/statistical-area-level-4.

[9]The report can be found in https://www.industry.gov.au/data-and-publications/industry-insights.

[10]The data tool can be found at http://legacy.dataviva.info/en/.

[11]The shapefiles can be found at https://www.ibge.gov.br/en/geosciences/territorial-organization/territorial-meshes/18890-municipal-mesh.html.

[12]The data can be found at https://www.ibge.gov.br/en/statistics/economic/national-accounts/16855-regional-accounts-of-brazil.html?=&t=downloads.

[13]This provider can be found at http://www.epschinadata.com. Specifically, employment by province-industry comes from the China Macro Economy dataset, while GDP by province comes from the China Regional Economy dataset.

[14]The IO table can be found in https://www.nature.com/articles/s41597-021-01023-5.

[15]The statistical yearbooks can be found in the webpage of the National Bureau of Statistics of China, http://www.stats.gov.cn/english/.

Taiwan nor Hong Kong). Additionally, and as we proceeded with other countries, we manually assign industries in the data to their corresponding SNA/ISIC aggregation level.

S3.1.6 India

For India, we use data from Fan et al. (2021). For each of their regions, the paper provides data on employment at the two-digit sector (using the NIC 2008 classification), and average income at the region-sector level.[16] Their regions correspond to 370 districts in India. Since districts in India have changed substantially over time, they define their own district boundaries and provide a crosswalk to map these to the Indian geography. Regarding sectors, we are able to map each two-digit sector into a SNA/ISIC section (from A to U), and then to the (A*10) aggregation.

S3.1.7 Russia

For Russia, we use data from Fedorov and Kuznetsova (2020). They compile information from the Russian Federal State Statistics Service (ROSSSTAT) and compute GVA per capita and per worker for 19 SNA sections and 85 regions, in 2018.[17] They also publish population counts for these 85 regions, which we use to obtain employment by sector-region as follows

$$L_{sr} = \frac{GVA_{pc,sr} \cdot pop_r}{GVA_{pw,sr}},$$

where L_{sr} is employment for sector s and region r, $GVA_{pc,sr}$, and $GVA_{pw,sr}$ are GVA per capita and per worker, respectively, for sector s and region r, and pop_r is population in region r.

S3.1.8 Other Countries

We also include whole countries using data from the World Bank. Specifically, we obtain 2015 GDP and GDP per worker, in PPP dollars, from the World Bank DataBank.[18] The list of countries we add from this source are Bahrain, Costa Rica, Cyprus, Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, United Arab Emirates, and Yemen.

We obtain employment at the country level dividing GDP by GDP per worker. Then, we split employment to our 10 sectors using country-level labor shares by sector obtained from GTAP (see section S3.2 for details). Finally, we assume the same GDP per worker across sectors.

[16] They proxy average income per capita by dividing total household expenditures over the household size.

[17] They provide 85 regions, including Republic of Crimea and Sevastopol. We only use the other 83 to follow the shapefiles from OECD. Additionally, the provided data contains SNA sections from A to S, but does not include sections T (Activities of households as employers) and U (Activities of extraterritorial organizations and bodies).

[18] The GPD series indicator is NY.GDP.MKTP.PP.CD, while the GDP per worker series indicator is SL.GDP.PCAP.EM.KD. The latter is in constant 2017 PPP dollars, so we use the conversion factor series (indicator PA.NUS.PPP) to translate it to 2015 PPP dollars.

S3.1.9 Final Production and Employment Dataset

After incorporating data from the aforementioned sources, we account for 2531 regions in 56 countries. The detailed list of countries, including the number of regions in each one and the aggregation level used is presented in Table S2. In Figure S3 is presented the final World map, as well as detailed maps for North America (Canada, Mexico, and the US), and Eurasia.

In a last step, we multiply each of the sector-region productivities by a country level constant. The goal is to mimic the country level productivity patterns observed in the World Bank Data.[19] Specifically, for each country we compute the share of US productivity in the dataset (α_{model}), and the share of US GDP per worker from the World Bank data (α_{WB}) and multiply its productivity value by $\alpha_{WB}/\alpha_{model}$.

[19]As mentioned in previous subsections, productivity is measured differently for each country (e.g., the US uses the CBP and Australia uses regional GDP per worker).

Figure S3: Regions in the Production and Employment Data.

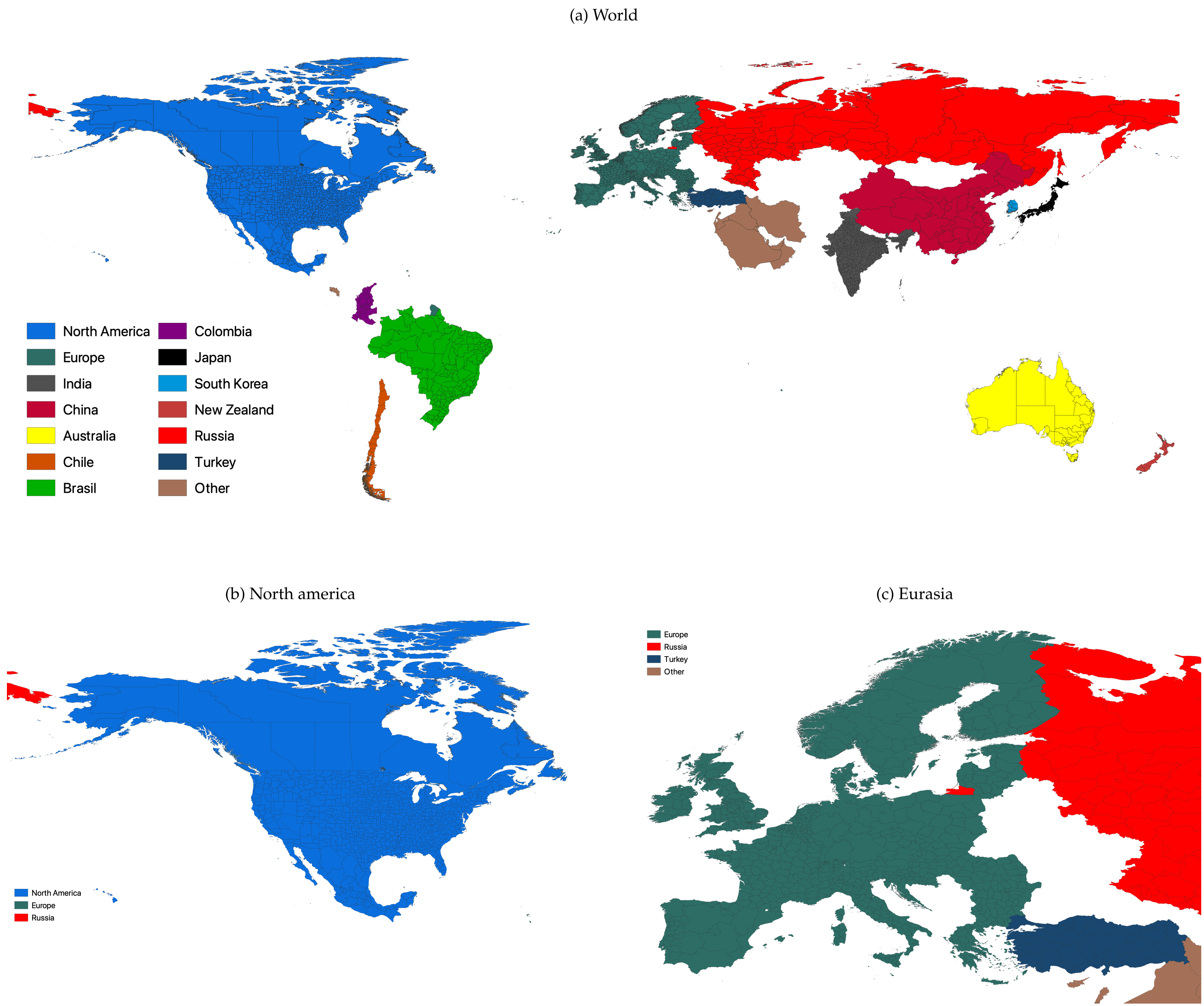


Table S2: Countries, Number of Regions, and Aggregation Level in the Production and Employment Data.

Country	Territorial Aggregation	Number of Regions
Australia	Statistical Area 4	87
Austria	TL2	9
Bahrain	Whole Country	1
Belgium	TL3	44
Brazil	Mesoregions	137
Bulgaria	TL3	28
Canada	TL2	13
Chile	TL2	15
China	Province	31
Colombia	TL2	24
Costa Rica	Whole country	1
Croatia	TL3	21
Cyprus	Whole country	1
Czech Republic	TL3	14
Denmark	TL3	11
Estonia	TL3	5
Finland	TL3	19
France	TL3	101
Germany	TL2	16
Greece	TL3	52
Hungary	TL3	20
India	Districts	370
Iran	Whole Country	1
Iraq	Whole Country	1
Ireland	TL3	8
Israel	Whole country	1
Italy	TL3	110
Japan	TL3	47

Country	Territorial Aggregation	Number of Regions
Jordan	Whole Country	1
Kuwait	Whole Country	1
Latvia	TL3	6
Lebanon	Whole Country	1
Lithuania	TL3	10
Luxembourg	TL3	1
Malta	TL3	2
Mexico	TL2	32
Netherlands	TL3	40
New Zealand	TL3	12
Norway	TL3	18
Oman	Whole Country	1
Poland	TL2	17
Portugal	TL3	25
Qatar	Whole Country	1
Romania	TL3	42
Russia	Oblasts	83
Saudi Arabia	Whole Country	1
Slovakia	TL3	8
Slovenia	TL3	12
South Korea	TL3	16
Spain	TL2	19
Sweden	TL3	21
Switzerland	TL3	26
Turkey	TL2	26
United Arab Emirates	Whole Country	1
United Kingdom	TL3	179
United States	Commuting Zones	741

S3.2 Factor Shares and Labor Shares by Sector

To calibrate factor shares in the final product firms' production function we use data from the Global Trade Analysis Project (henceforth, GTAP). This is a global input-output (IO) table, which features 65 sectors in 141 countries.[20] Specifically, GTAP contains the value of trade of intermediate inputs between pairs country-sector, the value of final consumption by government and private households of each pair country-sector, and the factor (capital and labor) endowments for each pair

[20]There is a 66th sector, called Capital Goods Commodities (or CGDS). This is a "fictitious" sector created by GTAP to have a complete general equilibrium model. We drop this sector for our calibrations. A more detailed explanation on CGDS can be found in https://www.gtap.agecon.purdue.edu/resources/faqs/faqs_display.asp?F_ID=147.

country-sector. To accommodate our sector definition we proceed by mapping each of the GTAP sectors to our 10 SNA/ISIC sectors. In what follows, unless specified otherwise, sectors will refer to the SNA/ISIC groups.

Using this data, we compute factor shares α_{csi} for factor i of sector s in country c as

$$\alpha_{csi} = \frac{E_{csi}}{E_{cs}},$$

where E_{csi} are expenditures on factor i by sector s in country c, and E_{cs} are expenditures by sector s in country c on all four production factors. That is,

$$E_{cs} = E_{csf} + E_{cse} + E_{csk} + E_{csL},$$

where f stands for fossil fuels, e for electricity, k for capital, and L for labor. To obtain total expenditures in each of these factors, we proceed as follows. For capital and labor, we use factor endowments directly. For fossil fuels and electricity, we label each of the original GTAP sectors as fossil fuels sectors, electricity sectors, or neither. Then, we compute E_{scf} and E_{sce} from the intermediate input trade data as total expenditure by each sector s in country c on fossil fuel sectors and electricity sectors, respectively.

We also use data from GTAP to construct labor shares by country-sector. We use these shares to allocate country-level employment to each of the SNA/ISIC sectors for the countries with data from the World Bank (see S3.1.8). These shares are computed as the share of endowments that go to labor, that is, the labor share for sector s in country c is defined as

$$\frac{E_{csL}}{E_{csL} + E_{csk}}.$$

S3.3 Consumption Shares Calibration

To calibrate consumption shares for the regional economy, we use data from EUREGIO (see details in S3.6.1). We first extract final consumption by households and the government from the IO table and match each of the seller sectors into our SNA/ISIC aggregation groups. Then, we compute the consumption share by region-sector as

$$\beta_{j,s} = \frac{E_{j,s}}{\sum_{s'} E_{j,s'}},$$

where $E_{j,s}$ is the value of consumption of region j in goods of sector s. We then manually match each of the regions in the model to a given region in EUREGIO. Since some regions in the EUREGIO data span multiple regions in our model, we assume the estimated parameters are constant between these regions.

Additionally, twenty one countries in our model have no direct match to EUREGIO data: Bahrain, Chile, Cyprus, Colombia, Costa Rica, Croatia, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, New Zealand, Norway, Oman, Qatar, Saudi Arabia, Switzerland, Syria, United Arab Emirates, and Yemen. For Chile, Colombia and Costa Rica, we use the "BRA" region which is labeled as "South and Middle America". For New Zealand we use the estimates for Australia. For Croatia, Norway, and Switzerland we estimate their consumption shares as the average of some countries. For Croatia we use Austria, Hungary, and Italy. For Norway we use Denmark and Sweden. Finally, for Switzerland we use Austria, France, Germany, and Italy. Additionally, for overseas regions of Portugal and France, we use the average consumption share of the mainland regions of their corresponding countries. Finally, for Bahrain, Cyprus, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, United Arab Emirates, and Yemen. We use the "ZROW" region, which is labeled as "Rest of the World".

S3.4 Wind and Solar Data

We obtain data on clean energy sources from the Global Wind Atlas and the Global Solar Atlas.[21] For solar energy, we obtain "Global irradiation for optimally tilted surface" from the Global Solar Atlas. This variable is measured as an average daily total in kWh/m^2 in GeoTIFF format. We then compute the annual average in each of our regions by averaging this variable in the region, and then multiplying the result by 365.

To obtain a comparable measure for wind energy, we obtain two variables from the Global Wind Atlas. The first is "Mean Power Density", which is measured as average daily totals in W/m^2 at height 150 meters. The second variable is "Capacity Factor IEC Class I", which is a number between 0 and 1 measuring the annual yield of a wind turbine. Both are provided by the Atlas in GeoTIFF format and we proceed to obtain values at the region level by averaging the values within each region. Finally, we combine these two averages to obtain a comparable wind measure according to

$$D_r \cdot CF_r \cdot \frac{365 \cdot 24}{1000},$$

where D_r is average Mean Power Density, and CF_r is the average of the capacity factor in region r. This formula implies that our measure of wind energy is also an annual average measured in kWh/m^2.

S3.5 Fossil Fuels

We obtain fossil fuel supply curves from Welsby et al. (2022). The paper provides marginal cost curves for 16 world regions and 3 fuel sources (oil, gas, and coal) that originate from the TIAM-

[21] Both sources are online applications developed with the help of ESMAP, a multi-donor trust fund administered by The World Bank. Data from the Global Wind Atlas can be found at `https://globalwindatlas.info`, while data from the Global Solar Atlas can be found at `https://globalsolaratlas.info`.

UCL model developed by the UCL Energy Institute.[22] These curves provide marginal costs at current prices and do not incorporate dynamic changes in the costs of production. We combine the curves of all three sources by expressing unit costs and production levels in the same units, following Clark (1982, p. 468). For the fossil fuel module, we allow technology improvements to reduce marginal costs over time. Following the EIA Annual Energy Outlook (U.S. Energy Information Administration, 2022, Pil and Gas Supply Module Assumptions, Table 5), we impute a 1% year-over-year reduction in marginal costs.

The supply curves from Welsby et al. (2022) also contain information on total reserves owned by each of the 16 regions in each of the three fuel sources. For our quantitative results, we assign each region the share of global fossil fuel reserves it owns. To this end, we perform the allocation in three steps. First, we apportion the reserves of each fuel source owned by each multi-country region into its members.[23] Second, we allocate country level reserves between their corresponding regions in proportion to each region's population. Finally, we compute the total share of global reserves of each country by dividing the reserves owned in each source by global fossil fuel reserves.[24]

For the first step, the detailed procedure is as follows. For each multi-country region in the TIAM-UCL model, we compute the fraction of reserves each country contributes, using the British Petroleum Statistical Review of World Energy (British Petroleum, 2022).[25] This report contains information on the total reserves of oil, gas, and coal held by each country. Depending on the size of the reserves, some countries appear individually, while the rest are aggregated with the remaining countries in their continent (e.g. Europe oil reserves are detailed for Denmark, Italy, Norway, Romania, and the United Kingdom, while the rest of Europe is aggregated into "Other Europe"). For the former, we compute the fraction of reserves within their corresponding TIAM-UCL region directly. For the latter, we divide the aggregated reserves evenly between all remaining countries in the TIAM-UCL region before computing their fraction.[26] Lastly, we apportion their corresponding TIAM-UCL region reserves for each fuel source according to the computed fractions.

[22]The regions in the model are Africa, Australia, Canada, Central and South America, China, Eastern Europe, Former Soviet Union, India, Japan, Mexico, Middle East, Other Developing Asia, South Korea, United Kingdom, United States, and Western Europe. More information on the TIAM-UCL model can be found at https://www.ucl.ac.uk/energy-models/models/tiam-ucl.

[23]Since our model does not contain African countries or any member of the "Other Developing Asia" region in TIAM-UCL, we only follow this step for the following regions: Australia, Central and South America, Eastern Europe, Former Soviet Union, Middle-east, and Western Europe.

[24]To combine different fossil fuel levels we convert reserves to similar units, as mentioned earlier in the section.

[25]The only exception is the Australia (AUS) region in TIAM-UCL. Since New Zealand does not account for any significative portion of reserves for any of our fuel sources, we apportion the Australia region reserves completely to Australia.

[26]For Europe, the BP Statistical Review does not differentiate Eastern Europe of Western Europe like the TIAM-UCL model does. In this case, we divide "Other Europe" reserves evenly between all Western and Eastern Europe countries that do not appear individually in the BP Statistical Review.

S3.6 Trade Cost Calibration

S3.6.1 Trade Flows Data

To calibrate trade costs we use data from EUREGIO, a global IO database with regional details for Europe. In particular, we use the 2010 version of this table. The dataset features 40 countries and 265 regions. Regions in Europe correspond to the NUTS2 regions of 24 countries, while each of the 16 non European countries are treated as one region in the dataset.[27] In the IO table, each observation is a trade flow value (in EUR) between a given pair region-industry of origin, and a pair region-industry of destination.

For our trade cost calibration, we sum over all industries of destination such that each observation is a trade flow value between a given pair region-industry of origin, and a region of destination.[28] Industries in EUREGIO are grouped in 14 different sectors, which we map to the SNA/ISIC aggregation mentioned above (see Table table S1). In Table S3 are presented the 14 sectors, their description, and their SNA/ISIC counterpart.[29]

A crucial element for the calibration is the ability to georeference each of the regions in the data. Using shapefiles from the OECD, we complement EUREGIO data with the latitude and longitude of the centroids of each region.[30] For this, we use the TL2 regions for all countries, except for Belgium, Germany, Finland, France, Ireland and the United Kingdom. For these 6 countries, we use the TL3 regions and manually create the correspondence to the larger EUREGIO regions. This is also done for some other regions that do not match between datasets due to changes in the NUTS2 regions. Then, we aggregate the polygons to obtain the final map with the geography of the regions in EUREGIO. We proceed in the same fashion for countries that consist of a single region in EUREGIO, but have multiple regions in the OECD shapefile. Additionally, for Indonesia, we obtain its shapefile separately, and include it with the geography of the rest of the regions.

[27] The dataset also includes a "Rest of the World" region. We do not use to calibrate trade costs due to the inability to assign a geographical location to it.

[28] One of the destination industries in the dataset is "Inventory adjustment", which only occurs between a region and itself. We drop these observations before collapsing.

[29] Sectors 14 and 15 are combinations of ISIC sections. In particular, sector 14 is a combination of sectors "L" and "M and N"; while sector 15 is made of ISIC sectors "O" through "U". This implies that when mapping EUREGIO sectors to ISIC sectors, the final number of different industries is 8, instead of 10. Because of this, for the calibration we use the same trade cost for sectors "L" and "M and "N", and proceed in the same fashion for sectors "O-Q" and "R-U".

[30] Shapefiles can be obtained from https://www.dropbox.com/sh/aqfzuofxocv6zgl/AABFWmuLByljQrvY1eXP8em8a?dl=0 or by request at RegionStat@oecd.org.

Table S3: EUREGIO Sector Description and SNA/ISIC Correspondence

Code	Description	SNA/ISIC Correspondence
1	Agriculture	A
2	Mining, quarrying, and energy supply	B, C, D, and E
3	Food, beverages and tobacco	B, C, D, and E
4	Textiles and leather	B, C, D, and E
5	Coke, refined petroleum, nuclear, fuel, and chemicals	B, C, D, and E
6	Electrical and optical equipment and transport equipment	B, C, D, and E
8	Other manufacturing	B, C, D, and E
9	Construction	F
10	Distribution	G, H, and I
11	Hotels and Restaurants	G, H, and I
12	Transport storage and communication	J
13	Financial intermediation	K
14	Real estate renting and business activities	L, M, and N
15	Non-market services	O, P, Q, R,S,T, and U

We complete the construction of the dataset to estimate trade costs by computing the distance between regions. For regions trading with themselves, we compute an average (inner) distance by sampling a large number of points within the regions and average the pairwise distances.[31] For regions trading with other regions, we compute the geodesic distance between their centroids using the haversine formula.[32]

S3.6.2 Baseline gravity regression specification

We postulate that trade costs are given by

$$\tau_{ijs} = (\mathcal{B}_{inter,s})^{\mathbb{1}_{C_i \neq C_j}} (\mathcal{B}_{intra,s})^{\mathbb{1}_{i \neq j, C_i = C_j}} (d_{ij})^{\beta_s}, \tag{S5}$$

and include a distance cost, d_{ij}, a sector-specific intra-country border cost, $(\mathcal{B}_{intra,s})^{\mathbb{1}_{i \neq j, C_i = C_j}}$, and a sector-specific inter-country border cost, $(\mathcal{B}_{inter,s})^{\mathbb{1}_{C_i \neq C_j}}$. Taking logs we can recover the trade cost

[31] For our experiments we sample 400 points per region.
[32] The explicit formula can be found at https://www.movable-type.co.uk/scripts/latlong.html

components by running the following gravity regression

$$\ln\left(X_{ijs}\right) = (1-\sigma_s)\ln\left(\mathcal{B}_{intra,s}\right)\mathbb{1}_{i\neq j, C_i=C_j} + (1-\sigma_s)\ln\left(\mathcal{B}_{inter,s}\right)\mathbb{1}_{C_i\neq C_j} + (1-\sigma_s)\beta_s\ln\left(d_{ij}\right) + \omega_i + \omega_j + \epsilon_{ijs}, \quad \text{(S6)}$$

where X_{ijs} is the value of the trade flow from region i, sector s, to region j, $\mathbb{1}_{i\neq j, C_i=C_j}$ is an indicator variable that takes the value of 1 if regions i and j belong to the same country (and are not the same region), $\mathbb{1}_{C_i\neq C_j}$ is an indicator variable that takes the value of 1 if regions i and j belong to different countries, d_{ij} is the distance between regions i and j (computed as described in S3.6.1), and ω_i and ω_j are fixed effects for region of origin and destination region, respectively.

We obtain sector-specific trade elasticities $1-\sigma_s$ from Fontagné et al. (2022). Specifically, the paper provides trade elasticities at the HS6 product level. We manually map each HS6 product to their corresponding SNA/ISIC (A*10) aggregation section and average elasticities at this level. [33]

To recover the trade cost components, we estimate equation (S6) by sector and recover the trade cost components dividing the estimates by $1-\sigma_s$. Then, we compute trade costs for all region pairs at the sectoral level using equation (S5). For the ISIC sectors, in Table S4 are presented the results of estimating equation (S6), and in Table S5 are presented the values of the components of the trade cost, along with the trade elasticities obtained from Fontagné et al. (2022).

[33] To be parsimonious with the mapping between the EUREGIO and ISIC sectors, we use the same elasticities for sectors “L” and “M-N”, and for sectors “O-Q” and “R-U”. Additionally, due to products not spanning all sectors, for sections "F", "G-I", and "K" we use the average elasticity of all other ISIC sections. Moreover, instead of using the trade elasticities that account for statistical significance, we employ the original estimates of the paper. These only exclude estimates of σ that result in a positive trade elasticity.

Table S4: Gravity regression estimates: SNA/ISIC sectors, baseline specification

	Coefficient		
	$(1-\sigma_s)\beta_s$	$(1-\sigma_s)\ln(\mathcal{B}_{intra,s})$	$(1-\sigma_s)\ln(\mathcal{B}_{inter,s})$
Sector	(1)	(2)	(3)
Agriculture, forestry and fishing, manufacturing	-1.395^{***}	-3.167^{***}	-3.550^{***}
	(0.015)	(0.149)	(0.146)
Mining, quarrying and other industrial activities	-1.614^{***}	-2.110^{***}	-2.079^{***}
	(0.012)	(0.100)	(0.099)
Construction	-1.339^{***}	-3.710^{***}	-9.815^{***}
	(0.028)	(0.290)	(0.288)
Wholesale and retail trade, transportation and storage, Accommodation and food service activities	-1.299^{***}	-3.183^{***}	-7.401^{***}
	(0.020)	(0.201)	(0.201)
Information and communication	-0.803^{***}	-4.007^{***}	-6.051^{***}
	(0.013)	(0.090)	(0.092)
Financial and insurance activities	-0.515^{***}	-6.017^{***}	-11.032^{***}
	(0.026)	(0.186)	(0.188)
Real estate/Professional, scientific, technical, administrative and support service activities	-0.495^{***}	-5.319^{***}	-9.061^{***}
	(0.022)	(0.141)	(0.144)
Public administration and defence, education, human health and social work activities/other service activities	-0.648^{***}	-5.966^{***}	-10.345^{***}
	(0.020)	(0.151)	(0.150)
Observations[a]	542,767		
R-squared[b]	0.68		

Coefficients are estimates for the regression of (log) trade flow between regions on the distance between regions, a dummy for different regions, and a dummy for different countries. The regression is estimated at the sector level and includes fixed effects for region of origin and destination region. Regressions are estimated by each SNA/ISIC (A*10) sector. In each estimation the observations are pairs origin region-destination region. Robust standard errors in parenthesis. All numbers rounded to the nearest thousandth. Robust standard errors in parentheses. All numbers rounded to the nearest thousandth.

[a] Observation count is the sum of individiual observation counts for each regression.

[b] R-squared is the average of R^2 values across all estimated regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table S5: Gravity parameters: SNA/ISIC sectors, baseline specification

	Parameter			
	β	$\mathcal{B}_{intra}$	$\mathcal{B}_{inter}$	$(1-\sigma_s)$
Sector	(1)	(2)	(3)	(4)
Agriculture, forestry and fishing, manufacturing	0.181	1.509	1.586	-7.698
Mining, quarrying and other industrial activities	0.200	1.299	1.294	-8.066
Construction	0.186	1.675	3.916	-7.190
Wholesale and retail trade, transportation and storage, Accommodation and food service activities	0.181	1.557	2.799	-7.190
Information and communication	0.098	1.628	2.088	-8.222
Financial and insurance activities	0.072	2.309	4.639	-7.190
Real estate/Professional, scientific, technical, administrative and support service activities	0.083	2.425	4.524	-6.003
Public administration and defence, education, human health and social work activities/other service activities	0.109	2.721	5.673	-5.960

Parameters β, $\mathcal{B}_{intra}$ and $\mathcal{B}_{inter}$ are obtained from equation (S6) using the estimates of Table S4 and $1-\sigma_s$ from Fontagné et al. (2022), shown in column (4). Numbers rounded to the nearest thousandth.

References

British Petroleum. Statistical review of world energy. Technical report, British Petroleum, 2022.

Julieta Caunedo, David Jaume, and Elisa Keller. Occupational exposure to capital-embodied technical change. 2021.

W C Clark. Carbon dioxide review 1982. *Science (Washington, D.C.); (United States)*, 1 1982. URL https://www.osti.gov/biblio/5963903.

Tianyu Fan, Michael Peters, and Fabrizio Zilibotti. Service-led or service-biased growth? equilibrium development accounting across indian districts. *NBER working paper*, (w28551), 2021.

J Doyne Farmer and François Lafond. How predictable is technological progress? *Research Policy*, 45(3):647–665, 2016.

Gennady M Fedorov and Tatyana Yu Kuznetsova. Datasets on the grp of russian regions, grp sectoral composition and growth rates in 2013-2018. *Data Brief*, 33:106551, nov 2020.

Lionel Fontagné, Houssein Guimbard, and Gianluca Orefice. Tariff-based product-level trade elasticities. *Journal of International Economics*, 137:103593, 2022. ISSN 0022-1996. doi: https://doi.org/10.1016/j.jinteco.2022.103593. URL https://www.sciencedirect.com/science/article/pii/S0022199622000253.

Dirk C Jordan and Sarah R Kurtz. Photovoltaic degradation ratesâan analytical review. *Progress in photovoltaics: Research and Applications*, 21(1):12–29, 2013.

Dale W Jorgenson. Capital theory and investment behavior. *The American Economic Review*, 53(2): 247–259, 1963.

John Perlin. *From space to earth: the story of solar electricity*. Earthscan, 1999.

SETO. 2030 solar cost targets. 2021.

U.S. Energy Information Administration. Annual energy outlook 2022, March 2022.

Dan Welsby, James Price, Steve Pye, and Paul Ekins. Author correction: Unextractable fossil fuels in a 1.5 °c world. *Nature*, 602(7896):E22–E23, 2022. doi: 10.1038/s41586-021-04334-0. URL https://doi.org/10.1038/s41586-021-04334-0.

Ryan H Wiser and Mark Bolinger. Benchmarking anticipated wind project lifetimes: Results from a survey of us wind industry professionals. Technical report, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), 2019.

Heran Zheng, Yangchun Bai, Wendong Wei, Jing Meng, Zhengkai Zhang, Malin Song, and Dabo Guan. Chinese provincial multi-regional input-output database for 2012, 2015, and 2017. *Scientific Data*, 8(1):244, Sep 2021. ISSN 2052-4463. doi: 10.1038/s41597-021-01023-5. URL https://doi.org/10.1038/s41597-021-01023-5.