# Green Industrial Policies and Energy Transition in the Globalized Economy *†‡

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**Abstract**

The transition to renewable energy depends on the trade of renewable energy equipment, such as solar panels and wind turbines. However, most existing studies on green industrial policies adopt a closed economy approach, overlooking critical margins in an open economy where subsidies can lead to different domestic industry responses due to global competition and have global spillover effects. This paper examines the dynamic effects of green industrial policy on global carbon emissions and welfare in a globalized economy, focusing on the Inflation Reduction Act (IRA), which includes subsidies for producing renewable energy and renewable energy equipment. I develop a multi-country dynamic general equilibrium trade model in which equipment is traded and accumulated as capital, and productivity improves through learning-by-doing. The quantitative analysis shows the IRA reduces global carbon emissions by 0.60% and increases US welfare by 0.02%, while decreasing global welfare by 0.03%. Considering equipment trade is crucial; without it, the model misrepresents the IRA's impact, predicting smaller carbon reductions, a loss in US welfare, and a gain in global welfare.

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# 1 Introduction

Global greenhouse gas emissions are not on track to meet the targets set by the Paris Agreement, raising concerns about the effectiveness of current climate policies (COP28 (2024)). The political challenges of implementing stringent carbon policies have led countries to pursue more politically feasible options, such as green industrial policies, which marry environmental goals with domestic industrial policy by subsidizing clean technology goods. Examples include EU's Green Deal Industrial Plan and India's production-linked incentive for solar modules, and Japan's Green Transformation plan. Another key example is the recent renewable energy provisions in the Inflation Reduction Act (IRA), which include both demand-side and supply-side subsidies; subsidy for renewable energy production (energy subsidy, hereafter) and subsidy for producing renewable energy equipment (equipment subsidy, hereafter).

A growing strand of the literature has investigated to examine the efficacy of such policies, such as the IRA (Arkolakis and Walsh (2023), Bistline et al. (2023), Casey et al. (2023), Donald (2024), Gentile (2024)) and similar policies in China and European countries (Banares-Sanchez et al. (2024), Abrell et al. (2019), Hitaj and Löschel (2019), Gugler et al. (2021)). The bulk of the literature conduct their analysis in a closed economy setting. However, an important aspect of the energy transition is that the equipment necessary to substitute fossil fuels is globally traded, with production concentrated in a handful of countries. For example, the US and the EU, which are the focus of the cited studies, import 83 percent and 95 percent of their solar equipment from abroad, respectively. The omission of trade can affect the assessment of green industrial policies for three key reasons. First, the same subsidy can lead to different responses in the domestic equipment industry as it faces global competition. Second, equally important, the incidence of subsidies varies depending on who supplies the equipment and who consumes the energy, which could involve different countries in an open economy.[1] Third, to the extent that some subsidies increase domestic equipment production, these effects can spread globally.

Incorporating such effects is crucial as carbon emissions are a global phenomenon. If a subsidy reduces domestic carbon emissions but leads to carbon leakage, the overall impact is diminished. Conversely, if a different subsidy is less effective at reducing domestic emissions but induces other countries to lower their carbon emissions, it could be a more effective policy tool from a global perspective.

Building on this gap in the literature, this paper explores the dynamic effects of green industrial policy—specifically, the renewable energy provisions of the IRA—on global carbon emissions and welfare in an open economy context. This paper addresses three key questions: What role does equipment trade play in the energy transition? How do energy and equipment subsidies in the IRA affect welfare and carbon emissions in the US and globally? Finally, how do these subsidies interact with trade policies and the green industrial policies of other countries?

To answer these questions, I build a dynamic general equilibrium model incorporating trade

[1] For example, consider a model where there is no trade in equipment and equipment is the sole input for producing renewable energy. Then a subsidy for energy and equipment may result in the same outcome, indicating that the model is not designed to study the separate impacts of the two types of policies.

in renewable energy equipment and green industrial policy instruments. In the static part of the model, producing solar and wind energy requires installed solar and wind equipment with decreasing returns to scale, where the equipment can be supplied domestically or from other countries. Then, solar, wind, and fossil fuels are combined using nested CES technology to generate composite energy, where each share of energy sources is endogenously determined by the relative price between them. This composite energy is integrated into a trade model with input-output linkages, as in Caliendo and Parro (2015). Countries can implement subsidies for renewable energy and renewable energy equipment production.

The model is dynamic to capture the nature of the energy transition; the transition happens by countries accumulating renewable energy equipment as capital. To reflect the long-term price decline in the equipment sector, I model the productivities of producing the equipment to be endogenously determined through external learning-by-doing.[2] Due to the learning-by-doing, subsidies have impact on shaping the dynamic specialization.

In the model, equipment trade reduces the investment costs of renewable energy in countries with lower equipment productivity, thereby accelerating the energy transition and fostering economic growth. At the same time, equipment trade shapes the impact of each subsidy. For instance, in an equipment net-importing country implementing an energy subsidy, the additional equipment demand can be met through imports, meaning it does not necessarily increase the domestic share of equipment in the global market. This leads to improved terms of trade for net-exporting countries and worsened terms of trade for the subsidizing country. Considering the effects of learning-by-doing, an energy subsidy further reinforces the status quo comparative advantage in equipment production. In contrast, a unilateral equipment subsidy potentially makes the subsidizing country a net exporter in the global equipment market, worsening the terms of trade for the status-quo net-exporting countries. Additionally, it has a lasting impact, as the subsidy shifts the comparative advantage toward the subsidizing country through learning-by-doing, further enhancing the welfare of the subsidizing country.

Each subsidy differs in terms of its global spillover effects on carbon emissions. An energy subsidy decreases domestic fossil fuel demand by increasing the relative price of fossil fuels, but it results in carbon leakage. Reduced domestic fossil fuel demand, combined with higher equipment demand, leads to increased fossil fuel use in other countries. On the other hand, when the US implements an equipment subsidy, it reduces carbon emissions in *other* countries by lowering the global price of equipment through equipment exports.

I bring the model to data and calibrate the model using various datasets from international agencies. Four sets of parameters are essential for my quantification. The first is the substitution elasticities across energy sources. For the inner nest between solar and wind, I estimate the elasticity using price and output ratios of solar and wind energy from country-level data. The second is the learning rate in renewable energy equipment production. I use model inversion to obtain a time series of productivity in renewable energy equipment production as a function of observable

[2]Under learning-by-doing, as Krugman (1987) mentioned, "a pattern of specialization, once established, will induce relative productivity changes which strengthen the forces preserving that pattern."

variables (input cost, price, and trade share) and the trade elasticity parameter. By introducing a novel dataset on solar and wind equipment production and output prices in each country, I estimate a learning rate of 18 percent for solar equipment and 19 percent for wind equipment. The third is the trade elasticity for solar and wind equipment, which I calibrate using product-level estimates from Fontagné et al. (2022), indicating that the trade elasticity for solar equipment is higher than that for wind equipment. Lastly, I measure the productivity and decreasing returns to scale in renewable energy production for solar and wind in each country using geospatial data on renewable potentials. I find larger decreasing return to scale effect in wind than in solar, with significant variations across countries.

To quantitatively answer the questions posed earlier, I simulate the model with the IRA subsidies, which consist of 20% subsidy in renewable energy and 30% subsidy in equipment production. The impact of the IRA on $CO_2$ emissions and welfare, defined as the discounted sum of real income incorporating the social cost of carbon, are as follows.

Quantitative analysis suggests that the IRA reduces global carbon emissions but still still politically feasible. The IRA reduces global carbon emissions by 0.60%, increases US welfare by 0.02%, but decreases global welfare by 0.03%, with varying impacts across countries. These effects are largely driven by the US becoming a net exporter of renewable energy equipment. The IRA significantly increases the US share of the global market for solar and wind equipment, peaking at 32% and 21%, respectively. Lower global equipment prices, resulting from increased US production, help accelerate the energy transition both domestically and internationally. The US welfare gains and global welfare losses primarily stem from the terms of trade effect, with learning-by-doing amplifying these effects. However, these impacts are temporary; once the subsidy period ends, the US equipment market share gradually returns to its original level over time.

Each subsidy component—energy and equipment—has distinct impacts on both welfare and carbon emissions, with equipment trade playing a critical role. Although the energy and equipment subsidies allocate nearly the same budget (118 billion and 125 billion US dollars, respectively), the equipment subsidy, compared to the energy subsidy, has several unique effects: (i) it significantly boosts the global market share of US-produced equipment (20.6% vs. 2.7% for solar equipment), (ii) it is less effective at reducing US carbon emissions but more effective at reducing global carbon emissions (-0.23% vs. -0.17%), and (iii) it increases the US welfare (0.06% vs. -0.04%) at the expense of global welfare (-0.02% vs. 0.01%) due to the terms of trade effect and learning-by-doing. As a result, the optimal policy for the US is to prioritize larger subsidies for equipment—up to 45%—rather than focusing on renewable energy subsidies. However, global welfare is maximized when the US subsidizes renewable energy up to 40% but refrains from subsidizing equipment.

Trade in equipment is a key component driving these results. To quantify the role of equipment trade in the impact of the IRA, I simulate the model without equipment trade. Not considering equipment trade misleads the impact of the IRA; the IRA lead to a smaller global carbon reduction (-0.42%), a loss in US welfare (-0.01%) and a gain in global welfare (0.01%). Without trade, the US cannot export its subsidized equipment to the global market, limiting the benefits of cheaper

equipment to the US alone. This results in smaller global carbon reduction effect. However, the absence of a terms of trade effect—since the US cannot export—leads to a modest improvement in global welfare due to global carbon reductions.

In this scenario, the energy subsidy results in a smaller global carbon reduction (-0.15%), a smaller US welfare loss (-0.02%), and a smaller global welfare gain (+0.00%) compared to the model with equipment trade. Without trade, the energy subsidy is less efficient at reducing carbon emissions due to higher equipment costs, as additional demand from the subsidy must be met solely by domestic supply. Consequently, the US gains more from learning-by-doing, while net-exporting countries worse off without trade, resulting in a smaller US welfare loss and global welfare gain. Quantitatively, the misleading outcomes of the IRA without trade are primarily driven by the equipment subsidy component. Under the no-equipment-trade scenario, the equipment subsidy results in a smaller global carbon reduction (-0.13%), a lower US welfare gain (+0.04%), and higher global welfare (+0.01%) compared to the baseline.

Based on the findings, I explore extensions of the IRA scenario. First, to examine the interaction between trade policy and green industrial policies, I simulate a scenario where the US implements both the IRA and a tariff on solar equipment imports from China and Southeast Asian countries. I find that the tariff, both alone and in combination with subsidies, reduces US and global welfare while increasing carbon emissions by delaying the transition in the US. This is primarily due to the negative local effects of higher solar equipment costs in the US in the early stages, and the global impact of reduced learning in Southeast Asia and China. Second, I consider a scenario in which other major countries, such as the EU and China, respond to the IRA by implementing identical policies. If the US, EU, and China all adopt policies identical to the IRA, the positive effect of the IRA on the US's global equipment market share disappears. However, US welfare still increases (0.04%) due to subsidized equipment imports from China as it fasten the transition and reduced fossil fuel demand in other countries resulting from their energy subsidies. Overall, I find larger global carbon emissions reduction effect (-3.16%). Despite this, global welfare declines (-0.11%) due to China's welfare loss from significant budgetary spending.

**Related Literature** This paper contributes to several strands of literature, particularly in the areas of trade, industrial policy, and the energy transition.

First, it builds on the growing body of literature that examines the effects of subsidies for renewable energy and equipment production including the IRA. Empirical studies such as Aldy et al. (2023), Gerarden (2023), De Groote and Verboven (2019), Gugler et al. (2021), Hitaj and Löschel (2019), Bollinger et al. (2024), and Banares-Sanchez et al. (2024) have analyzed the within-country impact of subsidies on solar or wind energy. My work complements the empirical works by quantifying the global impact of unilateral subsidies in a general equilibrium trade model. Other papers incorporate general equilibrium models under closed economy setting (Donald, 2024; Gentile, 2024; Bistline, Mehrotra and Wolfram, 2023; Casey, Jeon and Traeger, 2023). One notable exception is Arkolakis and Walsh (2023), which develops a dynamic spatial model incorporating detailed electricity grid that incorporates renewable energy and examines the impact of energy subsidy on welfare under the IRA but without the consideration of equipment trade and carbon

implications. My analysis extends this literature by including equipment trade, allowing for a more nuanced understanding of how energy and equipment subsidies affect global welfare and carbon emissions.

This paper contributes to the growing body of macro-trade literature that study the impact of trade on environmental outcomes (Kortum and Weisbach, 2021; Copeland, Shapiro and Taylor, 2021; Cruz and Rossi-Hansberg, 2024; Garcia-Lembergman, Rodríguez-Clare, , Ramondo and Shapiro, 2024; Xiang, 2023). I contribute to the literature by studying how clean technology trade affects the global economy. Xiang (2023) studies the role of environmental policies in promoting green technology innovations through multinational production. The main difference is that I explicitly model equipment tradeenabling a focus on how clean technology flows through trade, and I emphasize the impact of green industrial policies rather than environmental policies.

Third, this paper contributes to the literature on industrial policy in an open economy setting. Classical works on industrial policy (Baldwin (1969), Bardhan (1971), Ethier (1982), and Krugman (1987)), have been revisited by more recent studies (Juhász (2016), Juhász et al. (2023)), where some of them apply quantitative trade models to examine the effects of industrial policy (Goldberg et al. (2024), Lashkaripour and Lugovskyy (2023), Ju et al. (2024), and Bartelme et al. (2024)). My paper adds to this literature by analyzing the global welfare implications of unilateral green industrial policies, with a particular focus on the global externality of carbon emissions.

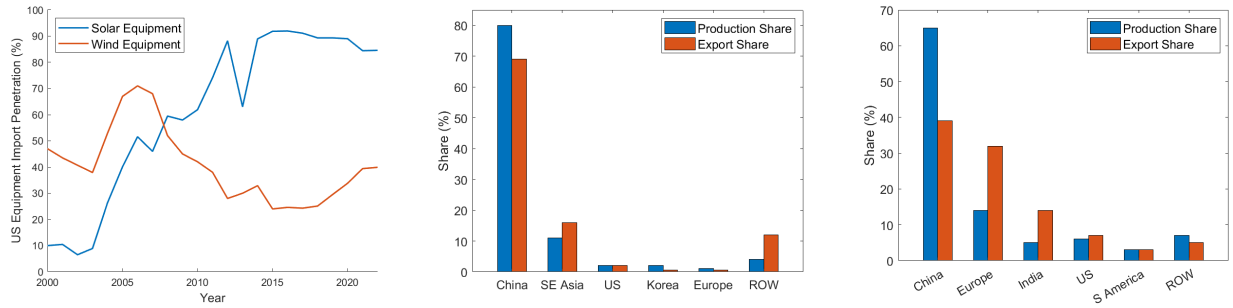
Finally, this paper contributes to the literature on the energy transition by providing estimates for two key variables that determine the pace of the transition: the substitution elasticity between energy sources and the learning rate in renewable energy equipment production. As far as I know, this paper is the first to estimate the substitution elasticity between solar and wind energy. My estimates suggest that solar and wind energy are weak complements, rejecting the common assumption of perfect substitutability in the literature.[3] Additionally, I estimate the learning rate for solar and wind energy equipment production in a model-consistent way using novel datasets, contributing empirical evidence on the rates of technological progress in equipment production. The estimated learning rate is 18 percent for solar equipment and 19 percent for wind equipment, which are comparable to the estimates in the literature (Baker et al. (2013), Bolinger et al. (2022), Arkolakis and Walsh (2023), and Covert and Sweeney (2024)).

This paper proceeds as follows. Section 2 briefly explains the background of this study. Section 3 presents the model, and Section 4 provides overview of the data and parameter calibration. Section 5 provides model validation. Section 6 then uses the model to conduct a set of counterfactuals which identify the role of different types of subsidies on global welfare and carbon emissions. Section 7 discusses the extensions of the counterfactual scenarios considering a trade policy and other countries' policy responses. Section 8 concludes.

[3]Forecasts regarding clean growth hinge significantly on the level of substitutability between renewables and fossil fuels. The importance of the elasticity of substitution becomes more evident when considering how quantitative predictions are highly influenced by the specific value assigned to this parameter in quantitative models. See Acemoglu et al. (2012), Golosov et al. (2014) for the discussion and see Papageorgiou et al. (2017), Jo (2023), and Wiskich (2023) for the estimation.

Figure 1: Trend in Equipment Trade/Production

(a) US Import Penetration (b) Global Share in Solar Equip. (c) Global Share in Wind Equip.




Note: Panel (a) depicts the import penetration ratio of US solar and wind equipment. Panel (b) depicts production share and export share of major countries in solar equipment, and panel (c) depicts production share and export share in wind equipment.

# 2 Background

## 2.1 Production and Trade in Renewable Energy Equipment

In this section, I present evidence of the importance of trade in renewable energy equipment by showing (a) the US import penetration ratio for equipment and (b) the share of major countries involved in the production and export of solar and wind energy equipment.[4]

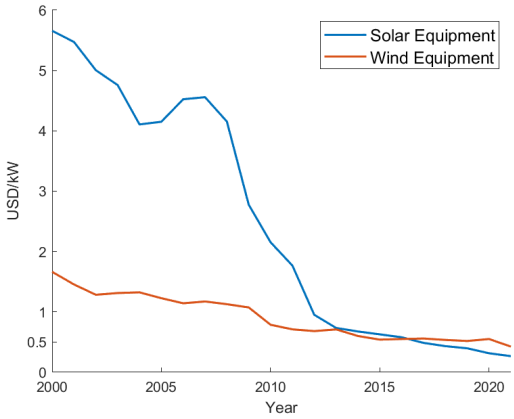
Panel (a) in Figure 1 shows the time-series import penetration ratio of equipment in the US from 2000 to 2022. The US reliance on imports is more pronounced for solar energy equipment compared to wind energy equipment. The import penetration ratio of solar equipment in the US (blue solid line) was around 10 percent in 2000, dipped in 2013 due to tariffs on Chinese solar equipment, but remained at 83 percent in 2022. Meanwhile, the import penetration ratio of wind equipment (red solid line) has been declining, peaking at 70 percent in 2006 and falling to 39 percent in 2022.

Panel (b) and (c) in Figure 1 shows the shares of major countries in the production and export of solar and wind energy equipment in 2022. The production of renewable energy equipment is highly concentrated in a few countries, with China as the dominant player. China accounts for 80 percent of global solar equipment production and 69 percent of global exports, while Southeast Asian countries contribute 11 percent of production and 16 percent of exports. Other countries hold relatively small shares; for example, the US accounts for 2 percent of both global production and export.

In wind equipment, although China's dominance is less pronounced than in solar equipment, it still leads with 65 percent of global production and 39 percent of exports. European countries play a significant role, accounting for 14 percent of production and 32 percent of export shares. The US accounts for 6 percent share of global production and 7 percent of global export.

[4]For the details about data, see the Appendix section B.2.

Figure 2: Price of Equipment




Note: This figure plots the price of solar and wind energy equipment in year 2000 to 2021.

## 2.2 Learning-by-doing in Renewable Energy Equipment

The costs of fossil fuels and nuclear power are mainly driven by two factors: the price of the fuel they consume and the plant's operating expenses. Electricity from renewable energy, on the other hand, have much lower operating costs, as they rely on freely available renewable potentials; sources like wind and sunlight. What primarily influences the cost of renewable energy is the price of the equipment.

The prices of renewable energy equipment, including both solar and wind equipment, have experienced significant declines since 2000. Figure 2 shows the time series of prices for solar and wind energy equipment per kW from 2000 to 2021. The price of solar equipment (blue solid line) decreased by 95 percent over 21 years, from 5.6 US dollars per kW in 2000 to 0.27 US dollars per kW in 2021. The price of wind equipment (red solid line) also experienced a substantial price decline, dropping from 1.63 US dollars per kW in 2000 to 0.43 US dollars per kW in 2021, a 74 percent decrease. In the literature, this process has been understood through "learning-by-doing," with the notion of the learning rate, defined as the percentage change in cost when production doubles.

Thanks to the large learning-by-doing effect in the renewable energy equipment, the price of electricity from solar and wind also has shown a dramatic decreasing pattern over time. Figure B.1 compares the price of electricity from various energy sources such as solar, wind, nuclear and coal with respect to cumulative installed capacity. While the price of solar (wind) electricity declined by 36% (23%) when doubling the installation, there is no such pattern observed in nuclear energy and coal.[5]

[5]Using US data, Bolinger et al. (2022) find that the learning rate for solar and wind equipment is 24 percent and 15 percent, respectively.

### 2.3 Renewable Energy Provisions in the IRA

In August 2022, the United States passed the IRA, representing the largest-ever investment in combating climate change and advancing clean energy.[6] The IRA provides $369 billion for energy security and climate change programs, including incentives for deploying renewable energy sources and producing renewable energy equipment (Congressional Budget Office (2024)). These provisions aim to reduce domestic carbon emissions by at least 40 percent below 2005 levels by 2030.

The IRA includes two key subsidies. The first type of subsidy is the tax credit for various renewable energy sources, including wind, biomass, geothermal, and solar. The Production Tax Credit (PTC) provides a per-kilowatt-hour (kWh) credit for electricity generated from qualified renewable energy resources, and the Investment Tax Credit (ITC) provides a credit for a percentage of the investment in renewable energy projects. This includes solar, wind, fuel cells, and certain other technologies, while in this paper, I only focus on solar and wind.

The second type of subsidy is for the equipment subsidies, which the clauses are contained in Advanced Manufacturing Act (Section 45X) which is designed to incentivize the domestic production of key components for renewable energy technologies. This includes solar panels, wind turbines, batteries, and other critical materials needed for clean energy infrastructure. This covers wide range of components in each supply chain. For solar, it covers polysilicon, photovoltaic (PV) wafer, PV Cell, PV module, and inverter. For wind, it covers blade, nacelle, and tower.

## 3 Model

In this section, I construct a dynamic multi-country-multi-sector general equilibrium model to study the impact of green industrial policies on global welfare and carbon emissions. In particular, the static part of the model extends Caliendo and Parro (2015) by incorporating detailed energy production, and then it connects to the dynamic growth model with capital accumulation and external learning-by-doing in equipment production.

### 3.1 Environment

Consider a multi-country multi-sector trade model. The economy has $N$ countries indexed by $n = 1, ..., N$ and $J$ sectors indexed by $j$. Time is discrete, $t = 1, ..., \infty$. Each country has energy (E) and non-energy sectors. Energy sector is consist of three sub-sectors; solar (s), wind, (w), and fossil fuel (f). Non-energy sector contains capital goods sectors (K) and non capital goods sector (O) where capital goods sector is consist of solar energy equipment (S), wind energy equipment (W), fossil fuel capital goods (F), and non-energy capital goods (D). For simplicity, in the model, I keep non-capital goods sector as a single sector, but I expand it into multiple sectors in the quantification. I denote by $\Omega_E = \{s, w, f\}$ the set of energy sectors and in particular, $\Omega_{RE} = \{s, w\}$ the set of renewable energy sectors. The set of capital good sectors is denoted by $\Omega_K = \{S, W, F, D\}$ and

[6] US Department of State, "The Climate Crisis: Working Together for Future Generations."

$\Omega_{REE} = \{S, W\}$ denotes the set of renewable energy equipment sectors. Once invested, each capital goods $j$ becomes corresponding capital stock in each country. Non-capital good sector is denoted by $\Omega_O$, and the set of all sectors is denoted by $\Omega \equiv \Omega_E \cup \Omega_K \cup \Omega_O$. I denote by $\Omega_j^*$ the Complement set of $\Omega^j$.

There is a continuum of intermediate goods $\omega^j \in [0, 1]$ in each sector $j$. The production process involves differentiated goods ($\omega^j$) which are combined using a CES aggregator with an elasticity across varieties denoted as $\sigma^j$. The market structure is characterized by perfect competition.

Government in each country $n$ can subsidize domestic production in renewable energy and equipment sectors using output price subsidy $s_{n,t}^j$, or charge an import tariff on equipment sectors against import from country $i$ denoted by $\tau_{ni}^j$. I assume output subsidy budget in each country is lump-sum transferred from the consumers.

### 3.2 Household

Representative household in each region $n$ has initial endowment of labor $L_n$ and capital stocks $K_{n,1}^k$ for $k \in \Omega_K$. Household supplies labor inelastically, mobile across sectors within each region. Representative household makes consumption ($C_{n,t}^j$) and investment ($I_{n,t}^k$) decisions in each period to maximize lifetime utility, which is a discounted sum of consumption with Cobb-Douglas weights $\mu_{n,t}^j$ with disutility from carbon emissions:

$$U_n = \sum_{t=1}^{T} \beta^t \Big[ \prod_{j \in \Omega_K^*} (C_{n,t}^j)^{\mu_n^j} \frac{1}{1 + SCC(Z_t - Z_0)} \Big], \text{ where } \sum_{j \in \Omega_K^*} \mu_n^j = 1. \tag{1}$$

The second term in square bracket captures the disutility from carbon. $Z_0$ is global emissions in the initial period from data and $Z_t$ are global emissions in period $t$. $SCC$ is a damage parameter which the value is calibrated to match social cost of carbon per unit ton increase in emissions. Carbon emissions is a pure negative externality following Shapiro (2021), which does not affect household's optimal decision.

### 3.3 Production

I first overview the production and investment in the economy. In the energy sector, producing solar and wind energy requires a single input: installed solar and wind equipment, respectively. Each production function exhibits decreasing returns to scale. Fossil fuel production, on the other hand, requires fossil fuel capital, labor, and intermediate goods. Solar, wind, and fossil fuels are then combined using a nested CES technology to generate composite energy.

Producing goods in the non-energy sector requires intermediate goods including composite energy, non-energy capital, and labor. The renewable energy equipment sector experiences external learning-by-doing effects, leading to dynamic economies of scale where cumulative past production experience determines current productivity. Once capital goods—solar and wind equipment, fossil fuel capital goods, and non-energy capital goods—are produced, they are traded across countries and accumulated as capital stock in each country through investment.Through

this investment process, these capital goods serve as inputs for further production.

**Renewable Energy Production.** Each solar and wind energy $j$ in region $n$ at time $t$ is produced using installed equipment in each region with production efficiency $z_n^j(\omega^j)$:

$$y_{n,t}^j(\omega^j) = z_n^j(\omega^j)\left(K_{n,t}^j(\omega^j)\right)^{\xi_n^j}, \text{ for } j \in \Omega_{RE} \tag{2}$$

where I assume $\xi_n^j < 1$, indicating decreasing returns to scale. The production efficiency $z_n^j(\omega^j)$ is country- and sector-specific, capturing heterogeneity in solar and wind potential across countries. $\xi_n^j < 1$ reflects within-country heterogeneity in solar and wind potential. The intuition is that as a country increases solar or wind equipment installations, areas with higher potential are utilized first, and additional installations are placed in locations with relatively lower potential *within* the country.

Then the unit cost is given by $\frac{c_{n,t}^j}{z_n^j(\omega^j)}$, where $c_{n,t}^j$ is a function of stock of capital and rental rate of capital in region $n$ at time $t$.

$$c_{n,t}^j = \frac{1}{\left(K_{n,t}^j\right)^{\xi_j - 1}} r_{n,t} \tag{3}$$

Due to $\xi_n^j < 1$ for $j \in \Omega_{RE}$, renewable energy production features dis-scale economy, that is, unit cost of producing renewable energy increases in stock of renewable equipment installed.

**Positive profit in Renewable Energy sectors.** As these sectors face decreasing return to scale and perfect competition, marginal cost, which equals the output price at the equilibrium, is higher than the average production cost, and the positive profit exists. The profit of for each goods in sector $j \in \Omega_{RE}$ is given by $\Pi_{n,t}^j(\omega^j) = p_{n,t}^j(\omega^j) y_{n,t}^j(\omega^j) - r_{n,t}^j K_{n,t}^j(\omega^j)$.[7] Later I assume the profits from renewable energy sectors are allocated to household budget.

**Fossil Fuel Energy Production.** Fossil fuel sector combines labor, fossil fuel capital, and intermediates in country $n$ at time $t$:

$$y_{n,t}^f(\omega^f) = z_n^f(\omega^f)(L_{n,t}^f(\omega^f))^{\gamma_n^{L,f}}(K_{n,t}^F(\omega^f))^{\gamma_n^{F,f}} \prod_{j'=\Omega_K^*} \left(M_{n,t}^{j'f}(\omega^f)\right)^{\gamma_{n,t}^{M,j'f}} \tag{5}$$

where $E_{n,t}^j(\omega^f)$, $L_{n,t}^j(\omega^f)$, $K_{n,t}^{r,j}(\omega^f)$, and $M_{n,t}^{j'j}(\omega^f)$ is the quantity of composite energy, labor, capital stock of $r \in \Omega_K$ used in sector $j$, and intermediate goods from sector $j'$ used in country $n$ to produce $y_{n,t}^f(\omega^f)$, respectively. The production technology for fossil fuel energy features constant return to scale, *i.e.*, $\gamma_n^{L,f} + \gamma_n^{F,f} + \sum_{j'=\Omega_K^*} \gamma_{n,t}^{M,j'f} = 1$.

[7] Solving for the first order condition, I can rewrite the profit at the equilibrium:

$$\Pi_{n,t}^j(\omega^j) = (1 - \xi_j) p_{n,t}^j(\omega^j)(K_{n,t}^j(\omega^j))^{\xi_j}. \tag{4}$$

The unit cost is given by $\frac{c^f_{n,t}}{z^f_n(\omega^f)}$, where

$$c^f_{n,t} = B^f_{n,t}(w_{n,t})^{\gamma^{L,f}_n}(r_{n,t})^{\gamma^{F,f}_n}\prod_{j'=\Omega^*_K}\left(P^{j'}_{n,t}\right)^{\gamma^{M,j'f}_{n,t}} \tag{6}$$

Here $B^f_{n,t}$ is a function of share of value added from each inputs.[8]

**Carbon Emissions.** In this model, carbon is released when fossil fuel energy is used and accumulated across time: $Z_t = \sum_{t'=1}^{t}\beta^{t'}\sum_n \bar{\epsilon}x^f_{n,t'}$, where $\bar{\epsilon}$ is a parameter that maps fossil fuel use into carbon emissions, and $x^f_{n,t'}$ is amount of fossil fuel used in country $n$ at time $t'$, which the formal definition will be introduced later. As in Garcia-Lembergman et al. (2024), I do not consider abatement technologies - which reduces carbon emissions with the same input of fossil fuel - being heterogeneous across sectors and countries.[9]

**Composite Energy Production.** Composite energy input $e_{n,t}$ in each country $n$ is a CES composite between energy generated by solar, wind, and fossil fuel, but with a nested structure. In the inner nest, renewable energy, $y^r_{n,t}$ is a CES composite of solar and wind energies:

$$y^r_{n,t} = \left[[\eta_r]^{\frac{1}{\rho}}[y^s_{n,t}]^{\frac{\rho-1}{\rho}} + [1-\eta_r]^{\frac{1}{\rho}}[y^w_{n,t}]^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{7}$$

where $\eta_r$ is a level shifter and $\rho$ captures substitution elasticity between solar and wind energies.

Then the composite energy $e_{n,t}$ is CES composite of renewable energy and fossil fuel energy:

$$e_{n,t} = \left[[\eta_e]^{\frac{1}{\psi}}[y^r_{n,t}]^{\frac{\psi-1}{\psi}} + [1-\eta_e]^{\frac{1}{\psi}}[y^f_{n,t}]^{\frac{\psi-1}{\psi}}\right]^{\frac{\psi}{\psi-1}}, \tag{8}$$

where $\eta_e$ is a level shifter and $\psi$ captures substitution elasticity between renewable energy and fossil fuel energy.

Due to CES technology in composite energy production, share of each energy source, $\gamma^{M,j'f}_{n,t}$, $j' \in \Omega_E$, is time dependent and endogenously determined by the relative price of energy sources. This implies that while the energy intensity of each country-sector's production is governed by the parameter $\gamma^{j,e}_n$ which is calibrated outside the model, fossil fuel intensity of production in each economy is endogenously determined within the model.

**Production Function for Non-energy Sectors.** Production technology for non-energy sectors, $j \in \Omega^*_E$, combines labor, non-energy capital $K^D_{n,t}$, and intermediates in country $n$ at time $t$:

$$y^j_{n,t}(\omega^j) = z^j_{n,t}(L^j_{n,t}(\omega^j))^{\gamma^{L,j}_n}(K^D_{n,t}(\omega^j))^{\gamma^{D,j}_n}\prod_{j'=\Omega^*_K}\left(M^{j'j}_{n,t}(\omega^j)\right)^{\gamma^{M,j'j}_{n,t}} \tag{9}$$

[8] In particular, $B^f_{n,t} = \left((\gamma^{L,f}_n)^{\gamma^{L,f}_n}(\gamma^{F,f}_n)^{\gamma^{F,f}_n}\prod_{j'=\Omega}(\gamma^{M,j'f}_{n,t})^{\gamma^{M,j'f}_{n,t}}\right)^{-1}$

[9] In this setting, fossil fuels are only used in producing composite energy, so this specification does not consider non-energy use of fossil fuel - for example, in a real world, fossil fuel is directly used in producing plastic or concrete, but this is not considered.

Again, I assume constant return to scale, *i.e.*, $\gamma_n^{L,j} + \gamma_n^{D,j} + \sum_{j' = \Omega_K^*} \gamma_{n,t}^{M,j'j} = 1$. Then the unit cost is given by:

$$c_{n,t}^j = B_{n,t}^j (w_{n,t})^{\gamma_n^{L,j}} (r_{n,t})^{\gamma_n^{D,j}} \prod_{j' = \Omega_K^*} \left( P_{n,t}^{j'} \right)^{\gamma_{n,t}^{M,j'j}} \text{ for } j \in \Omega_E^*, \tag{10}$$

where $B_{n,t}^j$ is a function of share parameters.[10]

For equipment sectors, $z_{n,t}^j$ for $j \in \Omega_{REE}$, is endogenously determined by learning-by-doing, which the exact specification is introduced in the later section (Section 3.8).

### 3.4 Composite Intermediate Goods

In this economy, there are producers of composite intermediate goods in each sector $j$ in country $n$ at period $t$, where the output is denoted by $Q_{n,t}^j$. Composite intermediate goods are produced by procuring $\omega^j$ from suppliers offering the lowest costs across countries using Dixit and Stiglitz (1977) Aggregator:

$$Q_{n,t}^j = \left[ \int f_{n,t}^j (\omega^j)^{1 - 1/\sigma^j} d\omega^j \right]^{\sigma^j / (\sigma^j - 1)}$$

where $f_{n,t}^j$ is demand of goods $\omega^j$ and $\sigma^j$ is the elasticity of substitution across intermediate goods within sector $j$. Solving the composite intermediate good producer's problem gives the demand for good $\omega^j$

$$r_n^j(\omega^j) = \left( \frac{p_{n,t}^j(\omega^j)}{P_{n,t}^j} \right)^{-\omega^j} Q_{n,t}^j$$

where $p_{n,t}^j$ denotes the lowest price of good $\omega^j$ and $P_{n,t}^j$ denotes the unit price of the composite intermediate good

$$P_{n,t}^j = \left[ \int p_{n,t}^j (\omega^j)^{1 - 1/\sigma^j} d\omega^j \right]^{\frac{1}{1 - \sigma^j}}.$$

### 3.5 Trade Costs and Prices

Trade in the outputs of tradable sectors incurs standard iceberg trade costs; $\kappa_{ni,t}^j$ amount of sector $j$ good is shipped from country $i$ to $n$ to deliver one unit of it, with $\kappa_{ii,t}^j = 1$. Then, combined with subsidies $s_{i,t}^j$, a unit cost of intermediate good $\omega^j$ produced in $i$ in available country $n$ is given by

[10] $B_{n,t}^j = \left( (\gamma_n^{L,j})^{\gamma_n^{L,j}} (\gamma_n^{D,j})^{\gamma_n^{D,j}} \prod_{j' = \Omega} (\gamma_{n,t}^{M,j'j})^{\gamma_{n,t}^{M,j'j}} \right)^{-1}$.

$c^j_{i,t}\kappa^j_{ni}(1-s_{i,t})/z^j_{i,t}(\omega^j)$. This implies that the price of intermediate good $\omega^j$ in country $n$ is

$$p^j_{n,t}(\omega^j) = \min_i \left\{ \frac{c^j_{i,t}\kappa^j_{ni}(1-s^j_{i,t})}{z^j_{i,t}(\omega^j)} \right\}$$

I follow probabilistic representation of technologies in Eaton and Kortum (2002). That is, production efficiency is a realization of random variable $z^j_n$ coming from a distribution:

$$Pr[z^j_n(\omega^j) \leq z] = \exp\{-A^j_n z^{-\theta^j}\}.$$

Here the location parameter $A^j_n$ which is sector-country specific, governs the average productivity in each sector, and the shape parameter $\theta^j$, which is sector-specific, captures the dispersion of productivity across goods $\omega^j$.[11] Then the price index for each sector $j$ in country $n$ is given by

$$P^j_{n,t} = \Big[ \sum_i (c^j_{i,t}\kappa^j_{ni,t}(1-s^j_{i,t}))^{-\theta^j} A^j_{i,t} \Big]^{-1/\theta^j} \tag{11}$$

where $c^j_{n,t}$ is the unit cost of producing sector $j$ goods in country $n$. I allow all sectors to be tradable but renewable energies, $\kappa^s_{in,t} = \kappa^w_{in,t} = \infty$ for $i \neq n$. This implies that for solar and wind energy, the price is given by $P^j_{n,t} = c^j_{n,t}(1-s^j_{n,t})(A^j_{n,t})^{-1/\theta^j}$ for $j \in \Omega_{RE}$, and other countries' energy subsidies has no direct impact to renewable energy prices in country $n$. On the other hand, as equipment is tradable, equipment subsidy in one country affects other countries' equipment prices through trade.

Deriving the price index for each region and sector allows me to analyze the (static) effects of renewable energy subsidies. As I mentioned before, due to CES, the share of fossil fuel input in producing $j$ goods, $\gamma^{M,fj}_{n,t}$, is endogenously determined by the following equation:

$$\gamma^{M,fj}_{n,t} = \gamma^{M,Ej}_{n,t} \Big[ 1 + \frac{\eta_e}{1-\eta_e} \Big( \frac{P^f_{n,t}}{P^r_{n,t}} \Big)^{\psi-1} \Big]^{-1} \tag{12}$$

An increase in the energy subsidy in country $n$ reduces the price of renewable energy in country $n$, $P^r_{n,t}$, and affects the share of fossil fuel through Equation (12). Proposition 1 shows that increasing the energy subsidy directly impacts fossil fuel demand by changing the price wedge between renewable and fossil fuel energy.

**Proposition 1.** ***Static Impact of Energy Subsidy*** *Given $P^f_{n,t}$, the energy subsidy $s^r_{n,t}$ for $r \in \{s, w\}$ decreases the fossil fuel share in production and consumption if and only if renewables and fossil fuel are substitutes, i.e., $\psi > 1$.*

*Proof.* See Appendix A.3. □

Proposition 1 reveals that the primary mechanism through which the energy subsidy operates

[11] Following Caliendo and Parro (2015), I assume the distributions of productivities are i.i.d across goods, sectors, countries, and time. Furthermore, assume $1 + \theta^j > \sigma^j$.

is similar to that of a typical carbon tax. It raises the relative price of fossil fuels compared to other inputs, specifically renewable energy, thereby reducing carbon emissions in the home country.

However, since both fossil fuels and equipment are tradable, two margins of carbon leakage emerge in a open economy. A reduction in domestic fossil fuel demand lowers the global price of fossil fuels, while an increase in domestic equipment demand raises the global price of equipment. Both effects contribute to increased carbon emissions in other countries.

Lastly, final goods price for consumers is given by $P^j_{n,t}$. Due to Cobb-Douglas preference in Equation (1), the consumption price index can be written as

$$P_{n,t} = \prod_j^J \left(\frac{P^j_{n,t}}{\mu^j_n}\right)^{\mu^j_n}. \tag{13}$$

### 3.6 Trade Share and Total Expenditure

Trade flows are expressed as the fraction of country $n$'s expenditures on sector $j$ goods produced by country $i$:

$$\pi^j_{ni,t} = \frac{(c^j_{i,t}\kappa^j_{ni,t}(1-s^j_{i,t}))^{-\theta^j}A^j_{i,t}}{\sum_k (c^j_{k,t}\kappa^j_{nk,t}(1-s^j_{i,t}))^{-\theta^j}A^j_{k,t}} = \frac{(c^j_{i,t}\kappa^j_{ni,t}(1-s^j_{i,t}))^{-\theta^j}A^j_{i,t}}{(P^j_{n,t})^{-\theta^j}} \tag{14}$$

Equation (14) reveals that the impact of the equipment subsidy $s^j_{i,t}$ depends on the trade elasticity $\theta^j$. The effect of the equipment subsidy on global market share can be larger with higher trade elasticity, as global demand becomes more sensitive to a bilateral import price change due to the subsidy.

I denote by $x^j_{n,t}$ country $n$'s total absorption in sector $j$, and by $x^j_{mn,t}$ country $m$'s absorption in sector $j$ from country $n$, i.e., $x^j_{m,t} = \sum_n x^j_{mn,t}$. Furthermore, I define the value of country $n$'s total expenditure on sector $j$ as $X^j_{n,t} = P^j_{n,t}x^j_{n,t}$. Let $Y^j_{n,t}$ denote the value of gross production in country $n$'s sector $j$ at time $t$. Then,

$$Y^j_{n,t} = \sum_{m=1}^N \frac{\pi^j_{mn,t}}{1-s^j_{m,t}} X^j_{m,t}. \tag{15}$$

Equation (15) shows that gross output in country $n$'s sector $j$ is equal to the sum of total exports and domestic sales, net of subsidy.

Define the final household spending on each sector in country $n$ as $X^{F,h}_{n,t} = P^h_{n,t}C^h_{n,t}$ for $h \in \Omega^*_K$ and $X^{F,k}_{n,t} = P^k_{n,t}I^k_{n,t}$ for $k \in \Omega_K$. Then, total expenditure on sector $j$ equals the sum of the use of sector $j$ output as intermediates in each sector $j'$ and final spending on sector $j$ in country $n$:

$$X^j_{n,t} = \sum_{j' \in \Omega} \gamma^{M,j'j}\gamma^{j'}_n Y^{j'}_{n,t} + X^{F,j}_{n,t} \tag{16}$$

**Market clearing.** The labor market clearing condition for country $n$ implies that labor income

equals value added across sectors:

$$w_{n,t}L_{n,t} = \sum_{j\in\Omega} \gamma_n^{L,j} Y_{n,t}^j \tag{17}$$

Similarly, the capital market clearing condition implies that capital income equals the value added of capital across sectors:

$$\sum_{k\in\Omega_K} r_{n,t}K_{n,t}^k = Y_{n,t}^s + Y_{n,t}^w + \gamma_n^{F,f} y_{n,t}^f + \sum_{j\in\Omega_E^*} \gamma_n^{D,j} Y_{n,t}^j. \tag{18}$$

Note that the share of capital in producing solar and wind energy is one, and fossil fuel capital goods are used only in fossil fuel energy production.

**Trade balance.** I assume trade is balanced at the global level:

$$\sum_{j\in\Omega}\sum_{n=1}^{N} \frac{\pi_{in,t}^j}{1-s_{i,t}^j} X_{i,t}^j - D_i = \sum_{j\in\Omega}\sum_{n=1}^{N} \frac{\pi_{ni,t}^j}{1-s_{n,t}^j} X_{n,t}^j \tag{19}$$

The left-hand side of equation (19) is country $i$'s total expenditure, net of subsidies, minus the country-level trade deficit, $D_i$. The right-hand side is the sum of country $i$'s exports, net of tariffs, across sector $j$. This formulation allows for sectoral and country-level trade deficits, capturing trade surpluses or deficits in renewable energy equipment trade as observed in the real world.

### 3.7 Capital accumulation

Capital accumulation is determined by adding investment $I_{n,t}^k$ to the stock of capital at $t$ depreciated at the rate of $\delta^k$ with an adjustment cost:

$$K_{n,t+1}^k = \chi_k \left(\frac{I_{n,t}^k}{K_{n,t}^k}\right)^{\alpha} (K_{n,t}^k) + (1-\delta^k) K_{n,t}^k, \quad \text{for } k \in \Omega_K, \tag{20}$$

where $I_{n,t}^k$ is investment in sector $k$ at time $t$, $\chi_k$ governs the productivity of investment, $\alpha$ governs the cost of capital adjustment, and $\delta$ is the depreciation rate. $\alpha < 1$ gives decreasing efficiency of investment with relative size of investment to capital stock, following Eaton et al. (2016) and Ravikumar et al. (2019). Here, investment is coming from capital goods purchased by the household, that is, $I_{n,t}^k = x_{n,t}^k$.

### 3.8 Learning-by-doing in Renewable Energy Equipment Production

In this model, cumulative past output determines current productivity in equipment production. A key assumption is that learning happens within each country and external to the firms in the sector. Each region $n$'s productivity in producing renewable energy equipment $k \in \Omega_{REE}$ in period

$t$, $A^k_{n,t}$, is governed by the cumulative production conducted in each country:

$$A^k_{n,t} = \nu^k \Big( \sum_{i=1}^{t-1} (\mu)^i y^k_{n,t-i} \Big)^{\nu^k_D}, \tag{21}$$

where $\nu^k$ is a sector-specific shifter, $\mu < 1$ is a forgetting rate, and $\nu^k_D$ governs the learning rate. $\mu < 1$ implies that impact of production in a more distant past on current productivity dissipates. This assures that productivity does not explode and the model to well-behave to have a steady state.

This country-specific learning-by-doing specification highlights the dynamic *beggar-thy-neighbor effect* of the subsidy policy. For example, equipment subsidy in the US results in higher output in the US which connects to a higher future productivity, but other countries' output decreases through trade, reducing future productivity gain from learning-by-doing in those countries.

### 3.9 Household Optimality

Now I consider household optimization. To do so, I first define the household's budget constraint:

$$\begin{aligned} &\sum_{j \in \Omega^*_K} P^j_{n,t} C^j_{n,t} \\ &= w_{n,t} L_{n,t} + \sum_{k' \in \Omega_K} r^{k'}_{n,t} K^{k'}_{n,t} - \sum_{j \in \Omega} s^j_{o,t} \sum_{o=1}^{N} \frac{\pi^j_{on,t}}{(1 - s^j_{n,t})} X^j_{o,t} + \sum_{j \in \Omega_{RE}} \Pi^j_{n,t} + D_n - \sum_{k \in \Omega_K} P^k_{n,t} I^k_{n,t} \\ &\equiv E_{n,t} \end{aligned} \tag{22}$$

Household consumption is on the left hand side. I denote by $E_{n,t}$ the net household income, which is the sum of labor income $w_{n,t}L_{n,t}$, capital incomes $\sum_{k \in \Omega_K} r^k_{n,t} K^k_{n,t}$, minus the deficit from subsidy, profit from renewable energy sector, and trade deficit.[12] Note that I define by $E_{n,t}$ the net income after investment.

Given this budget constraint and given the competitive rental rates of $r_{n,t}$ and prices of goods $P^j_{n,t}$, I can obtain within-period optimization. Within each period, the household expenditure on good $h \in \Omega^*_K$ should satisfy

$$P^h_{n,t} C^h_{n,t} = \mu^h_n E_{n,t}, \quad \text{for} \quad h \in \Omega^*_K, \tag{23}$$

and the investment decision problem is characterized by capital accumulation equation (equation

[12] I assume that output subsidies are distributed before import tariffs.

(20)) and the following Euler equation:[13]

$$\frac{u'(C_{n,t})}{u'(C_{nt+1})}\frac{P^c_{nt+1}}{P^c_{n,t}}\frac{p^k_{n,t}}{\chi_k}\left(\frac{I^k_{n,t}}{K^k_{n,t}}\right)^{1-\alpha} = \beta\alpha\left[r_{n,t+1} + \frac{(1-\alpha)p^k_{n,t+1}I^k_{n,t+1}}{\alpha K^k_{n,t+1}} + \frac{(1-\delta^k)p^k_{n,t+1}}{\alpha\chi_k}\left(\frac{I^k_{n,t+1}}{K^k_{n,t+1}}\right)^{1-\alpha}\right] \quad \text{for each } k \in \Omega_K. \tag{24}$$

On the left hand side, it is the marginal cost at $t$ to attain additional capital in $t+1$. On the right hand side, it is the marginal benefit of capital at $t+1$ (rent & future capital value). equipment subsidy reduces the $P^k_{n,t}$, which motivates to invest more in equipment than non-renewable capital goods.

### 3.10 Steady State

Productivities in equipment, $A^j_{n,t}$ for $j \in \Omega_{REE}$, are time-varying values governed by learning-by-doing. However, learning in equipment production eventually stops in the long run due to the forgetting parameter, $\mu$. In the steady state, productivities remain constant, and the capital stock stabilizes at a fixed level, $K^k_n$. The Euler equations (24) and the capital accumulation equations (20) determine the ratio of investment to capital stock for each type of capital and the ratio of rental income to investment spending:

$$\frac{I^k_n}{K^k_n} = \left(\frac{\delta^k}{\chi_k}\right)^{\frac{1}{\alpha}} \tag{25}$$

$$\frac{r^k_n K^k_n}{P^k_n I^k_n} = \left(\frac{1-\beta+\beta\delta^k\alpha}{\beta\delta^k\alpha}\right) \tag{26}$$

where other endogenous values under the steady state follow the equilibrium conditions.

### 3.11 Welfare

Welfare in each country $n$ as discounted sum of utility, which can be represented by real income incorporating disutility from carbon from consumer prolbem:

$$W_n = \sum_{t=1}^{T}\beta^t\left(\frac{E_{n,t}}{P_{n,t}}\frac{1}{(1+SCC(Z_t-Z_0))}\right), \tag{27}$$

where the first term captures real income and the second term captures disutility of stock of carbon emissions.

[13] If $\alpha = 1$ & $\chi_k = 1$, this becomes a more familiar Euler equation:

$$\frac{u'(C_{n,t})}{u'(C_{nt+1})}\frac{P^c_{nt+1}}{P^c_{n,t}}P^k_{n,t} = \beta\left[r_{n,t+1} + \left(1-\delta^k\right)P^k_{n,t+1}\right], \text{ for } k \in \Omega_K$$

### 3.12 Dynamic General Equilibrium

Definition 2 summarizes the equilibrium conditions.

**Definition 1.** ***A sequential equilibrium of the model*** *is a set of prices* $\left\{w_{n,t}, P^j_{n,t}, r^k_{n,t}\right\}^{N,J,K,T}_{n=1,j=1,k=1,t=1}$, *allocations of goods and labor* $\left\{\pi^j_{nit}, L^j_{n,t}\right\}^{N,N,J,T}_{n=1,i=1,j=1,t=1}$ *that satisfies the static equilibrium conditions: unit costs (equations (3), (6), and (10)), trade shares (14), local prices (11), labor and market clearing conditions (17,18), and trade balance (19), and dynamic conditions: law of motion of capitals (20), and Euler equation (24).*

In the Appendix D, I show the numerical algorithm to solve this model.

## 4 Calibration

### 4.1 Countries and Sectors Covered

Using OECD-Intput Output, I aggregate into 12 countries and 6 regions including EU, Southeast Asia, South America, Africa, Middle east, and rest of the world.[14] Regarding sectors, I aggregate into 10 sectors, which include 3 energy sectors, 3 energy equipment sectors, and 4 other sectors: Agriculture, Non-durable Manufacturing, Durable Manufacturing, and Services.

### 4.2 Parameters in Renewable Energy Production

**Measuring Absolute Advantage in Renewable Energy Production ($A^r_{n,t}$).** The absolute advantage parameter in renewable energy production captures across-country heterogeneity in renewable potentials. I estimate this parameter by combining geospatial data on global renewable potentials with the actual locations of renewable power farms in each country.

Renewable potential data come from the Global Solar (Wind) Atlas, while location data for renewable power farms are sourced from the Global Solar (Wind) Power Tracker. The Global Solar (Wind) Power Tracker includes start year, longitude, and latitude for plants with capacities greater than 10 MW, covering approximately 70% of global total capacity. To measure the absolute advantage component, $A^j_{n,t}$ for $j \in \Omega_{RE}$, I calculate the average potential of solar and wind farms installed up to the year 2021, which serves as the initial period in the quantitative analysis.[15] Second and third columns of Table B.2 summarizes the average renewable potentials in each country.

**Measuring Decreasing Return to Scale.** The decreasing return to scale parameter captures (within-country) heterogeneity in renewable potential, which varies across countries. The intuition is that additional installations result in placing the marginal unit of renewable equipment in locations with relatively lower renewable potential. The rate at which renewable potential de-

[14] See the Appendix (Section B.1) for details of the aggregation.

[15] I explain the details of the dataset in the Appendix Section B.3.2.

creases can differ by region, influenced by both the distribution of renewable potential and the available feasible area in each region.

I utilize geospatial data on renewable potential and development feasibility (DPI) compiled by Oakleaf et al. (2019). DPI combines social (distance from big cities, grid) and physical (elevation, slope) feasibility of developing each renewable energy.[16] I aggregate this data into country level and compute the slope of the distribution of renewable potentials (from the highest potential to the lowest potential) for each country. Forth and fifth columns of Table B.2 summarizes measured DRS in each country. The mean of the DRS parameter for solar is 0.965 with standard deviation of 0.004, and the mean for wind is 0954 with standard deviation of 0.007, suggesting that wind energy production faces steeper decreasing return to scale, with larger across-country variance.

### 4.3 Estimating CES in Energy Production

Energy production involves nested CES technology. I calibrate the outer nest parameter from Jo (2023), and I focus on discussing how to estimate the inner nest in this section. The identification of the inner-nest elasticity and share parameters is based on inner-nest quantity and relative price relationships:

$$\log\left(\frac{y^s_{n,t}}{y^w_{n,t}}\right) = \rho \log\left(\frac{\eta_r}{1-\eta_r}\right) - \rho \log\left(\frac{p^s_{n,t}}{p^w_{n,t}}\right).$$

With controlling country fixed effect and time trend, empirical specification for estimating the substitution parameter is:

$$\log\left(\frac{y^s_{n,t}}{y^w_{n,t}}\right) = -\rho \log\left(\frac{p^s_{n,t}}{p^w_{n,t}}\right) + FE_n + \lambda t + \varepsilon_{n,t}. \tag{28}$$

However, a fixed effect regression of relative output on relative price results in a simultaneity issue as price might not be exogenous. To address this, I instrument relative price share with the subsidy in wind energy in each year for each country. This identification strategy leverages exogenous shocks associated with subsidies in renewable energy production. The exclusion restriction for this instrumental variable (IV) setup is that the renewable subsidy affects electricity demand only through the relative price difference.

**Data** The data for solar and wind energy output is from International Renewable Energy Agency (IRENA). For price of solar and wind, I construct price data for 20 countries by combining levelized cost of electricity for solar and wind (from IRENA) with subsidy (from OECD) in each energy source for 2010-2022.

**Results** Table 1 reports the estimates of the elasticity of substitution between solar and wind energy. Column (1) presents the OLS estimate without any fixed effects. Column (2) includes country fixed effects, and Column (3) adds a linear time trend. Column (4) addresses the endogeneity of the price ratio by using the wind energy subsidy as an instrument, resulting in a

[16] See the Appendix (Section B.3.1) for the details on DPI.

Table 1: Estimates for Substitution Elasticity (Inner Nest)

| | Dependent Variable: $ln(\frac{y^s_{n,t}}{y^w_{n,t}})$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $ln\frac{p^s_{n,t}}{p^w_{n,t}}$ | -1.067 | -1.173 | -0.403 | -0.712 |
| | (0.211) | (0.156) | (0.188) | (0.401) |
| 1st Stage F-statistics | | | | 88.16 |
| F-statistics | 25.56 | 56.19 | 54.00 | 14.69 |
| $N$ | 144 | 144 | 144 | 144 |
| FE | | ✓ | ✓ | ✓ |
| Timetrend | | | ✓ | ✓ |
| IV | | | | ✓ |

slightly lower estimate. With country fixed effects and a time trend, the IV estimate of the elasticity of substitution between solar and wind energy is 0.712, rejecting the common assumption in the literature that solar and wind energy are perfect substitutes.[17] Solar and wind energy being weakly complementary can be attributed to the intermittence issue between solar and wind (Gentile (2024)). In particular, solar energy can only produce electricity during daytime, and wind energy production also faces intermittence. In this sense, solar and wind may not be perfectly substitutable.

As mentioned, I calibrate the outer nest parameter from Jo (2023) using French firm-level data, which the estimated elasticity of substitution is 3.08.[18] The reason that renewable energy and fossil fuel are not perfectly substitutable is obvious; renewable energy sources are mostly on-grid (=electricity), but fossil fuels are not necessarily. Fossil fuels can be used as a direct input in internal combustion engines, which is difficult to substitute by electricity. As a robustness check, I consider lower elasticity of substitution and report the results in the Appendix Section C.3.

### 4.4 Estimating Learning Rate of Equipment Production

To calibrate the learning rate of equipment production, I estimate a regression of the empirical specification of equation (21):

$$\log(A^j_{n,t}) = \nu^j_D \log(\sum_{s=1}^{t-1} y^j_{n,s}) + \nu^j_G \log(\sum_{i\neq n}\sum_{s=1}^{t-1} y^j_{i,s}) + \nu^j_n + \lambda t + u^j_{n,t} \tag{29}$$

where $y^j_{n,s}$ is an output of renewable energy equipment $j$ in country $n$ at time $s$. $(\sum_{i\neq n}\sum_{s=1}^{t-1} y^j_{i,s})$ is the global cumulative output except $n$, $\nu^j_n$ controls country fixed effect, and $\lambda t$ controls time trend. To run this regression, I first need to recover the time-series of renewable energy equipment

[17] One exception is Novan (2015), which highlights that renewable electricity from solar and wind are heterogeneous to each other in terms of marginal external benefits.

[18] There are some studies estimating the elasticity of substitution between clean and dirty energy source; see Papageorgiou et al. (2017), Jo (2023), and Wiskich (2023). Their estimates range from 2.033 to infinity, so 3.08 is within a range in the literature.

productivity across countries ($A^j_{n,t}$). To do so, I use model inversion; in the model, domestic expenditure shares, input cost, and price indices satisfy the following relationship:

$$\pi^j_{nn,t} = A^j_{n,t} \left( c^j_{n,t} / P^j_{n,t} \right)^{-\theta^j}, \tag{30}$$

where $c^j_{n,t}$ is the input cost, and $P^{nj}_t$ is the price index for renewable energy equipment. I can therefore measure $A^{nj}_t$ using the data I explain in below.

**Data** For input cost $c^j_{n,t}$, I use Penn World Table (Version 10.1). I assume input cost is composed of wage $w_{n,t}$, manufacturing goods, and service. Following Fan et al. (2023), I measure $w^{nj}_t$ as the ratio between total labor compensation and total number of employment (variable $emp$ in PWT), where labor compensation is calculated as the product of labor share (variable $labsh$) and GDP (variable $cgdpo$). I proxy for the index for manufacturing price using the average of the import and export prices of country $n$ in period $t$ (variables $pl_m$ and $pl_x$, respectively). For service price index, I use consumer price.

For solar energy equipment, I obtain the output $y^S_{n,t}$ and price data $P^S_{n,t}$ from PVPS. PVPS provides historic price and quantity of solar energy equipment in major countries. I construct the domestic expenditure share sequence $\pi^S_{nn,t}$ by combining export data from Comtrade and output and price data from PVPS. That is, I compute total value of production for solar by multiplying output by price from PVPS and then subtract the total value of export from Comtrade.

For wind energy equipment, there is no available time-series data for global production. To recover the annual output, I follow these steps:

1. I use the annual wind energy equipment installation data (in GW) and the average installation cost for each country from the International Renewable Energy Agency.[19]

2. Using the installation data and average installation costs, I compute the annual absorption of wind energy equipment.

3. By combining wind equipment import data from Comtrade with the absorbtion data I built, I obtain the domestic expenditure share sequence, $\pi^W_{nn,t}$.

4. I then use wind energy equipment export data from Comtrade along with absorption data to calculate production in each country.

This approach allows me to estimate annual wind energy equipment output despite the absence of country-level time-series production data.

Table 2 shows the estimation results. The preferred specification is the third column for solar energy equipment and the sixth column for wind energy equipment.

To compare with the estimates in the literature, I need to transform this estimate to 'learning-rate' in the literature.[20] To do so, I first compute the implied impact of learning-by-doing on price

[19] I assume there is a one-year time lag between production/trade and installation of renewable energy equipment.

[20] Common definition of learning rate in the literature is the percentage change in cost for each doubling of cumulative output.

Table 2: Estimating Learning-by-doing in Equipment Production

| | Solar ($ln(A^S_{n,t})$) | | | Wind ($ln(A^W_{n,t})$) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln(\sum_{s=1}^{t-1} y^S_{n,s})$ | 1.406*** | 1.301*** | 1.261*** | | | |
| | (0.126) | (0.294) | (0.301) | | | |
| $\ln(\sum_n \sum_{s=1}^{t-1} y^S_{n,s})$ | | | -0.592 | | | |
| | | | (0.915) | | | |
| $\ln(\sum_{s=1}^{t-1} y^W_{n,s})$ | | | | 0.315*** | 0.263** | 0.765*** |
| | | | | (0.0347) | (0.117) | (0.152) |
| $\ln(\sum_n \sum_{s=1}^{t-1} y^W_{n,s})$ | | | | | | -0.985 |
| | | | | | | (0.673) |
| F-statistics | 125.2 | 126.4 | 83.95 | 82.34 | 26.41 | 27.54 |
| N | 119 | 119 | 119 | 190 | 190 | 190 |
| $FE_N$ | | ✓ | ✓ | | ✓ | ✓ |
| Time Trend | | ✓ | ✓ | | ✓ | ✓ |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

by taking the log of equation (30) and rearrange it:

$$\ln(P^j_{n,t}) = \frac{1}{\theta^j}\ln(\pi^j_{nn,t}) - \frac{1}{\theta^j}\ln(A^j_{n,t}) + \theta^j \ln(c^j_{n,t}).$$

Then the implied (partial) impact of learning-by-doing on price is

$$\frac{\partial \ln P^j_{n,t+1}}{\partial \ln A^j_{n,t+1}} \frac{\partial \ln A^j_{n,t+1}}{\partial \ln \sum_s^t y^j_{n,s}} = -\frac{\nu^j_D}{\theta^j}, \tag{31}$$

where the first term on the right hand side captures the impact of productivity on price, and the second term captures the impact of cumulative output on next period's productivity. Using the preferred specification for each solar and wind, the implied impact of learning on price is $\nu^S/\theta^S$ = 1.261/ 4.762 = 0.264 and $\nu^W/\theta^W$ = 0.765 / 2.509 = 0.304. Then, the learning rate can be computed by $1 - 2^{-\nu^S/\theta^S} = 0.17$ and $1 - 2^{-\nu^W/\theta^W} = 0.19$. The learning rate of 17 percent and 19 percent for solar and wind equipment, respectively, are comparable to the estimates in the literature and relatively closer to the lower bound. Most estimates for solar equipment lie between 0.17 and 0.22 (Baker et al. (2013)). In recent study, Bolinger et al. (2022) find the learning rate in the US for solar is 24 percent and wind is 15 percent. Covert and Sweeney (2024) also find the learning rate for wind equipment is around 14 to 29 percent.[21]

[21] One potential reason for the estimates in this paper being different than those in the literature is that the estimates in the literature studies global level or firm level learning rate while I am studying country-level learning. When using global aggregated data, as most of the output is coming from China, the estimation is mostly driven by price and quantities in China. Firm level studies can potentially give smaller estimates than country-level analysis depending on the size of the inter-firm spillover effects. Covert and Sweeney (2024) finds that inter-firm spillover effect is small but

Table 3: Trade Elasticities ($\theta^j$)

| Sectors | Trade Elasticity ($\theta^j$) |
|---|---|
| Solar Energy | 4.55 |
| Wind Energy | 4.55 |
| Fossil Fuel | 15.08 |
| Solar Equipment | 4.76 |
| Wind Equipment | 2.51 |
| Agriculture | 8.11 |
| Non-Durable Manufacturing | 4.55 |
| Durable Manufacturing | 5.26 |
| Service | 4.55 |

### 4.5 Trade Elasticities

One of the key parameters that governs the impact of industrial policies is trade elasticity, $\theta^j$. I calibrate this parameter using data from Fontagné et al. (2022), Caliendo and Parro (2015), and Parro (2013). I calibrate the elasticity for solar and wind energy equipment using the closest HS 4-digit level for each sector provided in Fontagné et al. (2022), which are 4.76 and 2.51 for solar and wind equipment, respectively.[22] I calibrate the trade elasticity for fossil fuel capital goods and durable manufacturing as 5.26, following Parro (2013). The trade elasticity for fossil fuel is set to 15.08, and for the remaining sectors (solar energy, wind energy, non-durable manufacturing, and services), I calibrate the aggregate elasticity as 4.55, following Caliendo and Parro (2015). Table 3 summarizes the trade elasticity in each sector.

The higher trade elasticity for solar equipment compared to wind equipment has important implications for the impact of subsidies. An equipment subsidy may have a greater effect on the global market share of solar equipment, as global demand is more responsive to changes in bilateral import prices driven by the subsidy. Consequently, even if the learning rates for both types of equipment are identical, a subsidy for solar equipment could be more effective in expanding its global market share, and therefore more efficient in leveraging learning-by-doing, compared to wind equipment.

### 4.6 Other Parameter Values and Initial Values

**Share of inputs in production and consumption** Using OECD Input Output data, I calibrate the shares of labor, capital, and intermediate goods (including composite energy) in production and consumption. To obtain each input share, I divide the value added from each input by gross output. One issue is that the dataset does not distinguish value added from labor and capital.

not negligible in this sector.

[22] For solar equipment, the corresponding 4-digit HS code is HS 8541 (Diodes, transistors, and similar semiconductor devices; Photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or made up into panels; Light-emitting diodes; Mounted piezo-electric crystals). For wind equipment, the corresponding 4-digit HS code is HS 8502 (Electric generating sets and rotary converters; Generating sets with compression-ignition internal combustion piston engines).

Following Greenwood et al. (1997), I calibrate share of labor and capital by setting the capital share in value added 0.3. For the final goods consumption share $\mu_n^j$, I subtract the intermediate goods expenditure from the sector $j$ total expenditure, then divide by total absorption.

**Depreciation rate ($\delta_j$)** Following Arkolakis and Walsh (2023), I set the depreciation rates for each capital are given by $\delta_S = \delta_W = 0.03$, $\delta_F = 0.02$, $\delta_D = 0.07$.

**Capital Adjustment Cost ($\alpha$) and Investment Efficiency ($\chi^j$).** Following Ravikumar et al. (2019), I set $\alpha = 0.76$ and $\chi_j = (\delta_j)^{1-\alpha}$.[23] An advantage of this formulation is that, in the steady state, there are no adjustment costs associated with replacing depreciated capital.

**Trade Cost** $(\kappa_{in,t})$ To calibrate the trade costs of the model, following Head and Ries (2001), I recover trade cost from the trade data assuming symmetric trade cost:

$$\left(\frac{X^j_{ni,t}X^j_{in,t}}{X^j_{nn,t}X^j_{ii,t}}\right)^{-\theta^j/2} = \kappa^j_{ni,t}.$$

**Initial Regional Productivities ($A$)** All sectors except renewable energy sectors, I target the trade shares by region-sector and the regional output to calibrate the productivities of the model for each sector. For solar and wind energies, I use the calibrated value from renewable potential data explained in Section 4.2.

**Discount Rate ($\beta$)** Each period is treated as a year. Correspondingly, I set $\beta = 0.95$.

**Damage parameter (SCC)** The damage parameter $SCC$ is calibrated to match \$163 social cost of carbon per unit ton increase in emissions following EPA (2023) and Caliendo et al. (2024). In the appendix, I present the results with lower social cost of carbon.

**Initial labor and capital stock ($L$,$K$)** I measure initial labor using total number of employment in Penn World Table (variable $emp$ in PWT). I measure initial capital stocks utilizing various datasets. See the Appendix section B.4 for the details.

Table 4 summarizes the list of parameters, corresponding values, and source or method used to calibrate those.

## 5 Model validation

Panel (a) Table 5 presents the moments used to match the model outcomes with real-world data. I match trade shares, defined as the share of imported goods in domestic consumption for all sectors, under the assumption that renewable energy sectors are not tradable. This results in an exact match for China's share of global solar and wind equipment production, which is 82% and 65%, respectively. Additionally, I calibrate the level shifter in renewable energy production to align with the global share of renewable energy relative to primary energy consumption, which is 14% in the data.[24]

[23] $\alpha = 0.76$ corresponds to the annualized value of adjustment cost used in Eaton et al. (2016).

[24] As OECD-IO does not have distinctive renewable energy sectors, I obtain fossil fuel share in total primary energy consumption from a different dataset, which is from Energy Institute (2024), with major processing by Our World in Data.

Table 4: Parameter Values

| | Parameters | Values | Source or Method |
|---|---|---|---|
| *(Renewable)* | | | |
| $\xi$ | Decreasing returns to scale | Region-energy specific | Measuring slope using data from Oakleaf et al. (2019) |
| $\rho$ | (Inner nest) CES elasticity of substitution | 0.712 | Estimation |
| $\psi$ | (Upper nest) CES elasticity of substitution | 3.08 | Jo (2023) |
| $\mu$ | Forgetting rate in learning-by-doing | 0.99 | Arkolakis and Walsh (2023) |
| | | **(solar, wind)** | |
| $\nu_D$ | Learning rate of renewable equipment production | (1.261, 0.765) | Estimation |
| *(Other Parameters)* | | | |
| $A$ | Region-sectoral productivity | Region-sector specific | Renewable Potentials: see manuscript<br>Other sectors: model inversion |
| $\theta^j$ | Trade elasticities | Sector-specific | Caliendo and Parro (2015) and Fontagné et al. (2022) |
| $\gamma^L$ | Share of labor in production | Region-sector specific | Calibrated using OECD IO |
| $\gamma^j$ | Share of intermediate goods in production | Region-sector specific | Calibrated using OECD IO |
| $\gamma^F$ | Share of fossil fuel capital in production | Region-sector specific | Calibrated using OECD IO |
| $\gamma^D$ | Share of non-energy capital in production | Region-sector specific | Calibrated using OECD IO |
| $\mu^j$ | Consumption share | Region-sector specific | Calibrated using OECD IO |
| $\beta$ | Discount rate | 0.95 | |
| $SCC$ | Social cost of carbon | Time-specific | Match social cost of carbon \$163 (EPA (2023), Caliendo et al. (2024)) |
| $\kappa$ | Trade cost | Region-sector-pair specific | Head and Ries (2001) |
| *(Capital)* | | | |
| $\alpha$ | Capital adjustment cost | 0.76 | Ravikumar et al. (2019) |
| $\chi_k$ | Investment efficiency | $\delta_k^{1-\alpha}$ | Ravikumar et al. (2019) |
| | | **(solar, wind, fossil, non-energy)** | |
| $\delta^j$ | Depreciation rate | (0.03, 0.03, 0.02, 0.07) | Arkolakis and Walsh (2023) |

I evaluate the fit of the model using non-targeted moments. The first non-targeted moment is the share of equipment in global GDP. This moment influences both the impact and the budget size of subsidies. I assess whether the model can match the share of equipment in global GDP for 2021. The first row in panel (b) in Table 5 compares the model outcome with the data, showing that the gap is relatively small.

Another non-targeted moment is fossil fuel share in *each* country. The key information used includes measured country-level renewable energy potential and the decreasing returns to scale parameter measured outside the model. I assess whether the model can match the fossil fuel share in total primary energy consumption for each country in the year 2021, the initial year of the model. The correlation between the model outcome and data is 0.71, and Panel (a) in Figure 3 shows that the model fits the data well.

To validate the dynamic part of the model, I also check whether the simulated outcome under the IRA replicates the US solar equipment production pattern observed in the data after the IRA's implementation. The latest available data is manufacturing capacity data up to the second quarter of 2024, which is two years after the IRA bill was passed (Wood Mackenzie, 2024).

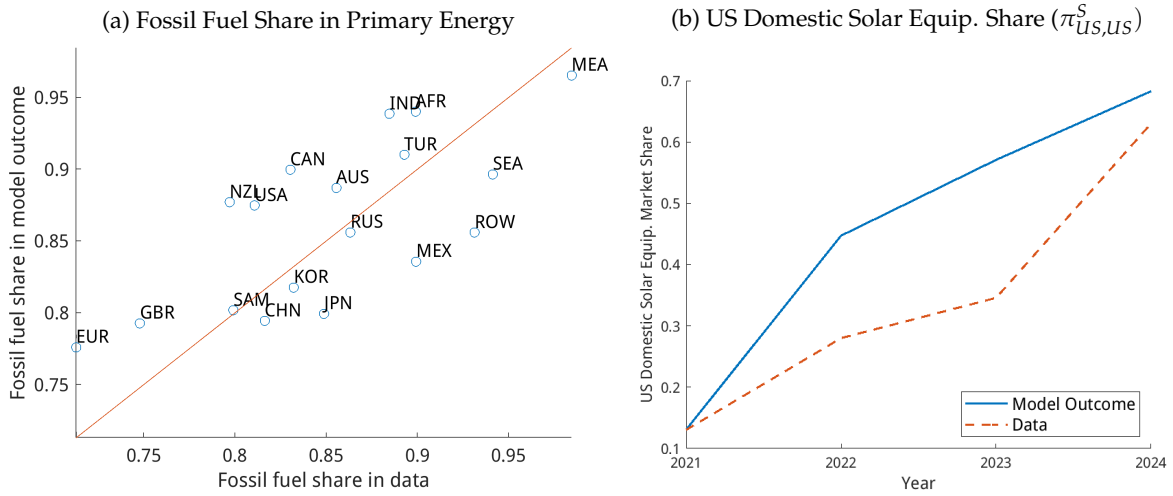
While the details of the IRA in the simulation will be covered in the next section, panel (b) in Figure 3 compares the model's outcome under the IRA on the US domestic share in the solar equipment market, $\pi^S_{US,US}$, shown in the blue line, with the data in the red dashed line.[25] In the model, US solar equipment manufacturing rapidly grows and meets 68% of domestic demand by 2024. In the data, the growth is relatively slow until 2023, but the share reaches 60% in 2024. The main reason for this discrepancy is that the model uses annual time units and assumes the IRA starts in 2022, while the IRA was actually passed in the second quarter of 2022. Additionally, the model does not account for the many construction delays caused by labor shortages in the real world.

Table 5: Model Validation

| **Moment** | **Model Outcomes** | **Data** |
|---|---|---|
| **(a) Matched moment** | | |
| Share of China in global solar equipment production | 82% | 82% |
| Share of China in global wind equipment production | 65% | 65% |
| Global share of renewable energy | 14% | 14% |
| **(b) Unmatched moment** | | |
| Share of equipment in global GDP | 0.16% | 0.12% |
| Initial share of renewable energy in each country | See Figure 3 Panel (a) | |
| US domestic solar equipment market share under IRA | See Figure 3 Panel (b) | |

[25] I make three assumptions on the data side. First, as I only have capacity data and not actual output data, I assume the utilization rate for module manufacturing is 71%, based on figures from InfoLink Consulting (2023). Second, to align with the model's time period, for the 2024 data value, I use projections from Wood Mackenzie (2024). Third, I assume all solar equipment manufactured in the US is consumed domestically. This assumption holds until 2023, as exports account for less than 1% of total shipments (EIA, 2023).

Figure 3: Model Validation




Note: Panel (a) presents the share of fossil fuel in data (in x-axis) and the model outcome of share of fossil fuel in each country (in y axis). Solid line is 45 degree line. Panel (b) shows the model prediction with IRA subsidies and actual data on US share in their domestic solar equipment market from 2021 to 2024, plotted by blue solid line and red dashed line, respectively.

# 6 Transition Scenario

**Welfare Decomposition.** The change in welfare in country $n$ can be captured by changes in real income and carbon emissions at each period:

$$dlnW_n = \underbrace{dln\left(\frac{E_n}{P_n}\right)}_{\text{Real income changes}} - \underbrace{dln\left(1+SCC(Z_t-Z_0)\right)}_{\text{carbon emissions changes}} \tag{32}$$

Equation (32) breaks down the change in welfare into two terms of sufficient statistics. First is the real income term.[26] The second term is carbon emissions term. Reduction in carbon emissions reduces disutility, which affects welfare.

[26] This term can be further decomposed by real wage and capital deepening. Capital deepening meaning increase in investments in renewable energy equipment. This lowers energy price, leading to growth in the economy. Real wage term can be again decomposed to account for welfare gains derived from accessing less expensive final and intermediate goods, taking into account sectoral connections, identical to Caliendo and Parro (2015).

$$\begin{aligned} dlnW_n &= dln\left(\frac{E_n}{P_n}\right) - dln\left(1+SCC(Z_t-Z_0)\right) \\ &\approx \underbrace{dln\left(\frac{w_n}{P_n}\right)\frac{w_nL_n}{E_n}}_{\text{real wage changes}} + \underbrace{dln\left(\frac{r_nK_n}{P_n}\right)\frac{r_nK_n}{E_n}}_{\text{capital deepening}} - \underbrace{dln\left(1+SCC(Z_t-Z_0)\right)}_{\text{carbon emissions changes}}, \text{ where} \end{aligned}$$

$$dln\left(\frac{w_n}{P_n}\right) = dln\frac{w_n}{P_n} = \underbrace{-\sum_{j=1}^{J}\frac{\mu_n^j}{\theta^j}dln\pi_{nn}^j}_{\text{Final goods}} \underbrace{-\sum_{j=1}^{J}\frac{\mu_n^j}{\theta^j}\frac{1-\gamma_n^j}{\gamma_n^j}dln\pi_{nn}^j}_{\text{Intermediate goods}} \underbrace{-\sum_{j=1}^{J}\frac{\mu_n^j}{\gamma_n^j}dln\prod_{k=1}^{J}\left(P_n^k/P_n^j\right)^{\gamma_n^{k,j}}}_{\text{Sectoral linkages}}$$

Table 6: Simulation Scenarios

| **Scenarios** | Energy subsidy | Equipment subsidy |
|---|---|---|
| (i) IRA | 20% | 30% |
| (ii) Energy subsidy only | 20% | 0% |
| (iii) Equipment subsidy only | 0% | 30% |
| (iv) IRA with no equipment trade | 20% | 30% |

### 6.1 Policy Scenarios

In this part, I explain the scenarios with unilateral green industrial policies for simulations.

**Baseline Scenario.** To conduct a counterfactual, I need to define the baseline scenario. I define the baseline scenario by no policy intervention in all countries, that is, no green industrial nor trade policy is implemented in all countries.

**Simulation on Renewable Energy Provisions of the IRA.** The main scenario examines the impact of the renewable energy provisions in the IRA, which includes both the energy subsidy and the equipment subsidy for ten years (2022-2031). For the energy subsidy, the production tax credit for renewable energy production is \$0.0275 per kWh in 2022. Considering that the average retail electricity price in the US was \$0.1236 per kWh in 2022 (EIA (2023)), I set a 20% price subsidy.[27] For the equipment subsidy, the tax credit for renewable energy equipment production is approximately \$0.14 per watt in 2022.[28] Considering that the average solar panel price produced in the US was \$0.42 per watt in 2022, I set a 30% price subsidy for the equipment subsidy.[29] In the final three years of the IRA period, the subsidy phases out gradually, with reductions of 25%, 50%, and 75% of the original subsidy each year.

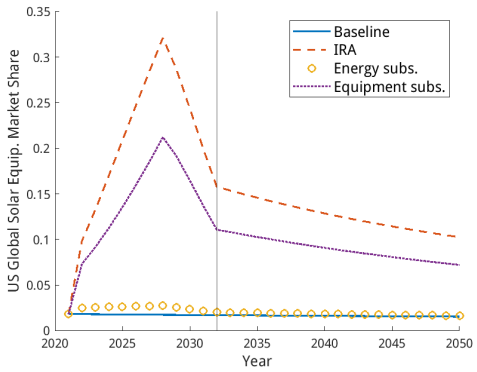
**Decomposition.** To analyze the impact of each subsidy component of the IRA, I simulate the model with each subsidy separately: one for renewable energy (energy subsidy) and one for renewable energy equipment (equipment subsidy) using the same subsidy ratio in the IRA with the identical phaseout periods. Under the current calibration, the total budget spent each subsidy under the IRA is approximately the same: total budget spent in the IRA is \$243 billion, with \$118 billion for the energy subsidy component and \$125 billion for the equipment subsidy component.

**Role of equipment trade.** Another key question of this paper is the analyzing the importance of equipment trade in the impact of the IRA. In the forth simulation, I implement the same subsidy ratios as in the IRA but without equipment trade by raising trade barrier to infinity.

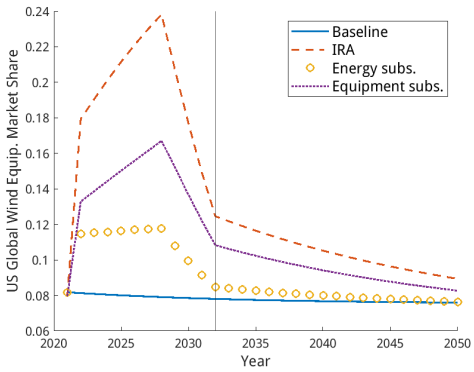
Table 6 summarizes the size of subsidies under each scenario.

Figure 4: US global renewable equipment market share under IRA

(a) Solar Equipment




(b) Wind Equipment




Note: This figure depicts the evolution of the US global equipment market share. Panel (a) shows the evolution of US global solar equipment market share. The solid blue line shows the share under baseline, the red dashed line represents the share under IRA subsidy. Yellow circles depict the share when only the energy subsidy in the IRA is implemented, and Purple dotted line shows the share when only the equipment subsidy in the IRA is implemented. Panel (b) presents the evolution of US global wind equipment market share under each scenario.

## 6.2 Impact of Renewable Energy Provisions of IRA

**US Share in Global Renewable Energy Equipment Market.** I illustrate in Figure 4 the impact of the IRA on the US's global renewable energy equipment market share from 2021 to 2050. The blue solid line shows the path under the baseline scenario, and the red dashed line represents the evolution under the IRA. I decompose the impact of the IRA by energy and equipment subsidy components using the purple dotted line and yellow circles, respectively.

Panel (a) in Figure 4 highlights the substantial rise in market share for solar equipment, reaching up to 32% at its peak under the IRA, compared to the baseline scenario (blue solid line), where the US market share remains below 2% throughout the entire period. Most of this pattern can be explained by the equipment subsidy component (purple dotted line), as the energy subsidy (yellow circles) has a very small effect. Furthermore, due to the productivity gains accumulated by the US through learning-by-doing during the IRA period, the US maintains a larger market share even after the IRA period ends (2031) compared to the baseline.

Interestingly, energy and equipment subsidies are complementary to each other. That is, the US global share grows faster under the IRA compared to the sum of the shares under each subsidy component individually. This is because, under the IRA, the share of US-manufactured solar equipment dominates the domestic market due to the equipment subsidy component, while the energy subsidy further increases demand, which is now mostly met by US-produced outputs. This accelerates learning-by-doing in the US, resulting in a faster growth in global market share

[27] Producers can choose between the Production Tax Credit (PTC) and the Investment Tax Credit (ITC). For consistency with the model, I assume producers always choose the PTC.

[28] Section 45X of the Advanced Manufacturing Production Tax Credit (PTC) included in the IRA provides subsidies for each component of renewable energy equipment. For solar panels, this includes subsidies for polysilicon, cells, modules, and wafers, totaling $0.14 per watt.

[29] This subsidy ratio is consistent with Bollinger et al. (2024).

under the IRA compared to when only the energy or equipment subsidy is implemented.

Panel (b) in Figure 4 depicts the evolution of the US global wind equipment market share. Initially, the US global wind equipment market share is approximately 6%, and it consistently decreases across years under the baseline scenario. The wind equipment market share under the IRA in Panel (b) shows a less pronounced increase compared to solar equipment. At its peak, the US market share reaches 24%. One key difference from the solar equipment case is that the energy subsidy (yellow circles) has a larger impact on increasing the US market share, which reaches 12% at the peak under the energy subsidy. I also find a complementary effect between the energy and equipment subsidies in the wind equipment market share. While the IRA has a long-run impact on market share, this impact fades out over time, and the market share converges to the baseline scenario.

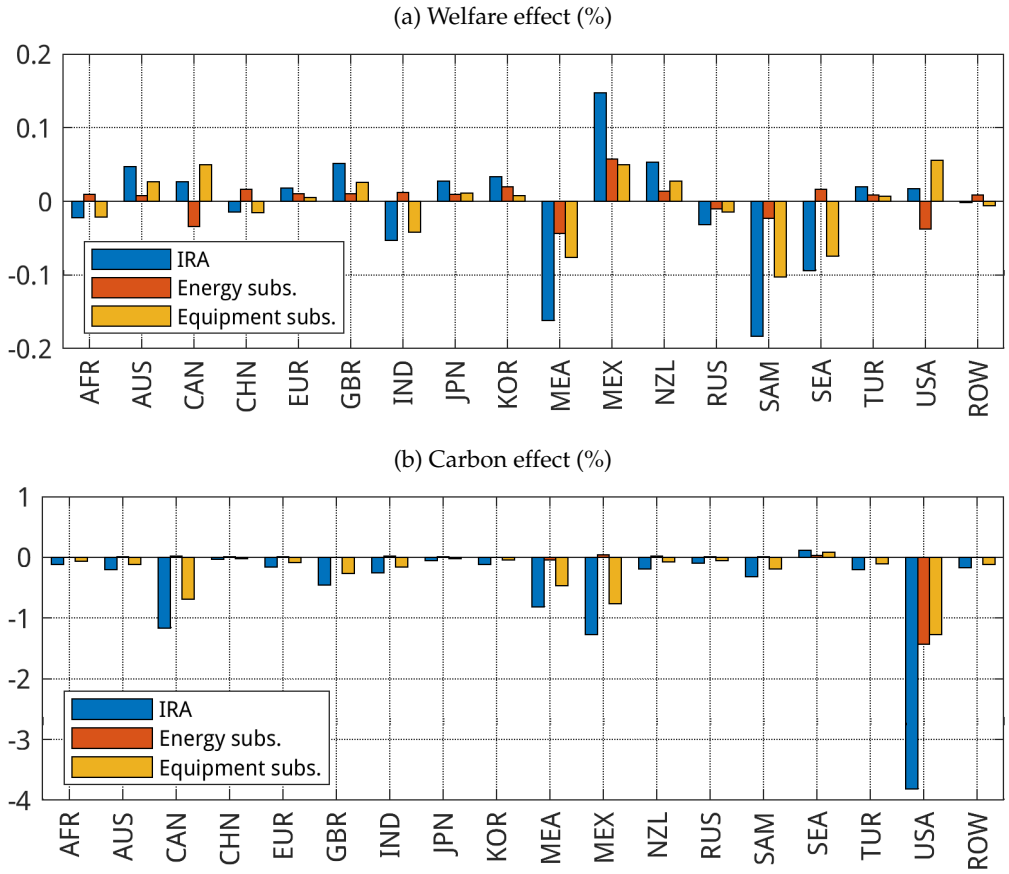
The impact of the equipment subsidy is more pronounced in the solar equipment market than in the wind equipment market in the short run. This disparity arises from two factors: first, the price gap between the US and China for solar equipment is smaller than for wind equipment, and second, the trade elasticity for solar equipment is higher, indicating that global demand for solar equipment responds more to the US equipment subsidy. This also explains why the energy subsidy is more effective in increasing the US share in the global wind equipment market. However, the impact of policy is transitory; as can be seen in the after-policy periods in Figure 4, the US shares decrease in both equipment, and neither energy nor equipment subsidies have a significant long-term impact. At steady state, the US share in solar equipment approaches 0%, and the share in the wind equipment market approaches 5%, regardless of the policies.

**Welfare and $CO_2$ emissions.** The IRA influences welfare differently across countries. Panel (a) in Figure 5 shows the welfare impact of i) the IRA (blue bar), ii) the energy subsidy component (red bar), and iii) the equipment subsidy component (yellow bar) compared to the baseline case. The IRA increases welfare in the United States by 0.02%, primarily driven by the equipment subsidy component. The IRA's aggregated global impact on welfare is -0.03%, with significant heterogeneity across countries.

This spatial heterogeneity arises for the following reasons. First, both subsidies reduce fossil fuel demand, which lowers real wages in fossil fuel net exporters such as Canada, Middle East Asia, Russia, South America, and the US. Second, the energy subsidy component increases welfare in net exporters of equipment, such as China, India, and Southeast Asia. These countries are also net importers of fossil fuels, thus further benefiting from the energy subsidy as well. Overall, the energy subsidy slightly increases the global welfare by 0.01% at the cost of the US welfare loss by 0.04%.

The equipment subsidy, on the other hand, shifts the comparative advantage in equipment toward the US, reducing welfare in equipment net exporters in the status quo. As the US increases equipment production, intermediate goods exporters to the US, such as Canada and Mexico, also benefit. Overall, the equipment subsidy component reduces the global welfare by 0.02% but increases US welfare by 0.06%, suggesting a *beggar-thy-neighbor* effect associated with the equipment subsidy.

Figure 5: Welfare and carbon effect of IRA




Note: Panel (a) plots the effect of IRA on welfare in discounted sum of real wage up to 2050 for residents in different countries. Panel (b) presents the effect of IRA on accumulated $CO_2$ emissions up to 2050 in different countries.

This can be seen in the change in equipment productivity across countries. I plot how the productivity in equipment changes under each subsidy in the US, China, Southeast Asia (India for wind equipment), and global weighted average in Figure E.1. IRA and equipment subsidy increases the productivity in the US, lowers the productivity in net-exporting countries under the baseline, and energy subsidy moves in the opposite direction with smaller magnitude. Globally, any subsidies *decrease* the productivity in the initial few periods as more countries with lower productivity involves in the equipment production (Panel (d)). However, equipment subsidy component concentrates production in the US and the global productivity goes up in the later periods of IRA as the US becomes net exporter and accumulates the production experience.

The impact of the IRA on $CO_2$ emissions is concentrated in the US (-3.81%), but the pattern differs between energy and equipment subsidies. Panel (b) in Figure 5 shows the impact of the IRA on accumulated carbon emissions compared to the baseline case. An interesting pattern is that while the impact of the energy subsidy is concentrated in the US, the impact of the equipment subsidy is more widely spread across countries. The energy subsidy directly reduces fossil fuel demand in the US by affecting the relative price between renewable and fossil fuels, but the spillover effect is small. Rather, it increases carbon emissions in most countries including Canada

and Mexico, an evidence of carbon leakage. While energy subsidy reduces US carbon emissions by 1.44%, non-US countries increase carbon emissions by 0.03%, and the global aggregate effect is a mere 0.17% reduction compared to the baseline.[30] On the other hand, equipment subsidy reduces non-US carbon emissions by 0.12% and reduces global carbon emissions by 0.23%.

The equipment subsidy in the US results in cheaper investment costs globally through trade, facilitating the installation of renewable energy equipment worldwide. This transition speeds up with the equipment subsidy, reducing fossil fuel demand *across countries* in the long run and decreasing accumulated carbon emissions in the US by 1.27% and globally by 0.23% compared to the baseline case. Combined, the IRA reduces global $CO_2$ emissions by 0.60% compared to the baseline.

Energy and equipment subsidies also differ in the impact across times. In Figure E.3, I plot the change in carbon emissions in the US and global excluding US under each subsidy across time. Two observations arise: first, with in the US, energy subsidy is more effective than equipment subsidy in carbon emissions reduction during the policy periods, but equipment subsidy has a larger long-run impact. Second, outside the US, equipment subsidy is more efficient in reducing carbon emissions, resulting in smaller carbon leakage than energy subsidy.[31]

To further examine the role of carbon emission reduction on welfare, I use Equation (32) to decompose the welfare effect into the real income effect and the carbon effect. Table 7 presents the welfare effect of the IRA across countries, decomposed into real income change and carbon emission change. From the second column of Table 7, we see that carbon emission reductions play an important role in the impact of the IRA on welfare. While the real income effect varies across countries, the reduction in carbon emissions increases welfare in all countries by an average of 0.02%.

Panel (a) of Table 8 summarizes the key outcomes on welfare and carbon impact of the IRA in an aggregate level.

**Estimated Budget and Marginal Value of Public Fund.** The model predicts the estimated budget for the renewable energy provisions of the IRA to be $243 billion US dollars. This is significantly larger than the Congressional Budget Office's prediction ($96 billion US dollars), but closer to the estimates provided by Arkolakis and Walsh (2023) and the Wharton Budget Model ($160 billion and $263 billion US dollars, respectively) (Congressional Budget Office, 2024; Wharton Budget Model, 2023). The key reason for the higher budgetary cost in my estimate, in particular compared to Arkolakis and Walsh (2023), is that the US becomes a net exporter of equipment, resulting in a substantial amount of the budget being allocated to subsidizing exports. This increases budget spending compared to models that do not account for equipment trade.

One point to note is that the budgetary cost of the IRA is higher than the combined budget costs of the energy and equipment subsidies ($97 billion and $80 billion, respectively) when considered separately. This is because the subsidies are complementary: the energy subsidy enhances

[30] The size of carbon leakage is consistent with the value in Teusch et al. (2024), which show carbon leakage through international trade offset approximately 13% of these domestic emission reductions.

[31] The same thing can be said by seeing the changes in renewable energy prices. Figure E.4 shows the very same pattern in renewable energy prices under each subsidy.

Table 7: Decomposing the Welfare Effect of IRA by Income and Carbon Effect

| **Countries** | Welfare Change (%) | Real Income Change (%) | Carbon emission Change (%) |
|---|---|---|---|
| AFR | -0.02 | -0.04 | 0.02 |
| AUS | 0.05 | 0.03 | 0.02 |
| CAN | 0.03 | 0.01 | 0.02 |
| CHN | -0.02 | -0.03 | 0.02 |
| EUR | 0.02 | -0.00 | 0.02 |
| GBR | 0.05 | 0.03 | 0.02 |
| IND | -0.05 | -0.07 | 0.02 |
| JPN | 0.03 | 0.01 | 0.02 |
| KOR | 0.03 | 0.01 | 0.02 |
| MEA | -0.16 | -0.18 | 0.02 |
| MEX | 0.15 | 0.13 | 0.02 |
| NZL | 0.05 | 0.03 | 0.02 |
| RUS | -0.03 | -0.05 | 0.02 |
| SAM | -0.18 | -0.20 | 0.02 |
| SEA | -0.09 | -0.11 | 0.02 |
| TUR | 0.02 | -0.00 | 0.02 |
| USA | 0.02 | -0.00 | 0.02 |
| ROW | -0.00 | -0.02 | 0.02 |

domestic equipment production when the equipment subsidy is in place, as domestic demand is primarily met by domestic supply, while the equipment subsidy supports domestic renewable energy production by lowering the price of equipment.

To compare the efficiency between energy and equipment subsidies, I compute the marginal value of public fund in terms of carbon reduction (Finkelstein and Hendren (2020)). The marginal $1 billion of tax reduces global carbon emissions by 0.0013% under IRA, 0.0004% under energy subsidy only, and 0.0015% under equipment subsidy only, suggesting that equipment subsidy is more efficient than energy subsidy.

### 6.3 Role of Equipment Trade in the Impact of IRA

In this analysis, trade in equipment is a key component that drives the results. To quantify the role of equipment trade in the impact of the IRA, I simulate the model without equipment trade. Specifically, I set the trade costs for equipment, $\kappa^{j}_{in,t}$ for $j \in \Omega_{REE}$ for all $n, i, t$, to be infinite.

Table 8 shows the welfare and carbon impact of the IRA under the baseline model (panel (a)) and the model without trade in equipment (panel (b)). Not considering equipment trade misleads the impact of the IRA in several aspects. Under no equipment trade scenario, the IRA lead to a smaller global carbon reduction (-0.42%), a loss in US welfare (-0.01%) and a gain in global welfare (0.01%).

The impact of energy and equipment subsidies also shows notable differences between under the baseline and under the "No equipment trade" scenario. Under no equipment trade scenario, energy subsidy component lead to a smaller global carbon reduction (0.15%), smaller US welfare loss (-0.02%) and global welfare gain (0.00%). This reflects that when considering equipment trade, additional demand for equipment from energy subsidy in the US increases the equipment import from other countries. Without trade, the energy subsidy is less efficient in carbon reduction as the

equipment cost is high. However, now the equipment demand from the subsidy is only met by domestic supply, so the US harnesses learning-by-doing, while the other countries do less compared to the baseline, suggesting higher US welfare and worse global welfare.

Without trade, equipment subsidy yields a smaller global carbon reduction (-0.13%), lower US welfare gain (+0.04%), and higher global welfare (+0.01%) compared to the baseline, respectively. Without trade, the US cannot export its subsidized equipment to the global market, so the effect of cheaper equipment limits to the US. However, there is no *beggar-thy-effect* as the US cannot export, and the global welfare improves in this aspect. Moreover, the share of peak US solar equipment is significantly impacted, dropping from 20.6% under the baseline model to just 12.8% under the "No equipment trade" scenario, highlighting that US becomes a net exporter under the baseline scenario. As the US becomes a net exporter under IRA subsidies, i) US real wages increase, and ii) the energy transition in other countries accelerates which leads to a reduction in global carbon emissions. These effects are not captured in the model without equipment trade.

Table 8: Welfare Comparison

| | Global $CO_2$ | Global Welfare | US Welfare | Peak US Solar Equip. Share |
|---|---|---|---|---|
| (a) *Baseline model* | | | | |
| IRA | -0.60% | -0.03% | 0.02% | 32.1% |
| Energy Subs. | -0.17% | 0.01% | -0.04% | 2.7% |
| Equipment Subs. | -0.23% | -0.02% | 0.06% | 20.6% |
| *(b) No equipment trade* | | | | |
| IRA | -0.42% | 0.01% | -0.01% | 20.1% |
| Energy Subs. | -0.15% | 0.00% | -0.02% | 16.0% |
| Equipment Subs. | -0.13% | 0.01% | 0.04% | 12.8% |

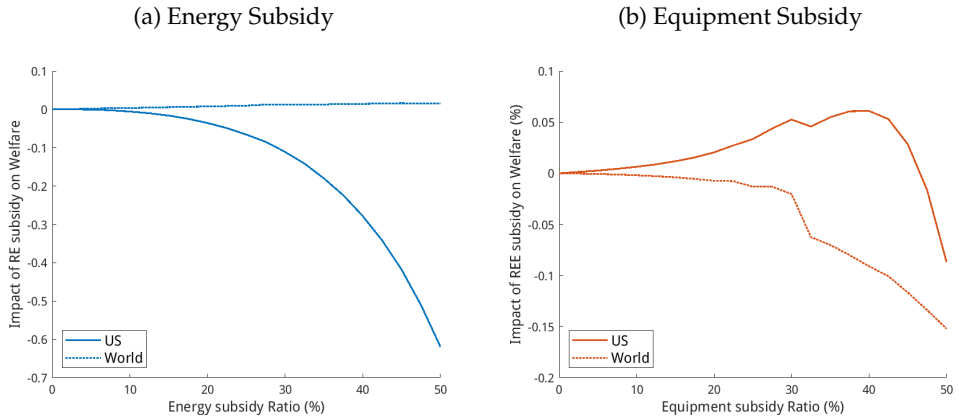
### 6.4 Optimal Subsidy

A natural question arises regarding the optimal (unilateral) subsidy for the US and the world. The analytical formula for optimal subsidies is beyond the scope of this paper. In this section, I compute the welfare for the US and globally under a range of subsidy ratios from 0% to 50%.

Figure 6 shows the relative change in welfare with different subsidy ratios for the energy subsidy (panel (a)) and the equipment subsidy (panel (b)) for the US, the world excluding the US, and the world as a whole.

Compared to the current IRA subsidy scheme, the subsidy rate is too high for the energy subsidy and too low for the equipment subsidy from the US perspective. Table 9 summarizes the welfare and carbon impact of the opitmal subsidies for US and global. The US optimal subsidy, which consist of no energy subsidy and 40% equipment subsidy, reduces global carbon emissions by 0.63%, global welfare by 0.10%, but increases the US welfare by 0.07%. Compared to the current IRA, the optimal subsidy reduces carbon emissions more and improves the US welfare at the cost of global welfare. The US subsidy rate that maximizes global welfare is 45% for energy subsidy

Figure 6: Welfare by Subsidy Ratio




Note: This figure plots the relative change in welfare under different subsidy ratios. Panel (a) plots the relative change in welfare under different energy subsidy ratios, and (b) plots the welfare change under equipment subsidy ratios. US welfare is plotted with solid line and global welfare is plotted with dotted line in each panel.

and 0% for equipment subsidy. Under this subsidy, global carbon emissions decreases by 0.63% and global welfare increases by 0.02%, but the US welfare decreases by 0.45%. This result suggests that the US's unilateral optimal equipment subsidy can reduces carbon emissions as much as energy subsidy does, at the same time increasing the US welfare.

The energy subsidy results in welfare loss for the US under any positive ratio, with the global optimal energy subsidy being 45%. The intuition is straightforward: renewable energy sector features decreasing returns to scale, and the energy subsidy mainly reduces carbon emissions in the US, but the benefits of this reduction accrue to other countries through carbon leakage and increased demand for equipment met by other countries. On the other hand, the optimal equipment subsidy for the US is 40%, while the global optimal equipment subsidy is 0%. This is because, while the equipment subsidy implemented by the US corrects the positive externality within the US, it diminishes other countries' learning-by-doing due to the relocation of equipment production. As a result, the US optimal level of the equipment subsidy is too high from a global perspective.

Table 9: Welfare Comparison with Optimal Subsidies

| | Global $CO_2$ | Global Welfare | US Welfare | Peak US Solar Equip. Share |
|---|---|---|---|---|
| IRA (Energy:20%, Equipment: 30%) | -0.60% | -0.03% | 0.02% | 32.1% |
| US Optimal Subsidy (Energy:0%, Equipment: 40%) | -0.63% | -0.10% | 0.07% | 47.8% |
| Global Optimal Subsidy (Energy:45%, Equipment: 0%) | -0.63% | 0.02% | -0.45% | 6.4% |

# 7 Extensions

In this section, I extend the previous counterfactual analysis in two dimensions. First, I introduce an additional policy dimension by considering a scenario where the US combines trade policy with the IRA. The second scenario incorporates policy responses from other countries. I summarize the key results from this section in Table 10.

## 7.1 Impact of IRA under Trade Policy

The trade policy considered here involves imposing 50% tariff on solar equipment imports from China and Southeast Asia to the US, which resembles the actual US trade policy.[32] I assume the policy lasts for 10 years (2022-2031). I refer to this scenario as "Solar tariff."

**Impact of trade policy.** Before exploring the combination of trade policy and the IRA, it is helpful to first consider the impact of trade policy alone. In the absence of an industrial policy, raising trade barriers can help address some of the misallocation resulting from local learning-by-doing. However, as noted by Lashkaripour and Lugovskyy (2023), while trade barriers can be employed, they are not an efficient solution for correcting misallocation because they worsen welfare by affecting the import prices of equipment. In our setting, the higher equipment import prices results in higher carbon emissions due to a delayed transition, which further worsen welfare through carbon emissions.

**US Share in Global Renewable Energy Equipment Market.** Next, I examine the combined impact of trade policy and the IRA.[33] Figure 7 illustrates the impact of the IRA (with and without tariff) on the US's global renewable energy equipment market share. Panel (a) shows the evolution of the US global solar equipment market share. Under the Solar tariff, the market share rises to 5% (red solid line), and the IRA under Solar tariff further increases the market share to up to 35% during the policy period, sustaining a higher share in the post-policy period (red dashed line) compared to the IRA without solar tariff (blue dashed line). Imposing tariff on solar equipment imports allows US-produced solar equipment to capture the domestic market more rapidly, resulting in greater productivity gains through learning-by-doing and a higher global market share.

Panel (b) in Figure 7 presents the outcome for wind equipment. Despite the weak complementary between solar and wind energy, solar tariff has a small negative impact on the US market share for wind equipment (red solid line) as the domestic production concentrates to solar equipment than wind equipment due to the tariff. The US market share for wind equipment with the IRA under solar tariff (red dashed line) is lower compared to the IRA under the baseline (blue dashed line), but with a smaller margin.

**Welfare and $CO_2$ Emissions.** Panel (ii) in Table 10 summarizes the welfare and carbon impact of the Solar tariff and the IRA. Imposing solar equipment tariff increases global carbon emissions

[32] In 2024, the Biden administration announced an increase in Section 301 tariffs on solar cells to 50% for imports from China. Southeast Asian countries are major locations for several Chinese equipment manufacturing affiliations, which export to the US. the US Department of Commerce set preliminary duties on solar cell imports from four Southeast Asian countries.

[33] The model with tariff is provided in the Appendix Section A.4.

by 0.01% and reduces global and US welfare by 0.01% due to the delayed transition in the US, and thus smaller learning-by-doing in exporting countries to the US - mainly Southeast Asia.

The second row of panel (ii) in Table 10 shows the effect of combining the IRA with Solar tariff on welfare and carbon emissions. Global welfare decreases by 0.04% and US welfare increases by 0.01%, which are worse than the welfare outcome from the IRA under the baseline (-0.03% and 0.02%, respectively). The reason the IRA has a worse impact on welfare on both the US and the world under solar tariff compared to the baseline IRA scenario is that, combined with solar tariff, US gains higher market share even with a lower productivity than other equipment exporting countries initially, and this increases equipment prices in the US. Decomposing the IRA shows the impact of both renewable energy and equipment subsidies (third and fourth rows of panel (ii), respectively) worsen welfare when combined with solar tariff, compared to the corresponding cases under baseline specification (panel (i)).

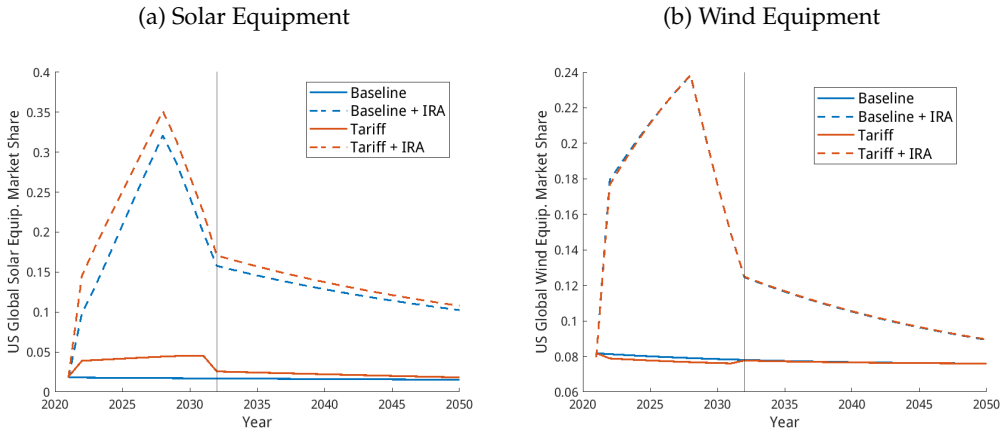
One interesting pattern is that combining solar tariff has different implication for energy subsidy and equipment subsidy in carbon emissions. Figure E.5 shows the relative change in the US (panel (a)) and non-US global (panel (b)) carbon emissions under solar tariff relative to baseline (blue solid line), combined Solar tariff & IRA compared to baseline IRA (red dashed line), Solar tariff & energy subsidy (yellow circles), and Solar tariff & equipment subsidy (purple dotted line), relative to corresponding subsidies without tariff. Solar tariff increasing the US carbon emissions, but energy subsidy combined with tariff increases carbon emissions compared to using energy subsidy only in the US, which is surprising. The key reason is that solar equipment in the US is more expensive due to the tariff, so subsidizing renewable energy is less effective in facilitating the transition in the US. However, energy subsidy combined with tariff also increases carbon emissions globally in the long-run as shown in in panel (b) as China and Southeast Asia lost learning experience due to the tariff .

On the other hand, compared to using equipment subsidy only, solar tariff combined with equipment subsidy (purple dotted lines) increases US carbon emissions in the short run as shown in panel (a) due to higher US equipment price initially, but further reduces global carbon emissions in the long run as shown in panel (b). The key difference between the results is whether US can become a net exporter with the implemented policy. Tariff, combined with the equipment subsidy, helps the US getting higher global market share in solar equipment, exporting its equipment and facilitates the global transition.

Combining tariff, energy and equipment subsidies together, global carbon emissions under IRA with Solar tariff decrease by 0.63%, which is also larger compared to the IRA only case. This can be attributed to the fact that tariff and IRA boosts US equipment production.

Again, the impact of the subsidies combined with Solar tariff on welfare and carbon emissions is heterogeneous across countries. Figure E.6 shows the impact of the IRA combined with Solar tariff on welfare (panel (a)) and accumulated carbon emissions (panel (b)) compared to the corresponding subsidy scenarios without the tariff across countries. The welfare losses in countries directly affected by the tariff—China, Southeast Asia, and the US—are relatively prominent. Korea and Mexico benefit from this tariff as the demand for the US used to met by China before

Figure 7: US global equipment market share under IRA with 50% Solar Tariff




Note: Panel (a) shows the evolution of US global solar equipment market share. The solid blue (red) line shows the share under baseline (with tariff), whereas the blue dotted (red dotted) line represents the share under IRA subsidy. Panel (b) presents the evolution of US global wind equipment market share.

is now met by outputs from Mexico. In terms of carbon emissions, tariff combined with IRA and equipment subsidy reduce global emissions compared to the using a subsidy only. However, combining energy subsidy with Solar tariff results in higher carbon emissions in Southeast Asia as the tariff hurts their productivity growth from learning-by-doing, and US carbon emissions is also significantly higher compared to the baseline IRA case due to higher equipment price in initial periods. Other countries' carbon emissions are also affected through input-output linkages in the production network, but in general we see slightly larger reduction in carbon emissions overall.

## 7.2 US - China - EU Policy Competition

A natural extension to consider is the case where other countries also implement green industrial policies. In this section, I examine the scenario in which China and the EU also implement subsidies similar to those of the US's IRA.[34]

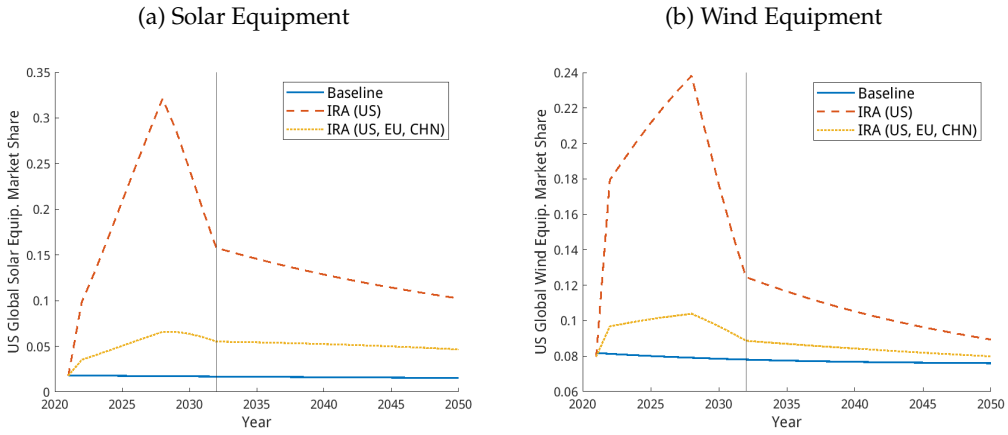
**US Share in Global Renewable Energy Equipment Market.** Panel (a) in Figure 8 plots the evolution of the US global solar equipment market share. The US share increases to 6.4% at the end of the policy period (yellow dotted line), which is smaller compared to the scenario where only the US implements the IRA (red dashed line). This is due to the fierce competition from China and the EU, which are also subsidizing their domestic solar equipment manufacturing.

The US share in wind equipment follows a similar pattern. Panel (b) in Figure 8 shows the evolution of the US global wind equipment market share. The share only reaches 11% at its peak when the US, China, and EU all implement subsidies (yellow dotted line), compared to 23% when only the US implements the policy (red dashed line).

**Welfare and $CO_2$ Emissions.** Panel (iii) in Table 10 summarizes the outcomes under the scenario where the US, China, and EU all implement identical green industrial policies.

[34]While this extension does not directly study a non-cooperative Nash equilibrium or global optimal, it provides insights into both multilateral policy cases.

Figure 8: US global equipment market share under US, China, EU policies




Note: Panel (a) shows the evolution of the US global solar equipment market share. The solid blue (red) line shows the share under baseline, the blue dotted (red dotted) line represents the share when only the US implements IRA subsidy, whereas the yellow dashed line shows the share when the US, China, and EU implement the same subsidy. Panel (b) presents the evolution of the US global wind equipment market share.

The key finding is that multilateral green industrial policies reduce carbon emissions more substantially, mitigates US equipment subsidy but increases the US welfare. The first row of panel (iii) in Table 10 shows a substantial aggregate reduction in carbon emissions of 3.16%, which is much larger than the reduction observed in the baseline IRA scenario where only the US implements the policy. Global welfare decreases by 0.15%, which is a much larger loss compared to the unilateral IRA case. At the same time, US welfare experiences a larger gain (0.04%). This occurs mainly for two reasons. First, the carbon leakage issue from the energy subsidy is mitigated when other countries also implement identical policies. Second, US can import cheaper equipment from China due to the China's equipment subsidy component, improving terms of trade and boosting the transition. Comparing the impact of the energy subsidy under unilateral and multilateral scenarios (panel (i) and panel (iii)) suggests that policy competition can lead to further reductions in carbon emissions with positive global welfare gains and smaller welfare losses for the US. However, most of the carbon and welfare implications are coming from equipment subsidy components. In the third row in panel (iii), I find that equipment subsidy competition results in larger global welfare loss. The US welfare goes up, but not because US becomes net exporter in equipment; rather, the US share in global solar equipment market is mere 6% at the peak. The gain is mostly coming from US being able to import cheaper equipment from China due to the China's subsidy, fastening the transition.

The welfare and carbon implications are heterogeneous across countries. Figure E.7 plots the relative change in welfare and accumulated carbon emissions across countries when the US, China, and EU all implement identical IRA policies, compared to the baseline scenario.

In panel (a) in Figure E.7, I find significant welfare losses in China, primarily due to the large amount of equipment subsidy provided. The welfare loss from the equipment subsidy in China occurs because the country already holds 82% of the global solar equipment market share, leaving limited room for additional gains from further subsidization. Equipment subsidy facilitates global

energy transition, decreasing fossil fuel demand. As a result, fossil fuel net exporters (Middle East, Russia, South America) experience further welfare losses, while net importers (Japan and Korea) benefit.

In terms of carbon emissions, as shown in panel (b), this scenario results in a substantial aggregate reduction of 3.16%, which is much larger than the reduction observed in the baseline IRA scenario where only the US implements the policy (0.60%). While the energy subsidy leads to significant declines in carbon emissions mainly in China, the EU, and the US without much spillover to other countries, the equipment subsidy component in each policy further amplifies the global reduction in carbon emissions (-1.73%).

Table 10: Equilibrium Comparison

| | Global $CO_2$ | Global Welfare | US Welfare | Peak US Solar Equip. Share |
|---|---|---|---|---|
| (i) Baseline specification | | | | |
| IRA | -0.60% | -0.03% | 0.02% | 32.1% |
| Energy Subs. | -0.17% | 0.01% | -0.04% | 2.7% |
| Equipment Subs. | -0.23% | -0.02% | 0.06% | 20.6% |
| (ii) IRA + Solar Tariff | | | | |
| Tariff | 0.01% | -0.01% | -0.01% | 4.5% |
| IRA + Tariff | -0.63% | -0.03% | 0.01% | 35.1% |
| Energy Subs. + Tariff | -0.16% | -0.00% | -0.04% | 7.7% |
| Equipment Subs. + Tariff | -0.27% | -0.03% | 0.05% | 23.8% |
| (iii) US-CHN-EU Policy | | | | |
| US-CHN-EU IRA | -3.16% | -0.15% | 0.04% | 6.6% |
| US-CHN-EU Energy Subs. | -0.89% | 0.01% | -0.02% | 2.0% |
| US-CHN-EU Equipment Subs. | -1.73% | -0.11% | 0.07% | 4.6% |

# 8 Conclusion

The transition to renewable energy involves the trade of renewable energy equipment, such as solar panels and wind turbines. Motivated by this, this paper presents a multi-country dynamic general equilibrium model with tradable equipment to explore the impact of green industrial policies—specifically, the renewable energy provisions of the IRA—on global welfare and carbon emissions. The findings underscore the importance of equipment trade, showing that (i) the US implementing the IRA can be effective in reducing global carbon emissions, with a positive welfare gain for the US but at the cost of global welfare, and (ii) not considering equipment trade can significantly mislead the impact of the IRA, as it predicts smaller carbon reduction effect, and opposite welfare implications.

The results reveal that equipment subsidies, compared to energy subsidies, benefits US welfare at the expense of non-US global welfare mainly due to terms of trade effect and learning-by-doing, while energy subsidies work in the opposite way. Additionally, while energy subsidies

are more effective at reducing US carbon emissions, equipment subsidies have a greater global carbon reduction impact by facilitating the energy transition in other countries through lowering the global cost of equipment.

The effectiveness of the IRA depends on the interplay between trade policies and the responses of other countries. Extensions of the model suggest that protectionist trade policies, such as the solar tariff against China and Southeast Asia, would diminish the positive effects of the IRA, reducing both global and US welfare. The analysis also indicates that if major economies like the EU and China were to implement similar green industrial policies, the policy impact of the US's equipment subsidy would be mitigated, although global carbon emissions could be further reduced and US welfare would improve as investment costs in the US decrease.

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# Online Appendix: Green Industrial Policies and Energy Transition in the Globalized Economy

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# Appendix A Derivations

## A.1 Deriving Share of Each Energy Source in Production and Consumption

Due to the Nested CES structure in energy production, the share of each energy source $e \in \{s, w, f\}$ in producing $j$ sector good is endogeneously determined.

$$\begin{aligned}
\gamma_n^{f,j} &= [\gamma_n^{E,j}\gamma_n^j]\Big[1+\frac{\eta_e}{1-\eta_e}\Big(\frac{p_n^f}{p_n^r}\Big)^{\psi-1}\Big]^{-1} \\
\gamma_n^{s,j} &= [\gamma_n^{E,j}\gamma_n^j]\Big[1+\frac{1-\eta_e}{\eta_e}\Big(\frac{p_n^r}{p_n^f}\Big)^{\psi-1}\Big]^{-1}\Big[1+\frac{1-\eta_r}{\eta_r}\Big(\frac{p_n^s}{p_n^w}\Big)^{\rho-1}\Big]^{-1} \\
\gamma_n^{w,j} &= [\gamma_n^{E,j}\gamma_n^j]\Big[1+\frac{1-\eta_e}{\eta_e}\Big(\frac{p_n^r}{p_n^f}\Big)^{\psi-1}\Big]^{-1}\Big[1+\frac{\eta_r}{1-\eta_r}\Big(\frac{p_n^w}{p_n^s}\Big)^{\rho-1}\Big]^{-1}
\end{aligned} \tag{A.1}$$

where $p_n^{r,j}y_n^{r,j} = p_n^s y_n^{s,j} + p_n^w y_n^{w,j}$ and $p_n^E y_n^{E,j} = p_n^f y_n^{f,j} + p_n^r y_n^{r,j}$

Similar formula can be derived for share of each energy source in utility:

$$\begin{aligned}
\mu_n^f &= [\mu_n^E]\Big[1+\frac{\eta_e}{1-\eta_e}\Big(\frac{p_n^f}{p_n^r}\Big)^{\psi-1}\Big]^{-1} \\
\mu_n^s &= [\mu_n^E]\Big[1+\frac{1-\eta_e}{\eta_e}\Big(\frac{p_n^r}{p_n^f}\Big)^{\psi-1}\Big]^{-1}\Big[1+\frac{1-\eta_r}{\eta_r}\Big(\frac{p_n^s}{p_n^w}\Big)^{\rho-1}\Big]^{-1} \\
\mu_n^w &= [\mu_n^E]\Big[1+\frac{1-\eta_e}{\eta_e}\Big(\frac{p_n^r}{p_n^f}\Big)^{\psi-1}\Big]^{-1}\Big[1+\frac{\eta_r}{1-\eta_r}\Big(\frac{p_n^w}{p_n^s}\Big)^{\rho-1}\Big]^{-1}.
\end{aligned} \tag{A.2}$$

## A.2 Consumption Equivalent Variation

Welfare in region $n$, $W_n$, is defined by the discounted sum of real income incorporating carbon emissions disutility:

$$W_n = \sum_{t=1}^{T} \beta^t \Big(\frac{E_{n,t}}{P_{n,t}} \frac{1}{(1+SCC(Z_t - Z_0))}\Big), \tag{A.3}$$

To study the change in welfare under a counterfactual, I define the compensating variation in consumption for region $n$ to be $CEV_n$ such that

$$W_n' = W_n \sum_{s=1}^{T} \beta^s (CEV_n). \tag{A.4}$$

where $W_n'$ is the welfare of country $n$ under the counterfactual. Rearranging this and taking log gives

$$\log(CEV_n) = \log(W_n'/W_n) exp\Big(\frac{1-\beta}{1-\beta^T}\Big). \tag{A.5}$$

## A.3 Proof of Proposition 1

Differentiating 12 with respect to $s^r_{n,t}$ gives

$$\begin{aligned}
\frac{d\gamma^{f,j}_{n,t}}{ds^r_{n,t}} &= \gamma^{E,j}_n\Big[1+\frac{\eta_e}{1-\eta_e}\Big(\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})}\Big)^{\psi-1}\Big]^{-2}\Big[\frac{\eta_e}{1-\eta_e}(\psi-1)\Big(\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})}\Big)^{\psi-2}\Big]\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})^2}\frac{dP^r_{n,t}(s^r_{n,t})}{ds^r_{n,t}} \\
&= (\psi-1)\underbrace{\gamma^{E,j}_n\Big[1+\frac{\eta_e}{1-\eta_e}\Big(\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})}\Big)^{\psi-1}\Big]^{-2}\frac{\eta_e}{1-\eta_e}\Big(\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})}\Big)^{\psi-2}\frac{P^f_{n,t}}{P^r_{n,t}(s^r_{n,t})^2}}_{>0}\underbrace{\frac{dP^r_{n,t}(s^r_{n,t})}{ds^r_{n,t}}}_{<0} \\
\implies \quad & \frac{d\gamma^{f,j}_{n,t}}{ds^r_{n,t}} < 0 \iff (\psi-1) > 0. \qquad \text{(A.6)}
\end{aligned}$$

## A.4 Model with Tariff

In this part, I incorporate sectoral tariff in the baseline model.

I consider an ad-valorem tariff $\tau^j_{ni,t}$ that country $n$ charges to the goods in sector $j$ imported from country $i$. Now denote the total trade cost *net* of tariff, i.e., $\kappa^j_{ni,t} \equiv d^j_{ni,t}(1+\tau^j_{ni,t})$. Equation (15) should include tariff effect,

$$Y^j_{n,t} = \sum_{m=1}^{N}\frac{\pi^j_{mn,t}}{(1+\tau^j_{mn,t})(1-s^j_{m,t})}X^j_{m,t}. \qquad \text{(A.7)}$$

This equation captures that gross output in country n's sector j is equal to the sum of total exports and domestic sales, *net* of tariffs.

Trade balance condition should also incorporate tariff:

$$\sum_{j\in\Omega}\sum_{n=1}^{N}\frac{\pi^j_{in,t}}{(1+\tau^j_{in,t})(1-s^j_{i,t})}X^j_{i,t} - D_i = \sum_{j\in\Omega}\sum_{n=1}^{N}\frac{\pi^j_{ni,t}}{(1+\tau^j_{ni,t})(1-s^j_{n,t})}X^j_{n,t} \qquad \text{(A.8)}$$

Lastly, household's budget should incorporate tariff revenue:

$$\begin{aligned}
&\sum_{j\in\Omega^*_K} P^j_{n,t}C^j_{n,t} \\
&= w_{n,t}L_{n,t} + \sum_{k'\in\Omega_K} r^{k'}_{n,t}K^{k'}_{n,t} - \sum_{j\in\Omega} s^j_{o,t}\sum_{o=1}^{N}\frac{\pi^j_{on,t}}{(1-s^j_{n,t})}X^j_{o,t} + \sum_{j\in\Omega}\tau^j_{ni,t}X^j_{n,t}\sum_{i=1}^{N}\frac{\pi^j_{ni,t}}{(1+\tau^j_{ni,t})(1-s^j_{n,t})} \\
&+ \sum_{j\in\Omega_{RE}}\Pi^j_{n,t} + D_n - \sum_{k\in\Omega_K}P^k_{n,t}I^k_{n,t} \\
&\equiv E_{n,t} \qquad \text{(A.9)}
\end{aligned}$$

**Definition 2.** ***A sequential equilibrium of the model with tariff*** *is a set of prices* $\left\{w_{n,t}, P^j_{n,t}, r^k_{n,t}\right\}^{N,J,K,T}_{n=1,j=1,k=1,t=1}$, *allocations of goods and labor* $\left\{\pi^j_{nit}, l^j_{n,t}\right\}^{N,N,J,T}_{n=1,i=1,j=1,t=1}$ *that satisfies the static equilibrium conditions: unit costs (equations (3), (6), and (10)), trade shares ((14)), local prices (11), labor and market clearing conditions ((17),18), and trade balance ((A.8)), and dynamic conditions: law of motion of capitals ((20)), and Euler equation ((24)), where gross output satisfies (A.7) and household budget constraint satisfies (A.9).*

Table B.1: Sector Aggregation

| Aggregated Industry | Code in OECD-IO | Industry in OECD-IO |
|---|---|---|
| Agriculture | A01_02 | Agriculture, hunting, forestry |
| Agriculture | A03 | Fishing and aquaculture |
| Agriculture | B07_08 | Mining and quarrying, non-energy producing products |
| Agriculture | B09 | Mining support service activities |
| Fossil fuel energy | B05_06 | Mining and quarrying, energy producing products |
| Non-durable manufacturing | C10T12 | Food products, beverages and tobacco |
| Non-durable manufacturing | C13T15 | Textiles, textile products, leather and footwear |
| Non-durable manufacturing | C16 | Wood and products of wood and cork |
| Non-durable manufacturing | C17_18 | Paper products and printing |
| Non-durable manufacturing | C19 | Coke and refined petroleum products |
| Non-durable manufacturing | C20 | Chemical and chemical products |
| Non-durable manufacturing | C21 | Pharmaceuticals, medicinal chemical and botanical products |
| Non-durable manufacturing | C22 | Rubber and plastics products |
| Non-durable manufacturing | C23 | Other non-metallic mineral products |
| Non-durable manufacturing | C24 | Basic metals |
| Non-durable manufacturing | C25 | Fabricated metal products |
| Durable manufacturing | C26 | Computer, electronic and optical equipment |
| Durable manufacturing | C27 | Electrical equipment |
| Durable manufacturing | C28 | Machinery and equipment, nec |
| Durable manufacturing | C29 | Motor vehicles, trailers and semi-trailers |
| Durable manufacturing | C30 | Other transport equipment |
| Durable manufacturing | C31T33 | Manufacturing nec; repair and installation of machinery and equipment |
| Service | D -T | Other sectors |

# Appendix B Data

## B.1 Geographic and Time Coverage

**List of countries and regions.** I calibrate the model to 18 countries/regions including a synthetic rest of the world. These countries/regions include Africa, Australia, Canada, China, Europe, Great Britain, India, Japan, Korea, Middle East Asia, Mexico, New Zealand, Russia, South America, South East Asia, Turkiye, United States, and the rest of the world.

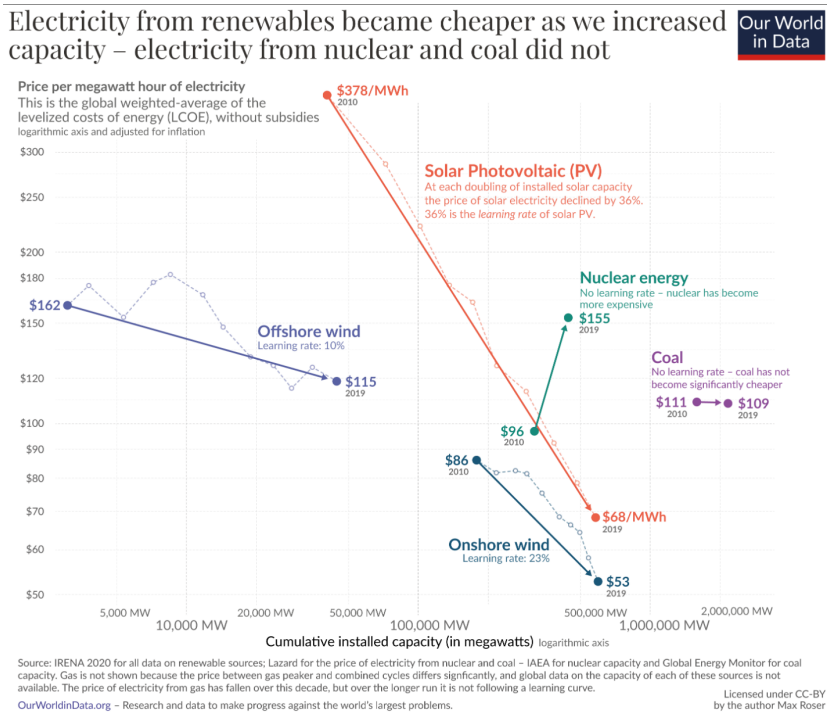
**Definition of the aggregated regions.** The aggregated regions are defined as follows:

- Africa: Cameroon, Côte d'Ivoire, Egypt, Morocco, Nigeria, Senegal, South Africa, Tunisia
- Europe: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Roumania, Slovakia, Slovenia, Spain, Sweden, Switzerland
- Middle East Asia: Jordan, Israel, and Saudi Arabia.
- South America: Argentia, Brazil, Chile, Colombia, Costa Rica, and Peru.
- South East Asia: Bangladesh, Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam.

**Sector aggregation.** The aggregated sectors are defined in table B.1.

**Time horizon** I treat 2021 as the starting point of the model and collect from various data sources the information necessary for constructing this initial economy. While the model has infinite horizon, I report some of the results focusing on the years 2021–2050. I treat each period in the model as one year.

Figure B.1: Price of Electricity by Source




Source: Our World in Data

## B.2 Data Description in Section 2.1

In this section, I describe the details of data used in Section 2.1.

Panel (a) in Figure 1: Time-series data for the import penetration for solar equipment in the US is from monthly photovoltaic module shipments published by EIA. For wind equipment, data is from annual Land-Based Wind Market Report published by US Department of Energy. This data publishes the share of domestic manufacturing component in each part of wind turbine - nacelle assembly, towers, and blades and hubs. I aggregate those components by value of each component.

Panels (b) and (c) in Figure 1: For trade data, I use 6-digit HS code from Comtrade. For solar equipment, the corresponding HS code is 854140 (Photosensitive semi-conductor devices, including photo voltaic cells whether or not assembled in modules or made up into panels; light-emitting diodes (LED): Products). For wind equipment, the corresponding HS codes are 850231 (wind power generating set), 850300 (parts of wind power generating set), and 841290 (other engines and motors). For production, PVPS dataset provides output of solar energy equipment. For wind equipment production in 2021, I use data on each country's share of value added in global wind supply chain from Global Wind Energy Council (2023).

For the solar equipment price in 2, the data is coming from PVPS solar module price. For the wind equipment, I use global price index for wind in IRENA.

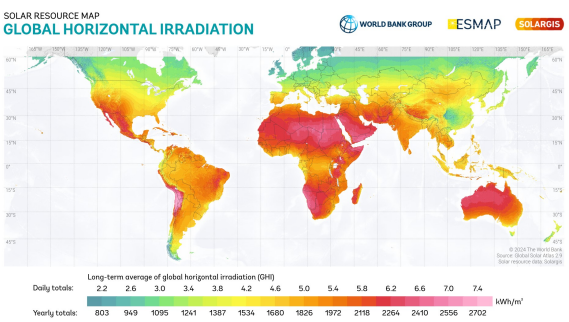
## B.3 Renewable Potential

### B.3.1 Geospatial Data for Renewable Potential

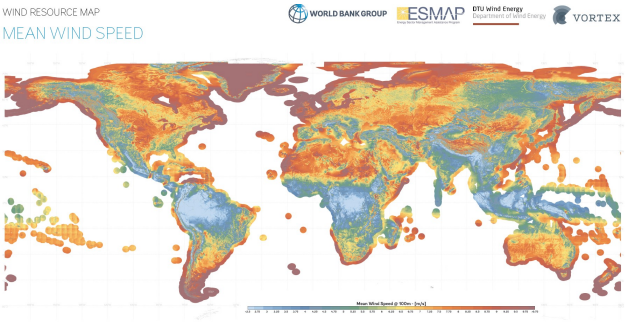
Despite the common belief that renewable energies are 'renewable', the amount of each renewable energy that can be produced in each place differs, and is governed by renewable potentials of

Figure B.2: Renewable Potentials

(a) Solar Potential




(b) Wind Potential




Note: Panel (a) displays solar potential measured by global horizontal irradiation across the world. (b) depicts wind potential measured by mean wind speed at 100m height across the world. Source: Panel (a): Global Solar Atlas, panel (b): Global Wind Atlas

each region. Figure B.2 plots the global distribution of renewable energy potentials, both solar and wind. In both panel, regions plotted with red have higher potential, and regions colored blue have lower potential. Not only there are large heterogeneity in potentials across-countries, but also there are large heterogeneity with-in each country.

Table B.2: Decreasing Return to Scale in Renewable Energy Production

| **Countries** | $A_n^s$ | $A_n^w$ | **DRS** ($\xi_n^s$) | **DRS** ($\xi_n^w$) |
|---|---|---|---|---|
| Africa | 609.95 | 569.33 | 0.965 | 0.957 |
| Australia | 583.22 | 571.84 | 0.967 | 0.960 |
| Canada | 492.03 | 625.16 | 0.972 | 0.959 |
| China | 490.78 | 776.99 | 0.963 | 0.955 |
| EU | 411.47 | 614.00 | 0.971 | 0.958 |
| Great Britain | 332.79 | 1,293.70 | 0.969 | 0.949 |
| India | 586.26 | 277.51 | 0.965 | 0.951 |
| Japan | 430.28 | 796.41 | 0.965 | 0.945 |
| Korea | 459.63 | 261.76 | 0.959 | 0.936 |
| Middle East Asia | 659.29 | 100.98 | 0.961 | 0.957 |
| Mexico | 679.59 | 868.07 | 0.961 | 0.951 |
| New Zealand | 384.00 | 1,281.91 | 0.964 | 0.946 |
| Russia | 467.20 | 1,145.75 | 0.971 | 0.959 |
| South America | 635.39 | 515.40 | 0.967 | 0.957 |
| Southeast Asia | 504.75 | 352.00 | 0.967 | 0.952 |
| Türkiye | 471.00 | 571.22 | 0.961 | 0.948 |
| United States | 552.05 | 767.75 | 0.966 | 0.960 |
| ROW | 585.73 | 877.43 | 0.969 | 0.964 |

### B.3.2 Alternative Method to Calibrate DRS

In this section, I provide an alternative method for calibrating decreasing returns to scale in renewable energy production by combining solar and wind power farm location data with renewable potential data over time. While the renewable potential at each location remains fixed, the locations of solar and wind power farms evolve over time. The power farm location dataset includes the start year of each farm, along with longitude and latitude, allowing me to calculate the average renewable potential of installed power farm locations in each country for each year.

Figure B.3 illustrates this approach. The upper panel shows global solar potential, with darker

Table B.3: Additional Evidence of DRS

| | $\xi^{s,ALT}$ | $\xi^{w,ALT}$ |
|---|---|---|
| $log(K^s_{n,t})$ | -0.012** | |
| | (0.0038) | |
| $log(K^w_{n,t})$ | | -0.071*** |
| | | (0.0083) |
| FE | ✓ | ✓ |
| $N$ | 949 | 1163 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

regions indicating poorer potential. The middle panel displays the locations of solar farms in 2011. The bottom panel combines the solar farm locations from 2021 with the solar potential data. By utilizing the annual additions of renewable power farms provided in the dataset, I can track the annual change in the *average* renewable potential of power farm locations in each country.

For each $j \in \Omega_{RE}$, I regress the average of renewable potential $j$ of installed locations in country $n$ at each year $t$ on (cumulative) installed renewable equipment controlling country fixed effect.

$$\log(A^j_{n,t}) = \xi^{j,ALT} \log(K^j_{n,t}) + FE^j_n + \varepsilon^j_{n,t}$$

Table B.3 shows the correlation between major countries' potential of additional solar and wind power farm location and cumulative installation after controlling country fixed effect.[1] Here I find that i) both solar and wind potential decrease with additional installation, and ii) wind potential decreases faster than solar potential, which is consistent with the direct measure I use in the main specification using DPI. Furthermore, the scale is relatively similar, while the measure using DPI gives slightly faster (slower) decreasing return to scale for solar (wind).

## B.4 Measuring Initial Capital Stock

I measure initial capital stock for each capital as follows:

1. First, I obtain the total capital stock for each country. To do so, I use Penn World Table, which has aggregate capital stock data for each country normalized to US = 1. I recover the level value for each country by multiplying the US capital stock level.[2]

2. Second, I obtain fossil fuel capital stock using World Input-Output Data (WIOD) capital data. For countries not covered by WIOD but included in my quantitative analysis, I impute the value using the average ratio between fossil fuel capital and fossil fuel output in countries from the OECD-IO dataset.

3. For solar and wind capital, I compute the dollar value from installed capacity (KW). In 2022, the total capital value of wind farms was 2.22 trillion US dollars.[3] I distribute 2.22 trillion US dollars across countries based on each country's share in global wind installation (in kW).

[1] Figure B.4 shows the correlation between major countries' potential of additional solar and wind power farm location and cumulative installation.

[2] Capital Stock at Constant National Prices for United States, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RKNANPUSA666NRUG, June 29, 2024.

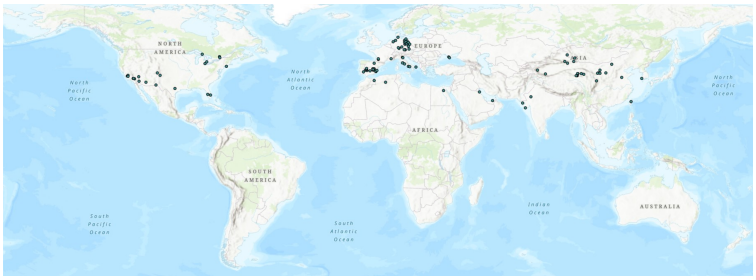
[3] https://www.chaucergroup.com/news/total-capital-value-of-wind-farms-worldwide-reaches-19tn

Figure B.3: Combining Renewable Power Farm and Renewable Potential Data

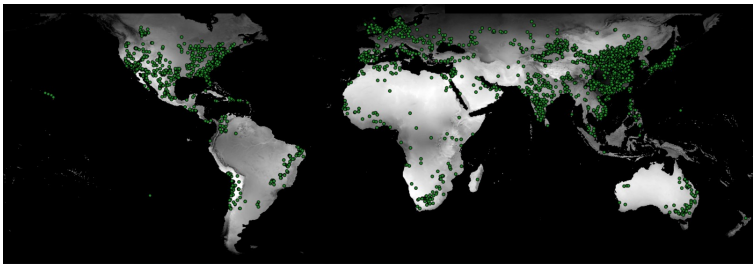
(a) Solar Potential



(b) Solar Power Farm Location in 2011




(c) Combining Solar Potential and Solar Power Farm Location in 2022

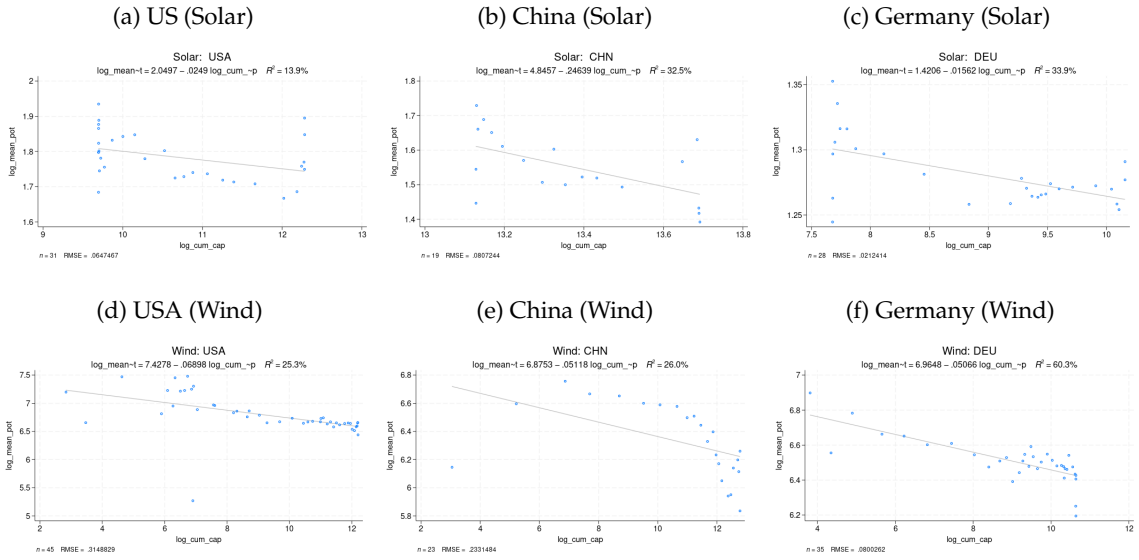


Note: Panel (a) shows the global solar potential. Region with worse potential is depicted with darker color. Panel (b) plots the locations of solar farm in 2011 from Global Solar Power Farm data. Panel (c) combines the location data of solar farms in 2021 and the solar potential.

Furthermore, assuming the same depreciation rate for solar and wind energy equipment, the capital value for installed solar energy equipment can be obtained from the relative share between globally installed solar and wind energy equipment (which is 1.26 : 1). By applying the same distribution rule, I obtain each country's initial stock of capital for solar energy equipment.

4. Non-energy capital stock can be obtained by subtracting other capital stocks from the aggregated capital stock level.

Figure B.4: Estimating Decreasing Return to Scale in Renewable Energy Production




Note: This figure plots the relationship between the log of annual cumulative renewable energy equipment installation on x-axis and the log of renewable potential in newly installed locations on y axis. Panel (a)-(c) plot the case for solar in the US, China, and Germany, and (d)-(f) plot the case for wind for corresponding countries.

# Appendix C Additional Results

## C.1 Comparative Statics

In this section, I conduct two comparative statics to see the role of learning-by-doing and renewable energy equipment trade in transition.

### C.1.1 Role of Learning-by-doing in transition

One of the key aspects of the model is learning-by-doing in renewable energy equipment production. To examine the role of learning-by-doing, I shut down this effect by setting $\nu_D^S = \nu_D^W = 0$ and simulate the transition path. Panel (a) of Figure C.1 compares the share of renewable energy in the US, EU, and China from 2021 to 2050, both with and without learning-by-doing. Under the model with learning-by-doing, the share of renewable energy in primary energy use is expected to reach 50% in the US and 60% globally by 2050. However, without learning-by-doing, the share of renewable energy in primary energy use only reaches up to 36% in the US and 25% globally.

To understand why this occurs, Panel (b) shows the price of solar energy equipment in the US, EU, and China. Without learning-by-doing in equipment, the equipment price index declines much more slowly in each country due to the lack of productivity growth. This slower price decline discourages investment in renewable energy compared to the baseline, resulting in a lower transition rate in each country.

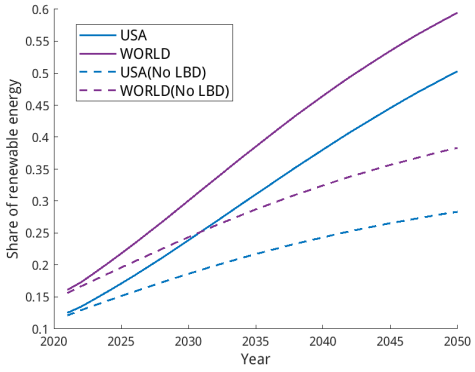
### C.1.2 Role of renewable energy equipment trade

To examine the role of renewable energy equipment trade in the transition, I consider three scenarios: free trade with no trade costs, the baseline with calibrated trade costs, and no trade.

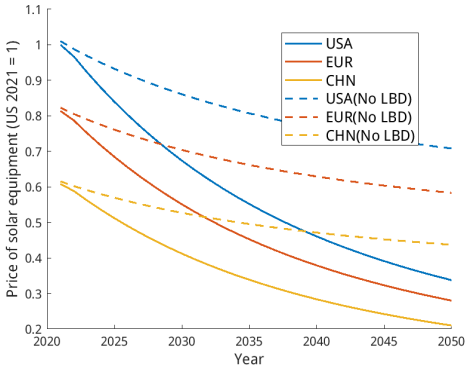
For the free trade case, I set the trade cost in renewable energy equipment to one for all country pairs, i.e., $d_{in,t}^j = 1$ for $j \in S, W$. For the no trade case, I shut down trade in renewable energy

Figure C.1: Role of Learning-by-doing

(a) Share of Renewable Energy




(b) Price of solar equipment




Note: Panel (a) plots the evolution of the share of renewable energy on total primary energy use from 2021 to 2050 in the US (blue line) and the world (purple line). Panel (b) plots the evolution of the price index of solar energy equipment from 2021 to 2050 in the USA (blue line), EU (red line), and China (yellow line). The outcomes under baseline with learning-by-doing are depicted in solid lines, and the outcomes without learning-by-doing are depicted in dashed lines.

equipment by increasing the trade cost to infinity, i.e., $d^j_{in,t} = \infty$ for $j \in S, W$ and $i \neq n$.

Panel (a) of figure C.2 compares the share of renewable energy in the US and globally under current calibration, free trade, and no trade scenarios. Under the free trade scenario, depicted by the dotted line, the share of renewable energy in primary energy use reaches up to 68% in the US and 66% globally. Without trade, the share of renewable energy in primary energy use only reaches up to 38% in the US and 40% globally (dashed lines). These results are driven by the equipment price trend shown in Panel (b).

Panel (b) plots the evolution of the price index of solar energy equipment from 2021 to 2050 in the US, EU, and China under each scenario. The price index of solar energy equipment under free trade (dotted line) is the lowest, which facilitates the transition in each country, as shown by the dotted lines in Panel (a). Under the no trade case, the price jumps in the US and EU, while the price increase in China is relatively small because China has been the main exporter under the baseline. Overall, the higher price index under no trade discourages investment in renewable energy in each country, slowing the transition to renewable energy.

## C.2 Extending Policy Periods

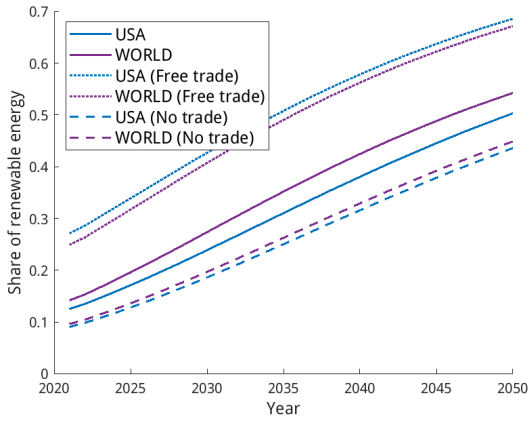
Another avenue for policy change is adjusting the length of policy periods. In this section, I change the policy period from 10 years (2022-2031) to 20 years (2022-2041). Table C.1 compares the equilibrium outcomes under the baseline IRA and the extended IRA. Extending the policy period increases the effects on carbon reductions, welfare, and the US equipment market share, but it does not change the qualitative results. However, even with the extended policy period, the impact of the subsidies remains transitory. In the steady state, the US share of the global equipment market becomes 0.1% for solar equipment and 5.4% for wind equipment.

## C.3 Robustness Check

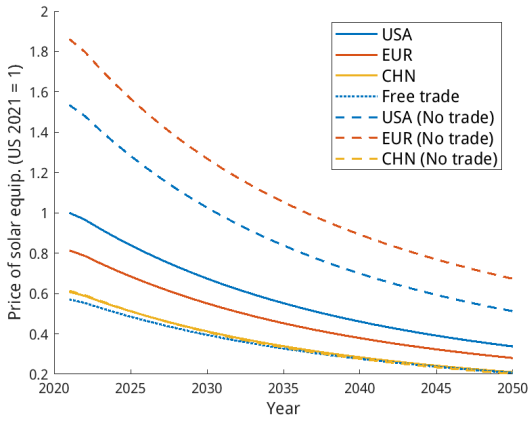
The impact of the IRA primarily depends on three sets of key parameters: (i) the elasticity of substitution between renewable energy and fossil fuels, $\eta_e$, (ii) the trade elasticities of equipment ($\theta^S$ and $\theta^W$), and (iii) the rates of learning-by-doing in equipment production, $\nu^S_D$ and $\nu^W_D$. In this section, I examine how variations in these parameters affect the results of the IRA.

Figure C.2: Role of renewable energy equipment trade

(a) Share of Renewable Energy




(b) Price of solar equipment




Note: Panel (a) plots the evolution of the share of renewable energy on total primary energy use from 2021 to 2050 in the US (blue line) and the world (purple line). Panel (b) plots the evolution of the price index of solar energy equipment from 2021 to 2050 in the USA (blue line), EU (red line), and China (yellow line). The outcomes under baseline with calibrated trade cost are depicted in solid lines, the outcomes under free trade in renewable energy equipment is depicted in dotted lines, and the outcomes under no trade in renewable energy equipment is depicted in dashed lines.

Table C.1: Welfare Comparison with Extended Policy Periods

| | Global $CO_2$ | Global Welfare | US Welfare | Peak US Solar Equip. Share |
|---|---|---|---|---|
| *(i) Baseline* | | | | |
| IRA | -0.60% | -0.03% | 0.02% | 32.1% |
| Energy Subs. | -0.17% | 0.01% | -0.04% | 2.7% |
| Equipment Subs. | -0.23% | -0.02% | 0.06% | 20.6% |
| *(ii) Extended Policy (20 years)* | | | | |
| IRA | -2.04% | -0.06% | 0.12% | 56.6% |
| Energy Subs. | -0.53% | 0.03% | -0.09% | 3.0% |
| Equipment Subs. | -1.03% | -0.06% | 0.10% | 44.8% |

**Higher Elasticity of Substitution Between Renewables and Fossil Fuels.** In this scenario, I simulate the IRA with a higher elasticity of substitution between renewables and fossil fuels, setting $\psi$ to 5, compared to the baseline value of $\psi = 3.08$.

The second panel in Table C.2 summarizes the results under $\psi = 5$. The results from the baseline specification remain qualitatively robust: the IRA results in welfare losses globally, and the equipment subsidy reduces global carbon emissions more effectively than the energy subsidy. Also, the equipment subsidy reduces other countries' welfare at the expense of US welfare gains. With higher elasticity of substitution, subsidies are more effective in replacing fossil fuels with renewable sources, thus the impact of subsidies on reducing global carbon emissions gets larger. This drives higher welfare gains from energy subsidy, for both the US and the world. However, higher elasticity of substitution increases equipment demand, and the equipment subsidy results in higher welfare gain for the US and welfare loss for the other countries due to the *beggar-thy-neighbor* effect.

**Higher Learning-by-Doing.** In this scenario, I simulate the IRA with higher learning-by-doing

parameters, $\nu_D^S = 1.89$ for solar and $\nu_D^W = 1.25$ for wind equipment, reflecting the higher range of learning rates found in the literature (Bolinger et al., 2022; Covert and Sweeney, 2024).

Figure C.3 shows the impact of learning-by-doing on the US share of the global equipment market. With a 24% learning rate for solar and 29% for wind equipment, the US dominates the solar equipment market by 2030. This accelerates productivity gains from learning-by-doing in the US, which improves global welfare through the installation of cheaper solar equipment produced in the US. For wind equipment, the effect is much smaller. Although the higher learning rate increases the peak US market share compared to the baseline IRA case, the share still falls after the policy period due to lower trade elasticity, similar to the baseline scenario.

The third panel in Table C.2 summarizes the results under higher learning-by-doing rates. Overall, the IRA is welfare improving by 1.96% for the US, primarily driven by the gains from equipment subsidies. Note the impact of the subsidies is not only transitory anymore. In the steady state, the US still dominates the solar equipment market, and this has a long-run positive impact on US and negative impact on global welfare. Higher learning-by-doing results in faster transition but also higher carbon emissions, which is due to the income effect combined with the low elasticity of substitution between renewables and fossil fuels. While the transition to renewable energy speeds up due to higher learning-by-doing, this leads to lower energy price and higher overall production in the economy. Consequently, higher emissions result in a backfire effect on global welfare.

**Trade Elasticities of equipment ($\theta^S$ and $\theta^W$).** Another set of key parameters is the trade elasticities of equipment. To examine how changes in trade elasticities affect the results, I calibrate the elasticity for solar energy equipment using the trade elasticity for electronics (10.60) and for wind energy equipment using the value for the machinery sector (1.52) from Caliendo and Parro (2015).

The fourth panel in Table C.2 compares the results under different trade elasticities for solar and wind equipment. Higher trade elasticity in equipment enhances the impact of subsidies on achieving a higher global market share. With $\theta^S = 10.6$, the US dominates the solar equipment market during the policy period and maintains a substantial share even after the IRA ends, due to accumulated productivity gains from increased production. The *beggar-thy-neighbor* effect of the equipment subsidy is negligible compared to the positive spillovers; the equipment subsidy not only benefits the US but also reduces investment costs in renewable energy for other countries through trade, facilitating the global energy transition. The global welfare gain results from both carbon reduction and lower energy costs due to capital deepening.

# Appendix D Algorithm

In this section, I describe the algorithm to solve the model.

To calculate the transition path and steady state, I set T to be sufficiently large to guarantee convergence to the steady state. In my computations, T=400 was adequate for this purpose.

1. Use the calibrated parameter values: $A_{n,t}^j, \sigma_n^j, \alpha, d_{in,t}^j, \tau_{in,t}^j, \mu_n^j, \gamma_{n,t}^j, \gamma_{n,t}^{L,j}, \gamma_{n,t}^{M,j'j}, \gamma_{n,t}^{j',j}, \eta^j \ \ \forall j, n, t$

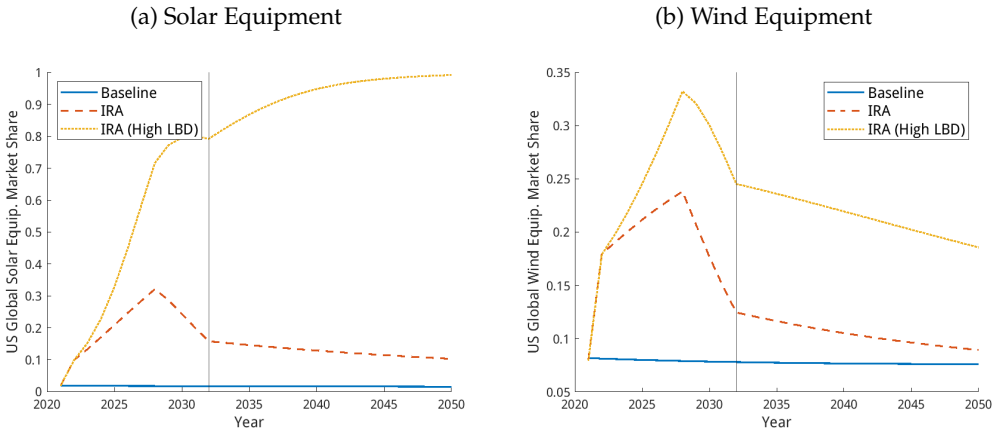
2. Make an initial guess on investment rate sequence $\{\varphi_{n,t}^k\}_{t=1,n=1}^{T,N}$ for each capital goods $k \in \Omega_K$ based on the current stock:

$$I_{n,t}^k = \varphi_{n,t}^k K_{n,t}^k. \tag{D.1}$$

3. Solve static Solow model using method from Alvarez and Lucas (2007)

   (a) Start in period 1 with capital endowments (and allocation of them) $\mathbf{k}_1^k \equiv (k_{11}^k, k_{21}^k, ..., k_{N1}^k)$ for all $k \in \Omega_K$.

Figure C.3: US global renewable equipment market share under higher LBD




Note: Panel (a) shows the evolution of the US global solar equipment market share under higher learning rate. The solid blue (red) line shows the share under baseline, the blue dashed line represents the share of the US under the IRA with the baseline learning-rate, whereas the blue dotted line shows the share of the US under the IRA with the higher learning-rate. Panel (b) presents the evolution of the US global wind equipment market share.

(b) Guess factor prices and energy prices: $\mathbf{w}_1 \equiv (w_{11}, w_{21}, ..., w_{N1})$, $\mathbf{r}_1^k \equiv (r_{11}^k, r_{21}^k, ..., r_{N1}^k)$ for $k \in \Omega_K$, and $\mathbf{P}_1^j \equiv (P_{11}^j, P_{21}^j, ..., P_{N1}^j)$, for $j \in \Omega$ where I take world GDP as the numeraire at each $t$.

i. Update $P_{n,t}^j$ for $j \in \Omega$ using (11)

ii. Obtain $P_{n,t}^E$ from Equation (8)

iii. Obtain the profit inrenewable energysectors, $\Pi_{n,t}^e$ for $e \in \Omega_{RE}$, from Equation (4).

iv. compute trade shares using Equation (14)

v. Solve for total expenditure $X_{n,t}^j$ using Equations (15) and (16).

- Combining (15) and (16) gives:

$$X_{n,t}^j = \sum_{j' \in \Omega} \gamma^{M,j'j} \gamma_n^{j'} \sum_{m=1}^{N} \frac{\pi_{mn,t}^{j'}}{(1+\tau_{mn,t}^{j'})(1-s_{m,t}^{j'})} X_{m,t}^{j'} + X_{n,t}^{F,j} \tag{D.2}$$

where $X_{n,t}^{F,j} = P_{n,t}^j C_{n,t}^j$ for $j \in \Omega_K^*$ and $X_{n,t}^{F,j} = P_{n,t}^j I_{n,t}^j$ for $j \in \Omega_K$. $P_{n,t}^j C_{n,t}^j$ is given by Equation (23) and $I_{n,t}^j$ can be obtained from (D.1).

vi. Obtain $Y_{n,t}^j$ using Equation (15).

(c) update $\mathbf{w}$, $\mathbf{r}$: Using the solution for the trade share with total expenditure, I verify whether market clearing conditions (Equations (17) and (18)) hold. Iterate until the market clearing conditions hold.

(d) move to the next period, and given the guess on the investment rate sequence $\{\varphi_{n,t}^k\}_{t=1,n=1}^{T,N}$, $\mathbf{k}_2^k$ is determined by (20) and (D.1). That is,

$$K_{n,2}^k = \chi_k \left(\varphi_{n,1}^k K_{n,1}^k\right)^{\alpha} (K_{n,1}^k)^{1-\alpha} + (1-\delta) K_{n,1}^k$$

(e) Do the same procedure ((a)-(e)) for t=2,...,T

4. Plug the values to each $K_{n,t}^k$ in the Euler Equation to compute the excess demand $Z_{n,t}^k$ for

Table C.2: Robustness Check

| | Global $CO_2$ | Global Welfare | US Welfare | Peak US Solar Equip. Share |
|---|---|---|---|---|
| (i) Baseline specification | | | | |
| IRA | -0.60% | -0.03% | 0.02% | 32.1% |
| Energy Subs. | -0.17% | 0.01% | -0.04% | 2.7% |
| Equipment Subs. | -0.23% | -0.02% | 0.06% | 20.6% |
| (ii) Elasticity of Substitution $\psi = 5$ | | | | |
| IRA | -1.96% | -0.08% | 0.43% | 40.9% |
| Energy Subs. | -0.46% | 0.02% | 0.02% | 3.2% |
| Equipment Subs. | -0.70% | -0.07% | 0.27% | 24.6% |
| (iii) Learning Rate $\nu_D^S = 1.89$ and $\nu_D^W = 1.25$ | | | | |
| IRA | 0.87% | -0.52% | 1.96% | 100.0% |
| Energy Subs. | -0.26% | -0.02% | -0.00% | 3.0% |
| Equipment Subs. | 2.47% | -0.59% | 1.61% | 100.0% |
| (iv) Equipment trade elasticity $\theta^S = 10.6$ and $\theta^W = 1.76$ | | | | |
| IRA | -0.46% | 0.20% | 0.60% | 100% |
| Energy Subs. | -0.12% | 0.17% | -0.03% | 0.7% |
| Equipment Subs. | -0.18% | 0.21% | 0.72% | 100.0% |

each $n$, $k$, and $t$:

$$Z^k_{n,t}(\{\varphi^k_{n,t}\}^T_{t=1}) = \beta\alpha\left[r^k_{n,t+1} + \frac{(1-\alpha)p^k_{n,t+1}I^k_{n,t+1}}{\alpha K^k_{n,t+1}} + \frac{\left(1-\delta^k\right)p^k_{n,t+1}}{\alpha\chi_k}\left(\frac{I^k_{n,t+1}}{K^k_{n,t+1}}\right)^{1-\alpha}\right] - \frac{u'(C_{n,t})}{u'(C_{nt+1})}\frac{P^c_{nt+1}}{P^c_{n,t}}\frac{p^k_{n,t}}{\chi_k}\left(\frac{I^k_{n,t}}{K^k_{n,t}}\right)^{1-\alpha} \tag{D.3}$$

5. Update the investment rate guess made in Step 2 using the excess demand for each $K$.

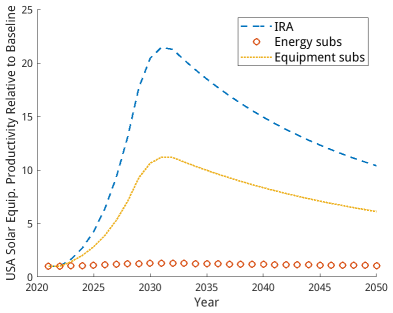
$$\{\varphi^{k,NEW}_{n,t}\}^{T,N}_{t=1,n=1} = \varphi^k_{n,t} + \psi Z^k_{n,t}(\{\varphi^k_{n,t}\}^T_{t=1}) \tag{D.4}$$

6. Repeat steps 2-5 until the fixed point for $\{\varphi^k_{n,t}\}^{T,N}_{t=1,n=1}$ is obtained.

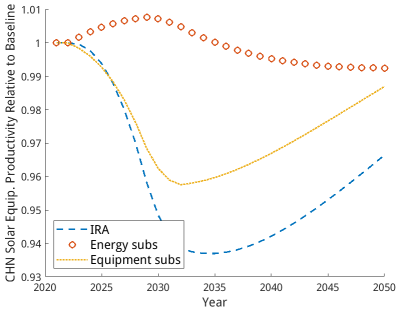
# Appendix E Additional Figures

## Figure E.1: Equipment Productivity

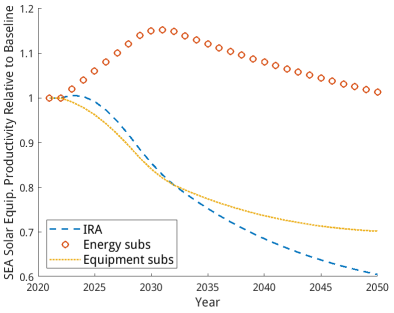
(a) US (solar equipment)



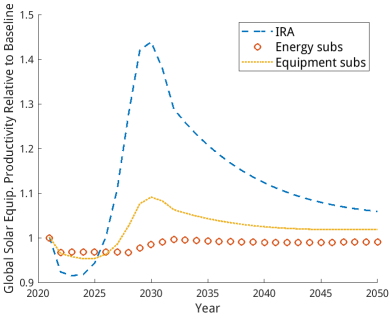

(b) China (solar equipment)



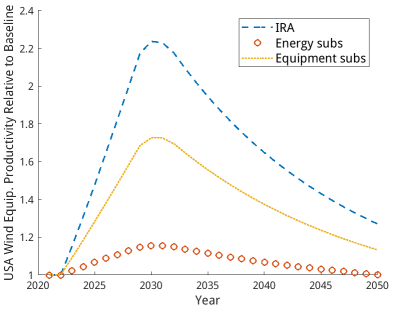

(c) Southeast Asia (solar equipment)



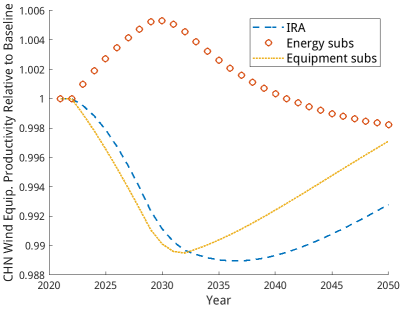

(d) Global (solar equipment)



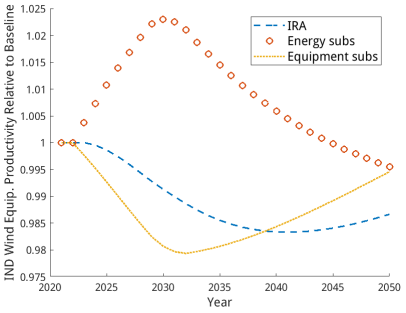

(e) US (wind equipment)



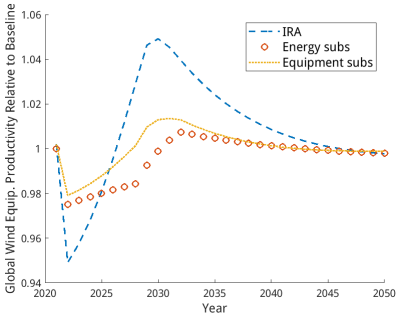

(f) China (wind equipment)




(g) India (wind equipment)



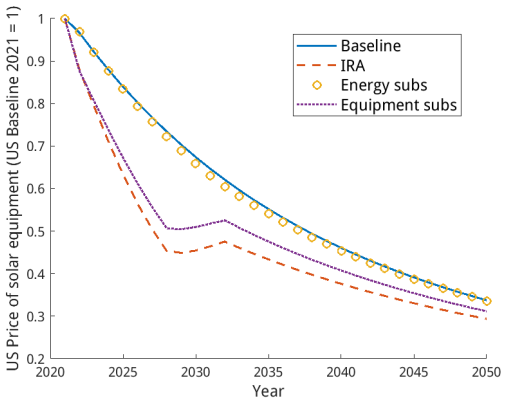

(h) Global (wind equipment)



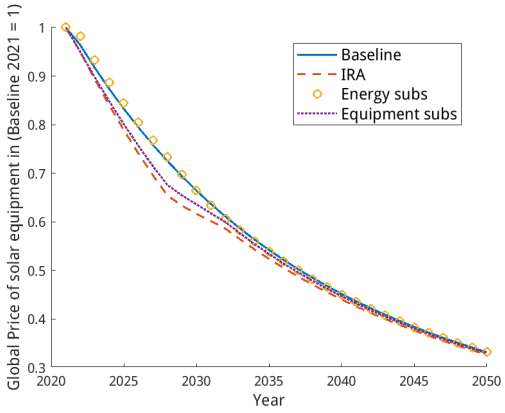

Note: Each panel plots the effect of subsidies on equipment productivity relative to the productivity under baseline. Impact of IRA is plotted by blue dashed line, energy subsidy by red circles, and equipment subsidy by yellow dotted line.

## Figure E.2: Equipment Price

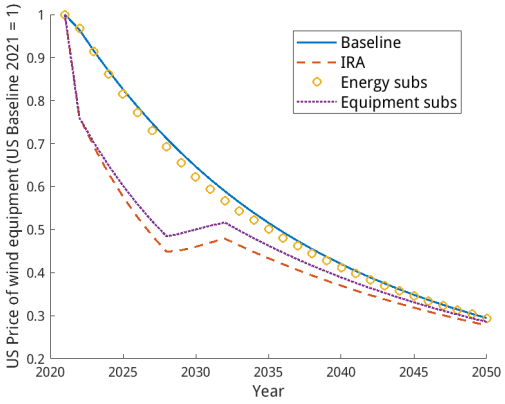
(a) US Solar Equipment Price



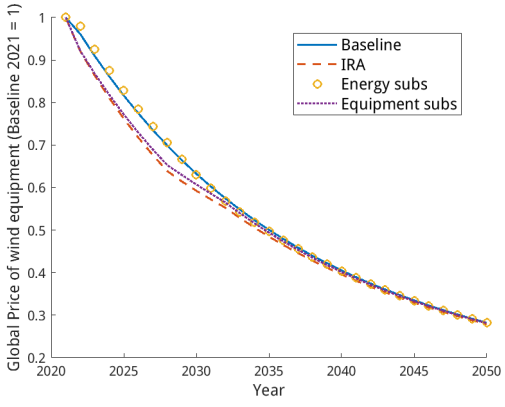

(b) Global Solar Equipment Price




(c) US Wind Equipment Price



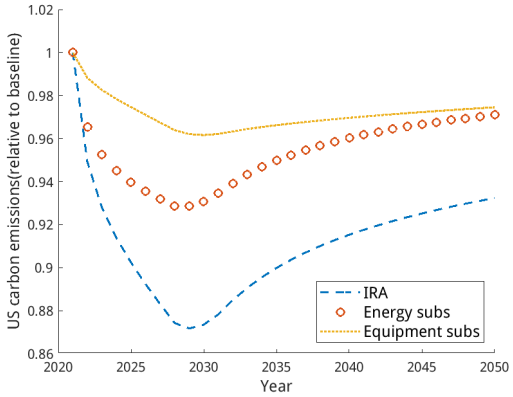

(d) Global Wind Equipment Price



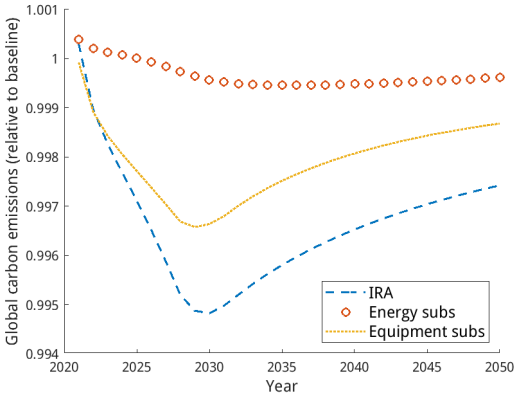

Note: Each panel plots the effect of subsidies on equipment price, in the US (panel (a) and (c)) and the aggregated global (panel (b) and (d)). Baseline price is plotted by blue solid line, price under IRA is plotted by red dashed line, energy subsidy by yellow circles, and equipment subsidy by purple dotted line.

## Figure E.3: Change in Carbon Emissions

(a) US



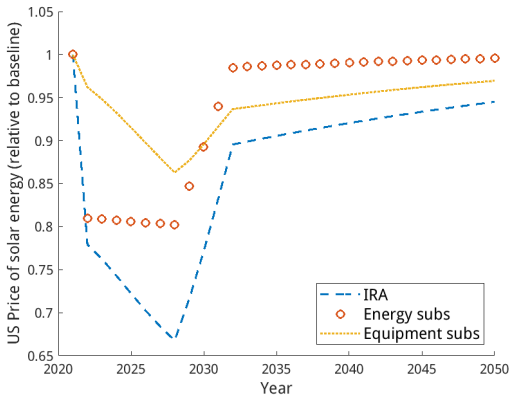

(b) Global (excluding US)



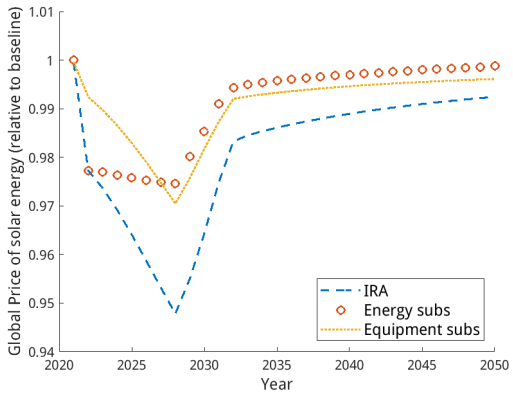

Note: This figure plots the relative change in the US (panel (a)) and non-US global (panel (b)) carbon emissions under IRA (blue dashed line), energy subsidy (red circles), and equipment subsidy (yellow dotted line).

## Figure E.4: RE Price

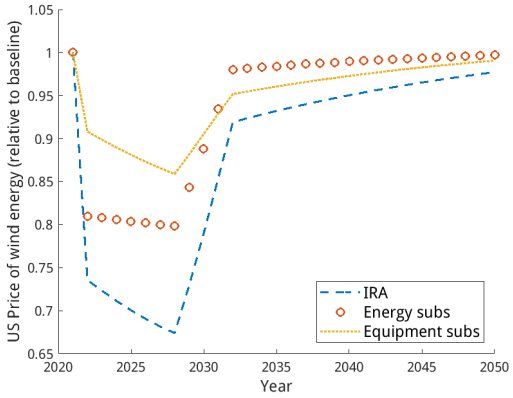
(a) US Solar Energy Price



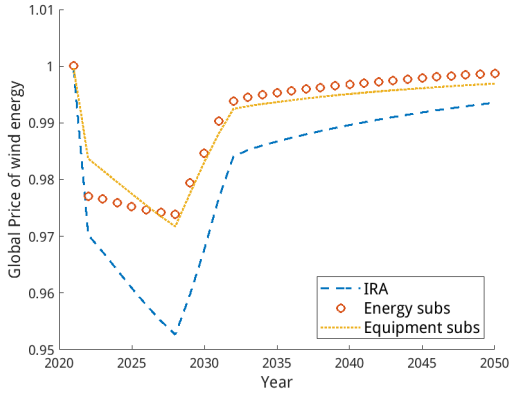

(b) Global Solar Energy Price




(c) US Wind Energy Price



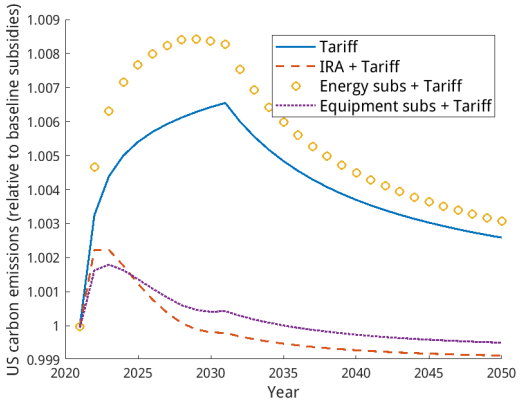

(d) Global Wind Energy Price



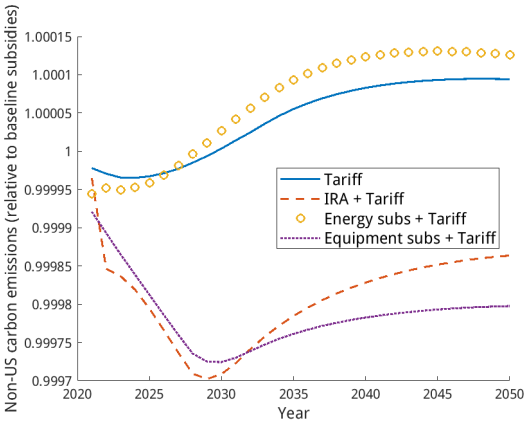

Note: Each panel plots the effect of subsidies on solar and wind energy price, in the US (panel (a) and (c)) and the aggregated global (panel (b) and (d)). The prices are relative to the baseline prices in *each time period*. Prices under IRA are plotted with blue dashed lines, energy subsidy with red circles, and equipment subsidy by yellow dotted line.

## Figure E.5: Change in Carbon Emissions with Solar Tariff

(a) US



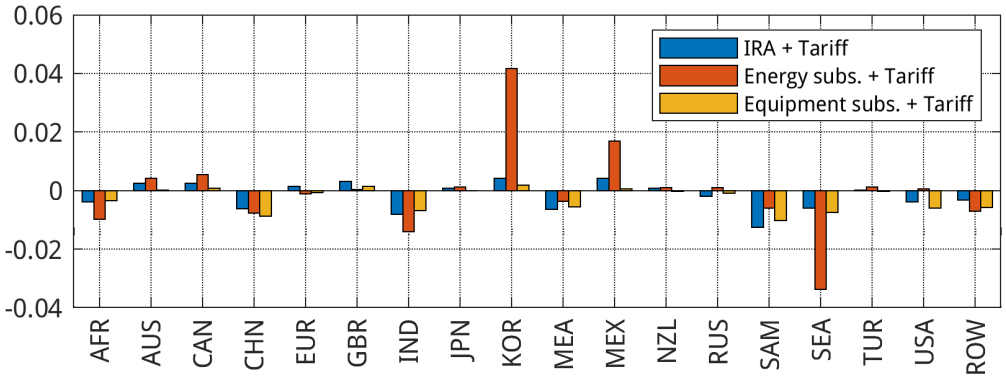

(b) Global (excluding US)



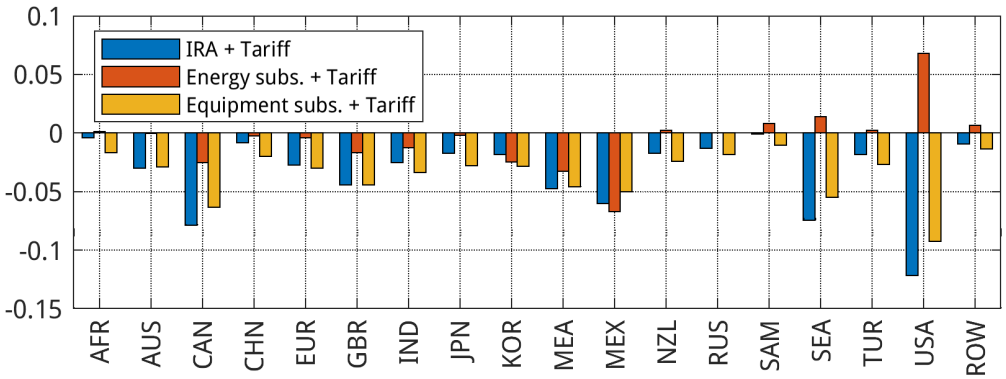

Note: This figure plots the relative change in the US (panel (a)) and non-US global (panel (b)) carbon emissions under solar tariff (blue solid line), solar tariff combined with IRA (red dashed line), energy subsidy (yellow circles), and equipment subsidy (purple dotted line), relative to corresponding subsidies without tariff.

Figure E.6: Welfare and Carbon effect of IRA with Solar Tariff Aross Countries

(a) Welfare effect (%)

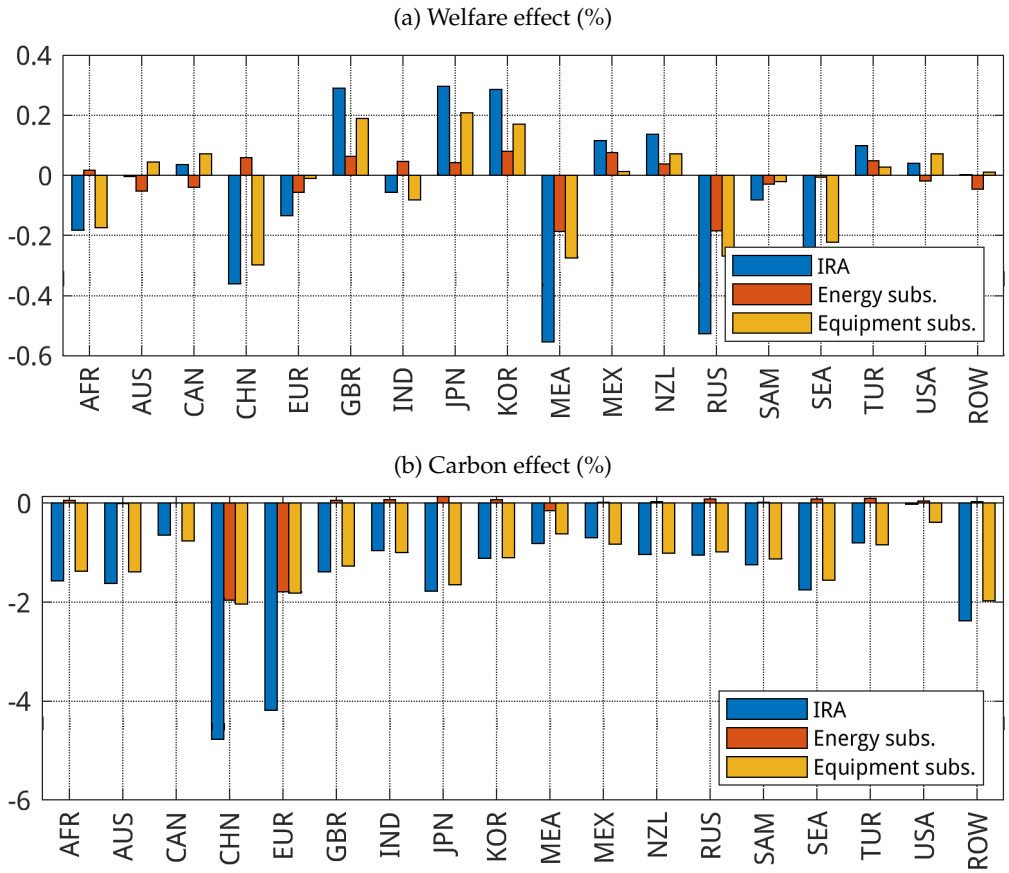



(b) Carbon effect (%)




Note: Panel (a) plot the effect of IRA under US imposing solar equipment tariff on welfare for residents in different countries relative to the corresponding subsidies without the tariff. Panel (b) plot the effect of IRA with solar equipment tariff on carbon emissions in different countries.

Figure E.7: Welfare and Carbon Effect of US, China, EU Policies Across Countries




Note: The figures plot the welfare (panel (a)) and accumulated $CO_2$ (panel (b)) in 2050 in different countries when the US, China, and EU implement identical green industrial policies to IRA relative to the baseline scenario.