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 predicts smaller carbon reductions, a loss in US welfare, and a gain in global welfare.

JEL codes: F13, F18, O25, Q4, Q54, Q56

Keywords: green industrial policy, Inflation Reduction Act, energy transition, renewable energy equipment trade

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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. A 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 producing renewable energy (energy subsidy, hereafter) and subsidy for producing renewable energy equipment (equipment subsidy, hereafter).[1]

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 while renewable energy itself is rarely traded across borders, the equipment required for its production 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 demand from abroad, respectively.

Considering trade in such equipment in a dynamic setting can affect the assessment of green industrial policies-namely, energy and equipment subsidies-for three key reasons. First, each type of subsidy influences trade patterns differently, leading to distinct welfare effects through changes in import or export prices. Second, to the extent that some subsidies increase domestic equipment production, there can be global spillover effect through exports. Lastly, each type of subsidy can have different implications in shaping dynamic comparative advantage. Incorporating such effects is crucial, as carbon emissions are a global externality that accumulates over time.

In this paper, I revisit this gap in the literature by studying the dynamic effects of unilateral 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 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 address these questions, I develop a dynamic general equilibrium model that incorporates trade 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, which can be supplied either domestically or from other countries. Energy is produced as a composite of renewable energy sources, which can either be substitutes or complements for one another, and fossil fuels. This composite energy is integrated into a standard trade model with input-

[1] Examples of green industrial policies include the EU's Green Deal Industrial Plan, India's Production-Linked Incentive (PLI) scheme for solar modules, and Japan's Green Transformation (GX) plan.

output linkages, as in Caliendo and Parro (2015). The model is dynamic to capture the nature of the energy transition, which occurs as countries accumulate renewable energy equipment as capital over time. Finally, I model equipment productivity as endogenously determined through external learning-by-doing that resides within a country, allowing subsidies to shape dynamic specialization patterns.

The model highlights three key mechanisms:

First, equipment trade lowers the investment costs of renewable energy in countries with lower equipment productivity, thereby accelerating the global energy transition. Thus, the gains from trade extend beyond economic benefits, having significant implications for carbon emissions as well.

Second, energy and equipment subsidies have distinct effects on welfare by affecting equipment prices. An energy subsidy increases domestic demand for renewable energy equipment, which can be met through imports. This improves the terms of trade for net-exporting countries while worsening it for the subsidizing country. This effect is amplified by learning-by-doing, benefiting countries already specialized in equipment production. In contrast, an equipment subsidy lowers the global price of equipment, deteriorating the terms of trade for current net exporters. Over time, this subsidy shifts comparative advantage toward the subsidizing country through learning-by-doing, ultimately enhancing its welfare by boosting productivity.

Third, each subsidy generates distinct global spillover effects on carbon emissions. An energy subsidy reduces domestic fossil fuel demand by increasing its relative price, with most effects confined to the subsidizing country since renewable energy is not traded. However, because fossil fuel and renewable energy equipment are tradable, an energy subsidy creates carbon leakage by lowering global fossil fuel prices and raising renewable equipment prices, which hinders adoption elsewhere and potentially increases emissions. In contrast, an equipment subsidy reduces renewable equipment prices globally, enabling other countries to accelerate their energy transition and reduce emissions worldwide.

Next, I bring the model to data and calibrate the model. Three sets of parameters are essential for my quantification. The first is the learning rate in renewable energy equipment production. Using datasets for solar and wind equipment production and output prices across countries, I estimate learning rates of 17 percent for solar equipment and 19 percent for wind equipment. Second, I measure productivity in renewable energy production for both solar and wind. Leveraging global geospatial data on renewable energy potential and locations of installed renewable energy equipment, I find substantial heterogeneity in both renewable potentials across countries. The last is the substitution elasticities across energy sources. I estimate the elasticity between solar and wind energy using panel data on their price and output ratios. The estimated elasticity of substitution suggest that solar and wind energy are weak complements, rejecting the common assumption of perfect substitutability in the literature.[2]

[2]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

To quantitatively analyze the impacts of the IRA subsidies on welfare, defined as the discounted sum of real income adjusted for the social cost of carbon, I simulate the model with a 20% subsidy for renewable energy and a 30% subsidy for equipment production over a 10-year period (2022–2031). The quantitative analysis suggests that the IRA reduces global carbon emissions while remaining politically feasible. Specifically, the IRA reduces global carbon emissions by 0.60% by 2100, increases US welfare by 0.02%, but decreases global welfare by 0.03%, with the effects varying across countries. The US welfare gains and global welfare losses are primarily driven by terms of trade effects, which are amplified by learning-by-doing. The IRA significantly increases the US share of the global market for solar and wind equipment, peaking at 32% and 21%, respectively. This lowers global equipment prices and accelerates the energy transition both domestically and internationally. However, the effects on market share are temporary; once the subsidy period ends, the US equipment market share gradually returns to its original level.

I also investigate the effects of subsidy compositions. 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 are allocated 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%) as equipment subsidy increases US exports which help reduce carbon emissions in other countries, 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 equipment subsidies, up to 40%, rather than focusing on renewable energy subsidies. However, global welfare is maximized when the US subsidizes renewable energy up to 45% but refrains from subsidizing equipment.

Trade in equipment is a key factor driving these results. To quantify the role of equipment trade in the impact of the IRA, I simulate the model without equipment trade, and find the following different implications: global carbon reduction is smaller (-0.42%), US welfare experiences a slight loss (-0.01%), and global welfare sees a modest gain (0.01%).

Without equipment trade, the impact of both subsidies is largely confined to the US. In particular, since the US cannot export, the US welfare gains from the equipment subsidy diminish due to i) smaller learning-by-doing in equipment production, and ii) no welfare gains from carbon reductions in other countries. When combined with the energy subsidy, this results in an overall welfare loss for the US.

The modest global welfare gain stems primarily from carbon reduction within the US. Additionally, without equipment trade, the welfare losses previously experienced by countries with a comparative advantage in equipment production vanish, as these countries are no longer adversely affected by the terms-of-trade impacts of the US equipment subsidy.

Based on the findings, I explore extensions of the IRA scenario. First, to examine the interaction

the estimation.

between trade policy and green industrial policies, I simulate a scenario where the US implements both the IRA and a 50% 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 periods, and the global impact of reduced learning in Southeast Asia and China. Second, I consider a scenario in which other major economies, such as the EU and China, respond to the IRA by implementing identical policies. If the US, EU, and China all adopt policies similar to the IRA, the positive impact of the IRA on the US's global equipment market share diminishes (6.6% at the peak), thus the welfare gains from the US's equipment subsidy should be reduced. Interestingly, however, US welfare still increases substantially by 0.04%. This is primarily due to subsidized equipment imports from China, which help accelerate the energy transition in the US and other countries, benefiting the US. This result implies that US welfare can be enhanced even when multiple countries implement overlapping subsidy policies, as the resulting larger reduction in global carbon emissions generates welfare gains.

Related Literature. This paper relates 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.

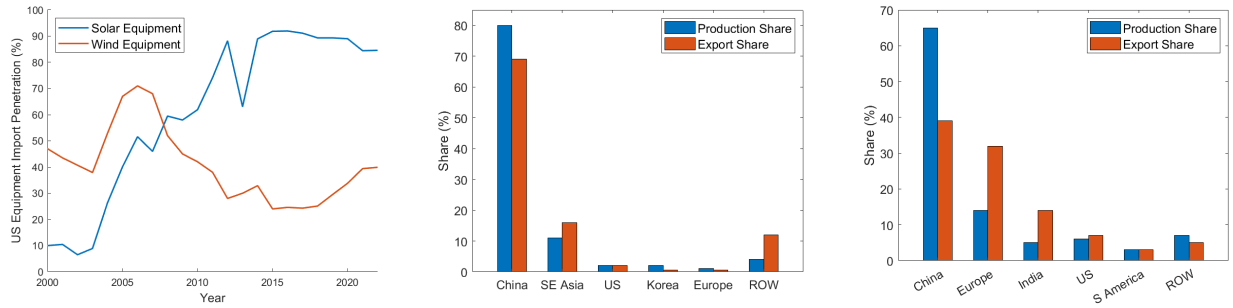
This paper also contributes to the growing body of literature that examines the effects of subsidies for renewable energy and equipment production including the IRA. Empirical studies such as Aldy et al. (2023), Gerarden (2023), De Groote and Verboven (2019), Gugler et al. (2021), Hitaj and Löschel (2019), 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 with renewable energy and examines the impact of energy subsidy component under the IRA on welfare but without the consideration of equipment trade and carbon implications.[3] My analysis extends this literature by including equipment trade with dynamics, allowing for a more nuanced understanding of how each energy and equipment subsidy affects global welfare and carbon emissions.

Lastly, this paper contributes to the macro-trade literature that studies the impact of trade and environmental policies on welfare and environmental outcomes (Kortum and Weisbach, 2021;

[3]Another important distinction lies in the specification of learning-by-doing. In Arkolakis and Walsh (2023), learning-by-doing has a frictionless spillover effect, whereas in my model, learning is contained within a country. This significant difference leads to contrasting implications for the impact of subsidies.

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.

Shapiro, 2021; Xiang, 2023; Cruz and Rossi-Hansberg, 2024; Caliendo, Dolabella, Moreira, Murillo and Parro, 2024; Garcia-Lembergman, Rodríguez-Clare, Ramondo and Shapiro, 2024; Farrokhi and Lashkaripour, 2024; Hsiao, 2024). I contribute to this literature by examining how clean technology trade affects the global economy. By explicitly modeling equipment trade within a dynamic framework, I focus on how clean technology flows through trade and how dynamic comparative advantages in producing such technologies are shaped, with particular emphasis on the effects of green industrial policies rather than the environmental policies commonly studied.

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.

2 Background

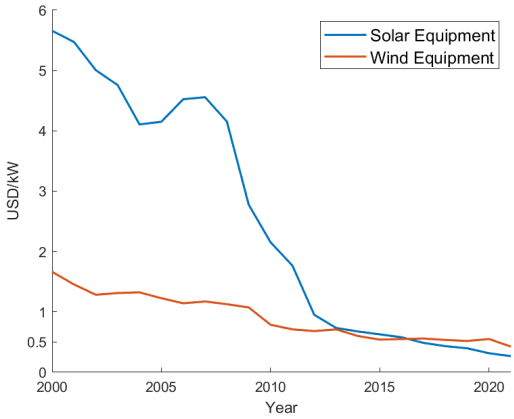
2.1 Production and Trade in Renewable Energy Equipment

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 U.S. reliance on imports is more pronounced for solar energy equipment than for wind energy equipment. The import penetration ratio for solar equipment (blue solid line) was around 10% in 2000, but dramatically increased to 83% by 2022. The import penetration ratio for wind equipment (red solid line) also remained substantial, reaching 39% in 2022.

[4]For the details about data, see the Appendix section B.3.

Figure 2: Price of Equipment



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

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.

2.2 Learning-by-doing in Renewable Energy Equipment

The costs of fossil fuels and nuclear power are primarily driven by two factors: the price of the fuel they consume and the plant's operating expenses. In contrast, the cost of electricity from renewable energy is mainly influenced by the price of the equipment required for its production.

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.[5]

[5]See, for example, Baker et al. (2013), Bolinger et al. (2022), and Arkolakis and Walsh (2023)

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.[6]

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 trade model with N countries indexed by $n = 1, \ldots, N$ and J sectors indexed by j. Time is discrete, $t = 1, \ldots, \infty$. Each country's economy consists of energy and non-energy sectors, with further sub-sectoral distinctions.

The energy sector includes three sub-sectors: solar (s), wind (w), and fossil fuel (f), collectively denoted by $\Omega_E = \{s, w, f\}$, where $\Omega_{RE} = \{s, w\}$ denotes the renewable energy sectors. The non-energy sector comprises a capital goods sector (K) and a non-capital goods sector (O). The capital goods sector is subdivided into solar energy equipment (S), wind energy equipment (W), fossil fuel capital goods (F), and non-energy capital goods (D), with the set of all capital goods denoted by $\Omega_K = \{S, W, F, D\}$. Within this, the renewable energy equipment sector is $\Omega_{REE} = \{S, W\}$. The set of all sectors in the economy is $\Omega \equiv \Omega_E \cup \Omega_K \cup \Omega_O$, and Ω_j^* refers to the complement of sector j.

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

In each country n, the government can subsidize domestic production in the renewable energy and equipment sectors using an output price subsidy $s_{n,t}^j$, where $j \in \Omega_{REE} \cup \Omega_{RE}$. I assume the subsidies are financed by lump-sum tax from the household in each country.

3.2 Household

In each region n, the representative household is endowed with an initial stock of labor L_n and capital stocks $K_{n,1}^k$ for $k \in \Omega_K$. Labor is supplied inelastically and is mobile across sectors within each

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

region. The representative household makes consumption decisions ($C^j_{n,t}$) and investment ($I^k_{n,t}$) decisions in each period to maximize lifetime utility. The household's utility is the discounted sum of consumption, weighted by Cobb-Douglas weights $\mu^j_{n,t}$ with disutility from carbon emissions factored into the utility function:

$$U_n = \sum_{t=1}^{T} \beta^{t-1} \log \Big[\prod_{j \in \Omega^*_K} (C^j_{n,t})^{\mu^j_n} \frac{1}{1 + SCC_t(Z_t - Z_0)} \Big], \text{ where } \sum_{j \in \Omega^*_K} \mu^j_n = 1. \tag{1}$$

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_t is a damage parameter, with a higher SCC_t indicating greater disutility from emissions. Following Shapiro (2021), carbon emissions Z_t are a pure negative externality, which household cannot directly choose.

3.3 Production

I begin by outlining the production and investment processes in the economy.

In the energy sector, the production of solar and wind energy requires a single input: installed solar and wind equipment, respectively. The production functions for both exhibit decreasing returns to scale. Fossil fuel production, on the other hand, requires a combination of fossil fuel capital, labor, and intermediate goods. Solar, wind, and fossil fuel are then aggregated using a nested CES technology to generate composite energy.

In the non-energy sector, production requires intermediate goods, including composite energy, non-energy capital, and labor. The renewable energy equipment sector benefits from external learning-by-doing effects, resulting in dynamic economies of scale, where cumulative past production experience enhances current productivity. Once capital goods—such as 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 through investment. This investment process enables these capital goods to serve as inputs for future 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 $z^j_n(\omega^j)$:

$$y^j_{n,t}(\omega^j) = z^j_n(\omega^j) \Big(K^j_{n,t}(\omega^j) \Big)^{\xi^j_n}, \text{ for } j \in \Omega_{RE} \tag{2}$$

where I assume $\xi^j_n < 1$, indicating decreasing returns to scale. The production efficiency $z^j_n(\omega^j)$ is country- and sector-specific, capturing heterogeneity in solar and wind potential across countries. $\xi^j_n < 1$ 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 $\frac{c^j_{n,t}}{z^j_n(\omega^j)}$, where $c^j_{n,t}$ is a function of stock of capital and rental rate

of capital in region n at time t.

$$c^j_{n,t} = \frac{1}{\left(K^j_{n,t}\right)^{\xi_j - 1}} r_{n,t} \tag{3}$$

Due to the decreasing returns to scale, the unit cost of producing renewable energy rises as the stock of installed renewable equipment increases. Holding other factors constant, a country facing stronger decreasing returns to scale will experience a slower rate of energy transition and have a lower demand for renewable equipment.

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 $\Pi^j_{n,t}(\omega^j) = p^j_{n,t}(\omega^j) y^j_{n,t}(\omega^j) - r^j_{n,t} K^j_{n,t}(\omega^j)$.[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:

$$y^f_{n,t}(\omega^f) = z^f_n(\omega^f)(L^f_{n,t}(\omega^f))^{\gamma^{L,f}_n}(K^F_{n,t}(\omega^f))^{\gamma^{F,f}_n} \prod_{j'=\Omega^*_K} \left(M^{j'f}_{n,t}(\omega^f)\right)^{\gamma^{M,j'f}_{n,t}} \tag{5}$$

where $L^j_{n,t}(\omega^f)$, $K^F_{n,t}(\omega^f)$, and $M^{j'j}_{n,t}(\omega^f)$ is the quantity of labor, fossil-fuel capital stock, and intermediate goods from sector j' used in country n, respectively. $\gamma^{L,f}_n$, $\gamma^{F,f}_n$, and $\gamma^{M,j'f}_{n,t}$ denotes the share of value added from each input for producing $y^f_{n,t}$, respectively. The production technology for fossil fuel energy features constant return to scale, *i.e.*, $\gamma^{L,f}_n + \gamma^{F,f}_n + \sum_{j'=\Omega^*_K} \gamma^{M,j'f}_{n,t} = 1$.

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]

Composite Energy Production. Composite energy input $e_{n,t}(\omega^e)$ 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:

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

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

$$\Pi^j_{n,t}(\omega^j) = (1-\xi_j) p^j_{n,t}(\omega^j)(K^j_{n,t}(\omega^j))^{\xi_j}. \tag{4}$$

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

where η_r is a level shifter and ρ captures substitution elasticity between solar and wind energies.

Then the composite energy $e_{n,t}(\omega^e)$ is CES composite of renewable energy and fossil fuel energy:

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

where η_e is a level shifter and ψ captures substitution elasticity between renewable energy and fossil fuel energy.

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

Carbon Emissions. In this model, carbon is released when fossil fuel energy is used and accumulates over time. The total carbon emissions at time t are given by $Z_t = \sum_{t'=1}^{t} \beta^{t'} \sum_n \bar{\epsilon} x^f_{n,t'}$, where $\bar{\epsilon}$ is a parameter that maps fossil fuel use into carbon emissions, and $x^f_{n,t'}$ represents the amount of fossil fuel used in country n at time t', which the formal definition will be introduced later. I do not consider abatement technologies that reduce carbon emissions while using the same amount of fossil fuel. In this model, carbon emissions can only be reduced by increasing the share of renewable energy in the composite energy mix.[9]

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:

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

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

$$c^j_{n,t} = B^j_{n,t}(w_{n,t})^{\gamma^{L,j}_n} (r_{n,t})^{\gamma^{D,j}_n} \prod_{j'=\Omega^*_K} \left(P^{j'}_{n,t} \right)^{\gamma^{M,j'j}_{n,t}} \text{ for } j \in \Omega^*_E, \tag{10}$$

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

For the equipment sectors, productivity $z^j_{n,t}$ for $j \in \Omega_{REE}$, is endogenously determined by learning-by-doing, with the exact specification provided in a later section (Section 3.8).

[9] In this setup, fossil fuels are used solely for producing composite energy. This specification does not account for the non-energy use of fossil fuels, such as their use in the production of plastic or concrete, which occurs in the real world but is beyond the scope of this model.

[10] $B^j_{n,t} = \left((\gamma^{L,j}_n)^{\gamma^{L,j}_n} (\gamma^{D,j}_n)^{\gamma^{D,j}_n} \prod_{j'=\Omega} (\gamma^{M,j'j}_{n,t})^{\gamma^{M,j'j}_{n,t}} \right)^{-1}$.

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 $Q^j_{n,t}$. Composite intermediate goods are produced by sourcing ω^j from suppliers offering the lowest costs across countries using Dixit and Stiglitz (1977) Aggregator:

$$Q^j_{n,t} = \Big[\int f^j_{n,t}(\omega^j)^{1-1/\sigma^j} d\omega^j \Big]^{\sigma^j/(\sigma^j-1)}$$

where $f^j_{n,t}$ is demand of goods ω^j and σ^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 ω^j

$$r^j_n(\omega^j) = \Big(\frac{p^j_{n,t}(\omega^j)}{P^j_{n,t}} \Big)^{-\omega^j} Q^j_{n,t}$$

where $p^j_{n,t}$ denotes the lowest price of good ω^j and $P^j_{n,t}$ denotes the unit price of the composite intermediate good

$$P^j_{n,t} = \Big[\int p^j_{n,t}(\omega^j)^{1-1/\sigma^j} d\omega^j \Big]^{\frac{1}{1-\sigma^j}}.$$

3.5 Trade Costs and Prices

Trade in the outputs of tradable sectors incurs standard iceberg trade costs; $\kappa^j_{ni,t}$ units of sector j good must be shipped from country i to n to deliver one unit, with $\kappa^j_{ii,t} = 1$. Combined with subsidies $s^j_{i,t}$, a unit cost of intermediate good ω^j produced in country i and available in country n is given by $c^j_{i,t}\kappa^j_{ni}(1 - s_{i,t})/z^j_{i,t}(\omega^j)$. This implies that the price of intermediate good ω^j in country n is

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

I follow probabilistic representation of technologies in Eaton and Kortum (2002). That is, production efficiency is modeled as a realization of the random variable z^j_n , which follows a Fréchet 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 θ^j, which is sector-specific, captures the dispersion of

productivity across goods ω^j.[11] Then the price index for each sector j in country n is given by

$$P_{n,t}^j = \Big[\sum_i (c_{i,t}^j \kappa_{ni,t}^j (1 - s_{i,t}^j))^{-\theta^j} A_{i,t}^j\Big]^{-1/\theta^j} \tag{11}$$

where $c_{n,t}^j$ is the unit cost of producing sector j goods in country n. I assume that all sectors are tradable except for renewable energy, *i.e.*, $\kappa_{in,t}^s = \kappa_{in,t}^w = \infty$ for $i \neq n$. This implies that for solar and wind energy, the price is given by $P_{n,t}^j = c_{n,t}^j (1 - s_{n,t}^j)(A_{n,t}^j)^{-1/\theta^j}$ 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.

As mentioned earlier, due to the CES structure, the share of fossil fuel input in producing goods in sector j, denoted by $\gamma_{n,t}^{M,fj}$, is endogenously determined by the following equation:

$$\gamma_{n,t}^{M,fj} = \gamma_{n,t}^{M,Ej}\Big[1 + \frac{\eta_e}{1-\eta_e}\Big(\frac{P_{n,t}^f}{P_{n,t}^r}\Big)^{\psi-1}\Big]^{-1} \tag{12}$$

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

Proposition 1. ***Static Impact of Energy Subsidy*** *Given $P_{n,t}^f$, the energy subsidy $s_{n,t}^r$ 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 is akin to that of a typical carbon tax. It reduces the share of fossil fuel in production by increasing their relative price compared to other inputs, particularly renewable energy, thereby lowering carbon emissions in the domestic economy.

However, in an open economy, since both fossil fuels and renewable energy equipment are tradable, two channels of carbon leakage emerge. First, a reduction in domestic fossil fuel demand lowers the global price of fossil fuels. Second, an increase in domestic demand for renewable energy equipment raises the global price of such equipment. Both of these effects can result in increased carbon emissions in other countries.

Finally, the price of final goods for consumers is denoted by $P_{n,t}^j$. Given the Cobb-Douglas preferences described in Equation (1), the consumption price index can be written as:

$$P_{n,t} = \prod_j^J \Big(\frac{P_{n,t}^j}{\mu_n^j}\Big)^{\mu_n^j}. \tag{13}$$

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

3.6 Trade Share and Total Expenditure

Trade Share. 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) shows that the impact of the equipment subsidy, $s^j_{i,t}$, is affected by the trade elasticity, θ^j. A higher trade elasticity amplifies the effect of the subsidy on global market share, as global demand becomes more responsive to changes in bilateral import prices resulting from the subsidy.

Total Expenditure. I denote country n's total absorption in sector j by $x^j_{n,t}$, and country m's absorption in sector j from country n by $x^j_{mn,t}$, such that $x^j_{m,t} = \sum_n x^j_{mn,t}$. Additionally, the value of country n's total expenditure in sector j is defined as $X^j_{n,t} = P^j_{n,t}x^j_{n,t}$. Let $Y^j_{n,t}$ denote the gross production value 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.

Let the final household spending on each sector in country n be defined as $X^{F,h}_{n,t} = P^h_{n,t}C^h_{n,t}$ for $h \in \Omega^*_K$, and $Xn, t^{F,k} = P^k_{n,t}I^k_{n,t}$ for $k \in \Omega_K$. Total expenditure on sector j is then the sum of the use of sector j's output as intermediates across sectors j', and the final spending on sector j in country n:

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

Market Clearing. The labor market clearing condition for country n implies that labor income equals value added across sectors:

$$w_{n,t}L_{n,t} = \sum_{j \in \Omega} \gamma^{L,j}_n Y^j_{n,t} \tag{17}$$

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

$$\sum_{k \in \Omega_K} r_{n,t}K^k_{n,t} = Y^s_{n,t} + Y^w_{n,t} + \gamma^{F,f}_n y^f_{n,t} + \sum_{j \in \Omega^*_E} \gamma^{D,j}_n Y^j_{n,t}. \tag{18}$$

Note that the capital share in the production of solar and wind energy is one, meaning it relies

entirely on capital inputs. In contrast, fossil fuel capital goods are exclusively used in fossil fuel energy production.

Trade Balance. Let D_i denote the aggregate trade deficit in country i. Using Equation (16), we have

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

The left-hand side of equation (19) represents country i's total expenditure, net of subsidies, minus its trade deficit, D_i. The right-hand side sums country i's exports, net of tariffs, across all sectors j. I assume trade is balanced at the global level: the total trade deficits across all countries sum to zero, $\sum_i D_i = 0$, and each country's aggregate trade deficit is treated as exogenous. However, this framework allows sectoral trade deficits to be endogenously determined, enabling the model to capture the impact of changes in trade surpluses or deficits within the renewable energy equipment sector due to the subsidies.

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 δ^k with an adjustment cost:

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

where $I_{n,t}^{k}$ is investment in sector k at time t, χ_k governs the productivity of investment, α governs the cost of capital adjustment, and δ 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 drives current productivity in equipment production. A key assumption is that learning occurs within each country and is external to the firms in the sector. The productivity of region n in producing renewable energy equipment $k \in \Omega_{REE}$ at time t, denoted by $A_{n,t}^{k}$, is determined by the cumulative production in each country:

$$A_{n,t}^{k}=\nu^{k}\Big(\sum_{i=1}^{t-1}(\mu)^{i}y_{n,t-i}^{k}\Big)^{\nu_D^k}, \tag{21}$$

Here, ν^k is a sector-specific shifter, $\mu < 1$ represents the forgetting rate, and ν_D^k governs the learning rate. The condition $\mu < 1$ implies that the impact of production from the more distant past on current productivity gradually diminishes. This ensures that productivity does not grow indefi-

nitely, allowing the model to remain well-behaved and reach a steady state.

This country-specific learning-by-doing framework emphasizes the role of subsidies in shaping dynamic comparative advantage. For example, an equipment subsidy in the US leads to higher domestic output, which in turn boosts future productivity through learning-by-doing. However, as trade causes output in other countries to decline, their potential productivity gains from learning-by-doing are reduced, widening the productivity gap over time.

From a modeling perspective, incorporating global spillovers, as in Arkolakis and Walsh (2023), is straightforward. However, I find no empirical evidence of significant global spillovers in the data, as discussed in Section 4.4.

3.9 Household Optimality

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

$$\begin{aligned}
&\sum_{j\in\Omega_K^*} P_{n,t}^j C_{n,t}^j \\
&= w_{n,t}L_{n,t} + \sum_{k'\in\Omega_K} r_{n,t}^{k'}K_{n,t}^{k'} - \sum_{j\in\Omega} s_{n,t}^j \sum_{o=1}^{N} \frac{\pi_{on,t}^j}{(1-s_{n,t}^j)} X_{o,t}^j + \sum_{j\in\Omega_{RE}} \Pi_{n,t}^j + D_n - \sum_{k\in\Omega_K} P_{n,t}^k I_{n,t}^k \\
&\equiv E_{n,t}
\end{aligned} \tag{22}$$

Household consumption appears on the left-hand side. I denote by $E_{n,t}$ the net household income, which comprises labor income $w_{n,t}L_{n,t}$, capital incomes $\sum_{k\in\Omega_K} r_{n,t}^k K_{n,t}^k$, and is adjusted by subtracting the cost of subsidies, profits from the renewable energy sector, and the trade deficit.[12] Additionally, $E_{n,t}$ represents net income after accounting for investment.

Given this budget constraint, along with the competitive rental rates $r_{n,t}$ and the prices of goods $P_{n,t}^j$, I can derive the within-period optimization. Within each period, the household's expenditure on good $h \in \Omega_K^*$ must satisfy the following condition:

$$P_{n,t}^h C_{n,t}^h = \mu_n^h E_{n,t}, \quad \text{for } h \in \Omega_K^*. \tag{23}$$

To characterize the investment decision, I first define the temporary utility function $u_t(C_{n,t}) \equiv \log(C_{n,t}) + \log(\frac{1}{1+SCC_t(Z_t-Z_0)})$ where $C_{n,t} \equiv \prod_{j\in\Omega_K^*}(C_{n,t}^j)^{\mu_n^j}$. The investment decision is then characterized by the capital accumulation equation (equation (20)) and the following Euler equation:[13]

$$\frac{u_t'(C_{n,t})}{u_{t+1}'(C_{n,t+1})} \frac{P_{nt+1}^c}{P_{n,t}^c} \frac{p_{n,t}^k}{\chi_k} \left(\frac{I_{n,t}^k}{K_{n,t}^k}\right)^{1-\alpha} = \beta\alpha \left[r_{n,t+1} + \frac{(1-\alpha)p_{n,t+1}^k I_{n,t+1}^k}{\alpha K_{n,t+1}^k} + \frac{(1-\delta^k)p_{n,t+1}^k}{\alpha\chi_k} \left(\frac{I_{n,t+1}^k}{K_{n,t+1}^k}\right)^{1-\alpha} \right] \quad \text{for each } k \in \Omega_K. \tag{24}$$

[12] I assume that output subsidies are distributed prior to the application of import tariffs.

[13] If $\alpha = 1$ and $\chi_k = 1$, this simplifies to the more familiar Euler equation:

$$\frac{u_t'(C_{n,t})}{u_t'(C_{nt+1})} \frac{P_{nt+1}^c}{P_{n,t}^c} P_{n,t}^k = \beta \left[r_{n,t+1} + \left(1-\delta^k\right) P_{n,t+1}^k \right], \quad \text{for } k \in \Omega_K$$

On the left hand side is the marginal cost at t to attain additional capital in $t+1$. On the right hand side 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 production, $A^j_{n,t}$ for $j \in \Omega_{REE}$, are time-varying and governed by learning-by-doing. However, due to the forgetting parameter, μ, this learning process eventually plateaus. In the steady state, productivities become constant, and the capital stock stabilizes at a fixed level, K^k_n. The Euler equations (24) and the capital accumulation equations (20) jointly determine both 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 is defined as the discounted sum of utility, which can be represented by real income, adjusted to incorporate the disutility from carbon emissions.

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

The first term represents real income, while the second term captures the disutility associated with the stock of carbon emissions.

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 the OECD Input-Output data, I aggregate the dataset into 12 countries and 6 regions, including the EU, Southeast Asia, South America, Africa, the Middle East, and the rest of the world.[14] For sectors, I aggregate them into 10 categories, comprising 3 energy sectors, 3 energy equipment sectors, and 4 additional sectors: Agriculture, Non-Durable Manufacturing, Durable Manufacturing, and Services.

4.2 Parameters in Renewable Energy Production

Dataset and Sources. To measure the absolute advantage parameter $A^r_{n,t}$ in renewable energy production, I utilize two main datasets. Renewable energy potential data come from the Global Solar and Wind Atlases, which provide geospatial data on global solar and wind potentials measured in kWh/m^2. Additionally, I introduce a novel dataset on the locations of renewable power plants, sourced from the Global Solar and Wind Power Trackers. These trackers offer detailed information on the start year, longitude, and latitude of solar and wind farms with capacities exceeding 10 MW, covering approximately 70% of global total capacity.

For assessing decreasing returns to scale (DRS), I introduce another novel dataset in economics: a geospatial dataset on renewable potential and development feasibility (DPI) from Oakleaf et al. (2019). This dataset accounts for social factors (such as proximity to cities and grid infrastructure) and physical factors (such as elevation and slope) that influence the feasibility of renewable equipment installation.[15]

Measuring the Absolute Advantage Parameter in Renewable Energy Production ($A^r_{n,t}$). The absolute advantage parameter $A^r_{n,t}$ captures cross-country heterogeneity in renewable energy potential. A simple method is to take the average of renewable potential values assigned to each grid cell within a country, using data from the Global Solar and Wind Atlases. However, this approach may be biased since not all locations are feasible for installing renewable energy equipment. To address this, I combine renewable potential data from the Global Solar and Wind Atlases with the actual location data of renewable power plants from the Global Solar and Wind Power Trackers. This allows for a more accurate measurement by focusing on the renewable potentials of sites where solar and wind equipment is actually installed. Specifically, I calculate the average renewable potential at the sites of solar and wind farms installed up to 2021, which serves as the initial period for the quantitative analysis.[16] The second and third columns of Table B.2 present the average renewable potentials for each country, based on this methodology.

Measuring Decreasing Returns to Scale (DRS) Parameter (ζ^r_n). The DRS parameter ζ^r_n reflects within-country heterogeneity in renewable potential, which varies across countries due to factors such as the distribution of renewable resources and the availability of feasible development areas.

[14] See the Appendix (Section B.2) for details on the aggregation.
[15] See Appendix Section B.4.1 for more details on DPI.
[16] Further details on the dataset are provided in Appendix Section B.4.2.

As renewable installations expand, new projects are often situated in locations with progressively lower renewable potential. This effect is can be important, as not all areas within a country are suitable for the installation of solar or wind equipment.

To account for this, I introduce geospatial data incorporating Development Potential Index (DPI) from Oakleaf et al. (2019). I then estimate the slope of the distribution of renewable potentials for each country, from the highest to the lowest. The fourth and fifth columns of Table B.2 summarize the DRS estimates for each country. On average, solar energy has a DRS parameter of 0.965 (standard deviation 0.004), while wind energy has a mean DRS parameter of 0.954 (standard deviation 0.007), indicating steeper decreasing returns for wind energy with greater variability across countries.

4.3 Estimating CES in Energy Production

Energy production involves nested CES technology. I first discuss the estimation of the elasticity of substitution between solar and wind. The identification of the inner-nest elasticity and share parameters is based on the theoretical relationship between inner-nest quantities and relative prices:

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

To account for unobserved cross-country heterogeneity and global technological progress that the theoretical model does not explicitly consider, the empirical specification introduces country fixed effects and a linear time trend. Country fixed effects control for cross-country differences in renewable potential and other time-invariant factors, while the time trend captures technological improvements over time that influence the productivity of each energy source.

The empirical specification for estimating the substitution parameter is as follows:

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

While this specification addresses some unobserved heterogeneity, a fixed-effects regression of relative output on relative price still faces a simultaneity issue, as the market equilibrium is determined by both demand and supply equations, where price and quantity are endogenous variables.

To address this, I instrument the relative price term with the wind energy subsidy for each country and year. This strategy leverages exogenous supply shocks driven by subsidies in renewable energy production. The relevance of this instrument aligns with the presence of decreasing returns to scale in renewable energy, where subsidies directly affect unit costs. The exclusion restriction assumes that renewable energy subsidies influence electricity demand only through their impact on relative price differences. Although subsidies might theoretically influence consumer behavior beyond price effects, the impact is likely to be gradual and captured by the time trend in

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				✓

our model.[17]

Data. The data on solar and wind energy output comes from the International Renewable Energy Agency (IRENA). For solar and wind energy prices, I construct price data for 20 countries by combining the levelized cost of electricity (LCOE) for solar and wind (sourced from IRENA) with wind energy subsidies (from OECD) for the years 2010-2022.

Results. Table 1 presents the estimates of the elasticity of substitution between solar and wind energy. Column (1) shows the OLS estimate without fixed effects. Column (2) introduces country fixed effects, and Column (3) adds a linear time trend. In Column (4), to address the endogeneity of the price ratio, I use the wind energy subsidy as an instrument, which results in a slightly lower estimate. With both 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 commonly held assumption in the literature that solar and wind are perfect substitutes.[18] The weak complementarity between solar and wind energy can be attributed to the intermittency issues associated with both energy sources (Gentile (2024)).

Finally, I take the outer nest elasticity of substitution from Jo (2023), which is based on French firm-level data, yielding a value of 3.08.[19] The reason renewable energy and fossil fuels are not perfectly substitutable is clear: renewable energy is primarily used for on-grid electricity, whereas fossil fuels have broader applications, such as direct inputs for internal combustion engines, which are difficult to replace with electricity.

[17] As for the exogeneity concern, while policymakers may consider demand factors when designing subsidies, the actual implementation often follows complex legislative processes with significant time lags. This administrative delay creates a temporal disconnect between market conditions influencing policy decisions and the actual subsidy implementation, supporting the instrument's exogeneity. Moreover, wind energy subsidies are frequently part of broader, long-term renewable energy strategies rather than reactive policies to short-term demand fluctuations.

[18] 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.

[19] Several studies estimate the elasticity of substitution between clean and dirty energy sources, including Papageorgiou et al. (2017), Jo (2023), and Wiskich (2023). Their estimates range from 2.033 to infinity, so 3.08 falls within the range found in the literature.

4.4 Estimating Learning Rate of Equipment Production

To calibrate the learning rate in equipment production, I estimate a regression using the following empirical specification from equation (21):

$$\log(A^j_{n,t}) = \nu^j_D \log(\sum_{s=1}^{t-1} y^j_{n,s}) + \nu^j_G \log(\sum_{i\neq n}\sum_{s=1}^{t-1} y^j_{i,s}) + \nu^j_n + \lambda t + \iota^j_{n,t} \text{ for } j \in \Omega_{REE}, \tag{29}$$

where $y^j_{n,s}$ is the output of renewable energy equipment j in country n at time s. The term $(\sum_{i\neq n}\sum_{s=1}^{t-1} y^j_{i,s})$ captures the global cumulative output, excluding country n. The variable ν^j_n accounts for country fixed effects, and λt controls for the linear time trend. Identification in this specification relies on within-country variation, while controlling for global spillover effects and common technological progress over time.

To run this regression, I first need to recover the time-series data for renewable energy equipment productivity across countries ($A^j_{n,t}$). To do this, I use model inversion, where the model ensures that domestic expenditure shares, input costs, 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 $c^j_{n,t}$ represents the input cost, and P^{nj}_t is the price index for renewable energy equipment. Using this relationship, I can measure A^{nj}_t with the data explained below.

Data. For input costs $c^j_{n,t}$, I use data from the Penn World Table (Version 10.1). I assume that input costs are composed of wages ($w_{n,t}$), manufacturing goods, and services. I calculate w^{nj}_t as the ratio of total labor compensation to total employment (using the variable emp in PWT), where labor compensation is the product of labor share (variable $labsh$) and GDP (variable $cgdpo$). I proxy the manufacturing price index using the average of a country's import and export prices (variables pl_m and pl_x, respectively). For the service price index, I use the consumer price index (CPI).

For solar energy equipment, I obtain the output $y^S_{n,t}$ and price data $P^S_{n,t}$ from International Energy Agency Photovoltaic Power Systems Programme (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 the following steps. First, I use annual wind energy equipment installation data (in GW) and the average installation cost for each country from IRENA, assuming a one-year time lag between the production/trade and installation of renewable energy equipment. Using this installation data and the average installation costs, I compute the annual absorption of wind energy equipment. By combining wind equipment import data from Com-

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

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

trade with the absorption data, I derive the domestic expenditure share sequence, $\pi^W_{nn,t}$. Lastly, I use wind energy equipment export data from Comtrade, along with the absorption data, to calculate production in each country. This approach allows me to impute 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. The preferred specification is in the third column for solar energy equipment and the sixth column for wind energy equipment. The results suggest that a 1% increase in production experience leads to a 1.26% increase in productivity for solar equipment and a 0.765% increase for wind equipment.

To compare these estimates with those in the literature, I need to convert them into the commonly used "learning rate" definition.[20] To do this, I first calculate the implied impact of learning-by-doing on price by taking the logarithm of equation (30) and rearranging 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

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

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 ν^S/θ^S = 1.261 / 4.762 = 0.264 and ν^W/θ^W = 0.765 / 2.509 = 0.304.[21] 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.[22]

4.5 Trade Elasticities

One of the key parameters that governs the impact of industrial policies is trade elasticity, θ^j. I adopt the parameter values from Fontagné et al. (2022), and Parro (2013), Caliendo and Parro (2015). Specifically, I take the trade elasticity for solar and wind energy equipment using the closest HS 4-digit level for each sector, as provided by Fontagné et al. (2022), which are 4.76 for solar equipment and 2.51 for wind equipment.[23] I take 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 set 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 implications for the impact of subsidies. An equipment subsidy is likely to have a greater effect on the global market share of solar equipment, as global demand is more sensitive to changes in bilateral import prices resulting from the subsidy. As a result, even if the learning rates for both solar and wind equipment are identical, a subsidy for solar equipment could be more effective in expanding its global market share and leveraging learning-by-doing compared to a subsidy for 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

[21] These estimates are consistent with the findings on external economies of scale reported in Lashkaripour and Lugovskyy (2023) and Bartelme et al. (2024).

[22] 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 different estimates from 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 not negligible in this sector.

[23] 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).

Table 3: Trade Elasticities (θ^j)

Sectors	Trade Elasticity (θ^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

consumption. To obtain each input share, I divide the value added from each input by the gross output. One challenge is that the dataset does not differentiate between the value added from labor and capital. Following Greenwood et al. (1997), I address this by calibrating the labor and capital shares, assuming a capital share of 0.3 in the value added. For the final goods consumption share, μ_n^j, I subtract the intermediate goods expenditure from the total expenditure in sector j, and then divide by total absorption.

Depreciation rate (δ_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 (α) and Investment Efficiency (χ^j). Following Ravikumar et al. (2019), I set $\alpha = 0.76$ and $\chi_j = (\delta_j)^{1-\alpha}$.[24] 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 Sector-Regional Productivity (A) For all sectors except renewable energy, I recover the initial productivities by inverting the model using Equation (30). For solar and wind energy, I rely on the calibrated values derived from renewable potential data, as detailed in Section 4.2. The level shifter in renewable energy productivity aligns this sector's productivity with that of other sectors, calibrated to match the observed global share of renewable energy in primary energy consumption.

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

Damage parameter (SCC_t) The damage parameter SCC_t is calibrated to match \$163 social cost of carbon per unit ton increase in emissions following EPA (2023) and Caliendo et al. (2024).

Initial labor and capital stock (L,K) I measure initial labor using the total number of employed workers from the Penn World Table (variable "emp" in PWT). I measure initial capital stock for

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

each capital as follows:

1. First, I calculate the total capital stock for each country using data from the Penn World Table, which provides aggregate capital stock data for each country normalized to a US value of 1. I recover the absolute capital stock level for each country by multiplying it by the US capital stock level.[25]

2. Second, I obtain the fossil fuel capital stock using nominal capital data from the World Input-Output Database (WIOD Socio Economic Accounts). For countries not covered by WIOD but included in my quantitative analysis, I impute the values by using the average ratio of fossil fuel capital to fossil fuel output for countries in the OECD-IO dataset.

3. For solar and wind capital stock, I calculate the dollar value based on installed capacity (in kW). In 2022, the global capital value of wind farms was 2.22 trillion US dollars.[26] I first recover gross capital stock using cumulative depreciation rate, and then I allocate this capital stock across countries according to each country's share of global wind installations (in kW). Additionally, assuming the same depreciation rate for solar and wind energy equipment, I derive the capital stock for installed solar energy equipment based on the relative global share of installed solar to wind capacity (which is 1.26:1). By applying the same distribution method, I estimate each country's initial stock of capital for solar energy equipment.

4. The non-energy capital stock can be calculated by subtracting the energy-related capital stocks from the aggregate capital stock level.

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 from Energy Institute (2024).[27]

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

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

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

[27] Since the OECD-IO dataset does not have distinct renewable energy sectors, I use a separate dataset from Energy Institute (2024), processed by Our World in Data, to obtain the fossil fuel share in total primary energy consumption.

Table 4: Parameter Values

	Parameters	Values	Source or Method
(Renewable)			
ξ	Decreasing returns to scale	Region-energy specific	Measuring slope using data from Oakleaf et al. (2019)
ρ	(Inner nest) CES elasticity of substitution	0.712	Estimation
ψ	(Upper nest) CES elasticity of substitution	3.08	Jo (2023)
μ	Forgetting rate in learning-by-doing	0.99	Arkolakis and Walsh (2023)
		(solar, wind)	
ν_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 Other sectors: Model inversion using Equation (30)
θ^j	Trade elasticities	Sector-specific	Caliendo and Parro (2015) and Fontagné et al. (2022)
γ^L	Share of labor in production	Region-sector specific	Calibrated using OECD IO
γ^j	Share of intermediate goods in production	Region-sector specific	Calibrated using OECD IO
γ^F	Share of fossil fuel capital in production	Region-sector specific	Calibrated using OECD IO
γ^D	Share of non-energy capital in production	Region-sector specific	Calibrated using OECD IO
μ^j	Consumption share	Region-sector specific	Calibrated using OECD IO
β	Discount rate	0.95	
SCC_t	Damage parameter	Time-specific	Match social cost of carbon \$163 (EPA (2023), Caliendo et al. (2024))
κ	Trade cost	Region-sector-pair specific	Head and Ries (2001)
(Capital)			
α	Capital adjustment cost	0.76	Ravikumar et al. (2019)
χ_k	Investment efficiency	$\delta_k^{1-\alpha}$	Ravikumar et al. (2019)
		(solar, wind, fossil, non-energy)	
δ^j	Depreciation rate	(0.03, 0.03, 0.02, 0.07)	Arkolakis and Walsh (2023)

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 the fossil fuel share in each country. Key inputs for this analysis include country-level renewable energy potential and the decreasing returns to scale parameter, both of which are measured outside the model. I assess whether the model can accurately capture the fossil fuel share in total primary energy consumption for each country in 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 aspect of the model—specifically, how subsidies influence equipment production over time—I examine whether the simulated outcomes under the Inflation Reduction Act (IRA) replicate the observed pattern of U.S. solar equipment production following the IRA's implementation. The most recent available data includes manufacturing capacity up to the second quarter of 2024, two years after the IRA was enacted (Wood Mackenzie (2024)).

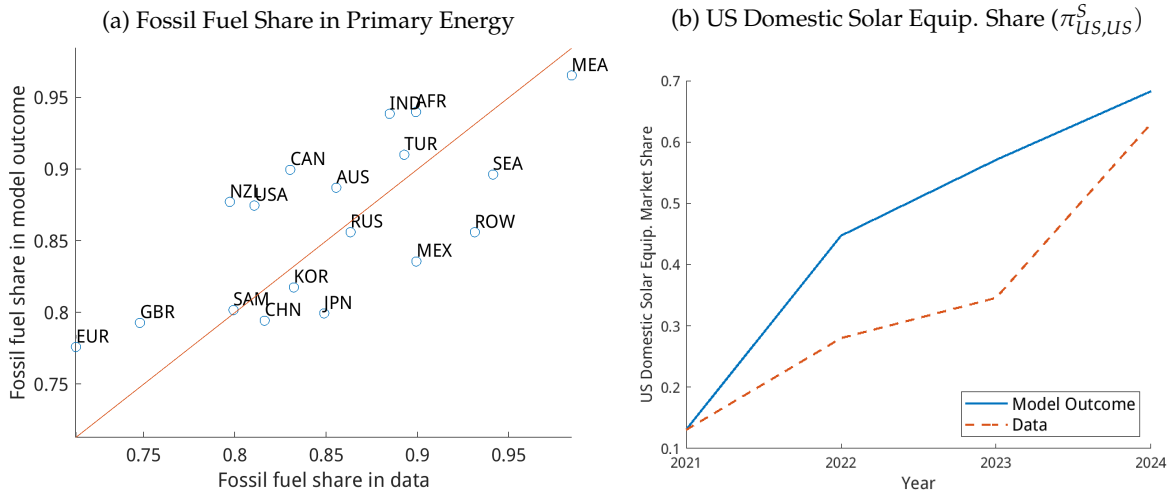
Panel (b) in Figure 3 compares the model's projection of the US domestic share in the solar equipment market, $\pi^S_{US,US}$ (shown in the blue line), with actual data (represented by the red dashed line).[28] Overall, the model captures the upward trend observed in the data. According to the model, U.S. solar equipment manufacturing grows rapidly, increasing its share of domestic demand from 14% in 2021 to 68% by 2024. This closely aligns with the observed data, which reports a domestic share of 60% in 2024. I find that the model predicts a faster response in the equipment share compared to the observed data. This discrepancy stems from the model's use of annual time units and the assumption that the Inflation Reduction Act (IRA) took effect at the start of 2022, whereas the IRA was actually enacted in the third quarter of 2022, leading to a delayed response in the observed data.

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)	

[28] I make two assumptions regarding the data: First, as I only have capacity data and not actual output data, I assume a module manufacturing utilization rate of 71%, based on InfoLink Consulting (2023). Second, to align with the model's timeline, I use projections from Wood Mackenzie (2024) for the 2024 data value.

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:

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

Equation (32) breaks down the change in welfare into two terms. First is the real income term.[29] The second term is carbon emissions term. Reduction in carbon emissions reduces disutility, which increases welfare.

6.1 Policy Scenarios

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

Baseline Scenario. To conduct a counterfactual analysis, I first define the baseline scenario.

[29] 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.

$$\begin{aligned} dlnW_n &= dln\left(\frac{E_n}{P_n}\right) - dln\left(1 + SCC_t(Z_t - Z_0)\right) \\ &\approx \underbrace{dln\left(\frac{w_n}{P_n}\right)\frac{w_n L_n}{E_n}}_{\text{real wage changes}} + \underbrace{dln\left(\frac{r_n K_n}{P_n}\right)\frac{r_n K_n}{E_n}}_{\text{capital deepening}} - \underbrace{\sum_{j\in\Omega} dln\left(\frac{S_n^j}{P_n}\right)\frac{S_n^j}{E_n}}_{\text{subsidy changes}} + \underbrace{dln\sum_{j\in\Omega_{RE}}\left(\frac{\Pi_n^j}{P_n}\right)\frac{\Pi_n^j}{E_n}}_{\text{RE firm profit changes}} - \underbrace{dln\left(1 + SCC_t(Z_t - Z_0)\right)}_{\text{carbon emissions changes}} \end{aligned}$$

where S_n^j denotes the budget spent for subsidy in sector j in country n, *i.e.*, $S_n^j \equiv s_n^j \sum_{i=1}^N \frac{\pi_{in}^j}{(1-s_n^j)} X_i^j$.

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%

In this scenario, there are no policy interventions in any country—meaning no green industrial or trade policies are implemented globally.

Simulation on Renewable Energy Provisions of the IRA. The main scenario examines the impact of the renewable energy provisions in the Inflation Reduction Act (IRA), which includes both energy subsidies and equipment subsidies for a ten-year period (2022–2031).[30]

- Energy Subsidy: The production tax credit (PTC) for renewable energy production is \$0.0275 per kWh in 2022. Given that the average retail electricity price in the US was \$0.1236 per kWh in 2022 (EIA, 2023), I apply a 20% price subsidy.[31]

- Equipment Subsidy: The tax credit for renewable energy equipment production is approximately \$0.14 per watt in 2022.[32] Considering that the average price of solar panels produced in the US was \$0.42 per watt in 2022, I set the equipment subsidy at 30%.

In the final three years of the IRA, the subsidies phase out gradually, decreasing by 25%, 50%, and 75% of the original subsidy in each successive year.

Decomposition. To analyze the effects of each subsidy component in the IRA, I run separate simulations for the energy subsidy and the equipment subsidy, applying the subsidy ratios as in scenario (ii) and (iii) of Table 6 with phaseout periods. Under the current calibration, the total budget for the IRA is approximately \$243 billion, with \$118 billion allocated for the energy subsidy and \$125 billion for the equipment subsidy.

Role of Equipment Trade. The key question of this paper is analyzing the importance of equipment trade in shaping the impact of the IRA. To see this, in the fourth simulation, I run the model with the IRA in place but without equipment trade, achieved by raising trade barriers to infinity.

6.2 Impact of Renewable Energy Provisions of the 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

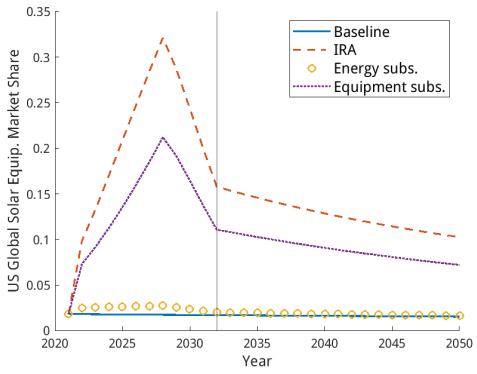
[30] For detailed information on the renewable energy provisions of the IRA, refer to Appendix Section B.1.

[31] 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.

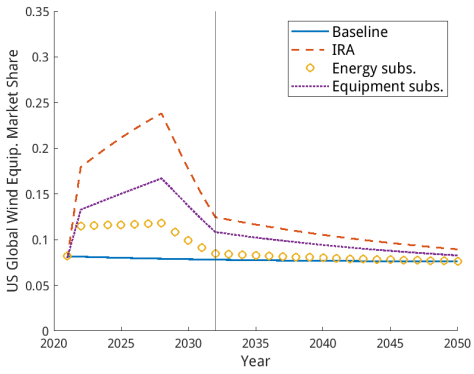
[32] Section 45X of the Advanced Manufacturing Production Tax Credit (PTC) in the IRA provides subsidies for each component of renewable energy equipment. For solar panels, this includes subsidies for polysilicon, cells, modules, and wafers, totaling \$0.14 per watt.

Figure 4: US global renewable equipment market share under IRA

(a) Solar Equipment



(b) Wind Equipment



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

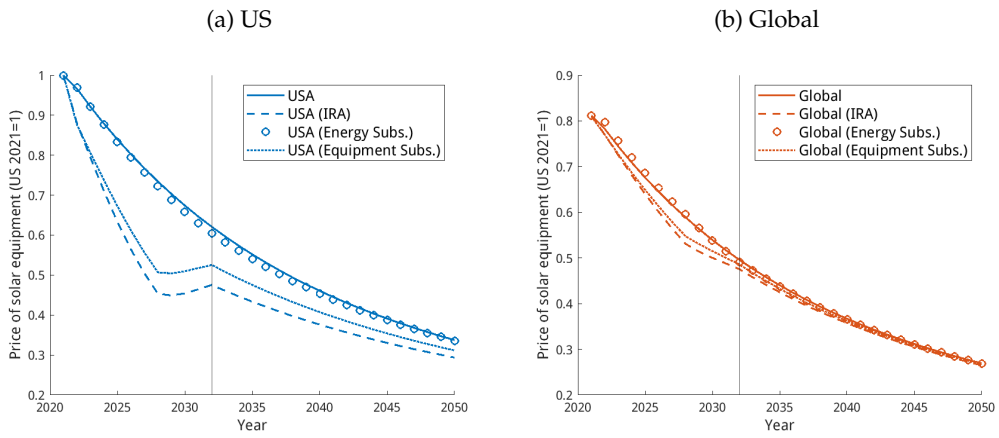
blue solid line represents the baseline scenario, while the red dashed line shows the market share evolution under the IRA. I decompose the impact of the IRA into energy and equipment subsidy components, shown by the purple dotted line and yellow circles, respectively.

Panel (a) in Figure 4 highlights the significant increase in the US market share for solar equipment, peaking at 32% under the IRA, compared to the baseline scenario (blue solid line), where the US market share remains below 2% throughout the period. Most of this increase can be attributed to the equipment subsidy component (purple dotted line), as the energy subsidy (yellow circles) has a much smaller effect. The excess demand for equipment from the energy subsidy is mostly met by imports, not by the domestic supply. Additionally, due to productivity gains from learning-by-doing during the IRA period, the US retains a larger market share even after the IRA ends (in 2031) compared to the baseline.

Interestingly, 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 combination accelerates learning-by-doing in the US, leading to faster growth in global market share under the IRA compared to implementing only one of the subsidies.

Panel (b) in Figure 4 depicts the evolution of the US global wind equipment market share. Initially, the US holds approximately 6% of the global wind equipment market, but this share consistently declines over the years in the baseline scenario. Under the IRA, the wind equipment market share experiences a less pronounced increase compared to solar equipment, peaking at 24%. A notable difference from the solar equipment case is the greater impact of the energy subsidy (yellow circles), which increases the US market share to a peak of 12%. As with solar equipment, there is a complementary effect between the energy and equipment subsidies for wind equipment.

Figure 5: Price of Solar Energy Equipment



This figure shows the evolution of solar energy equipment prices from 2021 to 2050. Panel (a) illustrates the price of solar energy equipment in the US under four scenarios: baseline (solid blue line), IRA (blue dashed line), energy subsidy (blue circles), and equipment subsidy (blue dotted line). Panel (b) presents the global price of solar equipment under the scenarios in red lines, where the price is computed as the weighted average of each country's solar equipment price index.

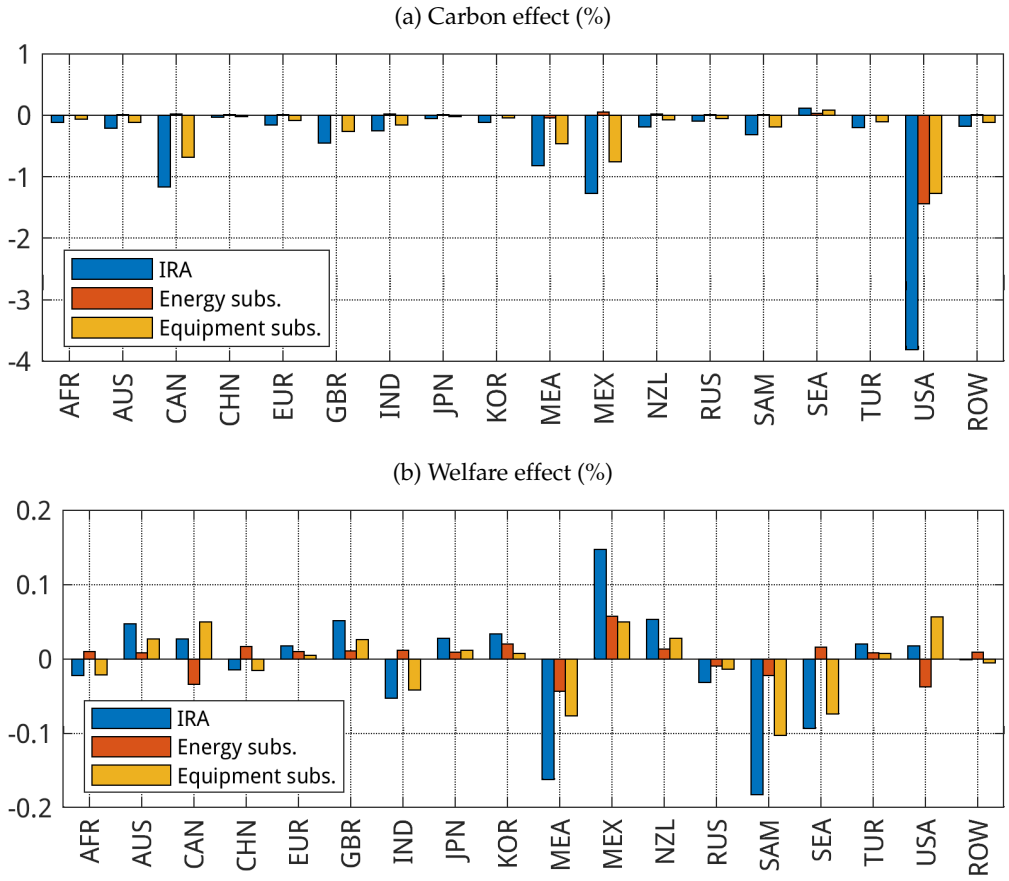
The impact of the equipment subsidy on the market share is more pronounced in the solar equipment market than in the wind equipment market in the short run. This difference arises from the higher trade elasticity for solar equipment, meaning global demand is more responsive to the US equipment subsidy. This also explains why the energy subsidy is more effective at 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, US market shares for both solar and wind equipment decline, and neither the energy nor equipment subsidies have a lasting impact. In the steady state, the US share in solar equipment approaches 0%, while the share in the wind equipment market stabilizes around 5%, irrespective of the policies.

Price of Equipment. Subsidies have impact on the price of equipment. Figure 5 illustrates the evolution of solar equipment prices in the US (Panel (a)) and globally (Panel (b)) under various scenarios: baseline (solid line), IRA (dashed line), energy subsidy (circles), and equipment subsidy (dotted line). The IRA reduces equipment prices in the US below baseline levels, with the price gap widening as the US increases its domestic market share, amplifying the impact of the equipment subsidy on the US price index. A decomposition of the subsidy components shows that most of the price reduction comes from the equipment subsidy, rather than the energy subsidy.

Subsidies also affect global equipment prices through trade. Panel (b) of Figure 5 shows that the IRA and the equipment subsidy reduce solar equipment prices in other countries, with the IRA having a larger impact as it boosts domestic production more significantly than the equipment subsidy alone. On the other hand, the energy subsidy increases demand for equipment in the US, raising global equipment prices during the policy period, which contributes to carbon leakage.

CO_2 Emissions and Welfare. The impact of the IRA on CO_2 emissions upto 2100 is concentrated in the US (-3.81%), but the pattern differs between energy and equipment subsidies. Panel (a) in Figure 6 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

Figure 6: Carbon and Welfare Effect of IRA



Note: Panel (a) presents the effect of IRA on accumulated CO_2 emissions up to 2100 in different countries. Panel (b) plots the effect of IRA on welfare in discounted sum of real wage up to 2100 for residents in different countries.

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, the energy subsidy increases carbon emissions in other countries due to the reduced fossil fuel demand in the US and higher global equipment price due to additional equipment demand in the US. 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.[33]

On the other hand, equipment subsidy reduces non-US carbon emissions by 0.12% and reduces global carbon emissions by 0.23%. With the equipment subsidy, the US becoming a net exporter of renewable energy equipment, which reduces global equipment prices through trade. It helps accelerate the energy transition both domestically and internationally, reducing carbon emissions in the US by by 1.27% and also 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

[33]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.

change in carbon emissions in the US and global excluding US under each subsidy across time. Two observations arise: first, within the US, energy subsidy is more effective than equipment subsidy in carbon emissions reduction, reducing the emissions by 7% at the peak (2029), while the equipment subsidy reduces by 4% at the peak. Combined together, The IRA reduces the US carbon emissions by 13% at the peak. Second, outside the US, equipment subsidy is more efficient in reducing carbon emissions, resulting in smaller carbon leakage than energy subsidy.[34]

Table 7 presents the welfare effects of the IRA across countries, decomposed into real income changes and carbon emission reductions using Equation (32). Welfare is defined as the discounted sum of real income, adjusted for the social cost of carbon, up to the year 2100. From the second column of the Table 7, we see that carbon emission reductions play a significant role in shaping the welfare impact of the IRA. While the real income effect varies across countries, the reduction in carbon emissions consistently increases welfare in all countries by an average of 0.02%, a magnitude comparable to the changes in real income in some countries.

Despite the positive welfare gain for all countries from carbon reduction, the IRA influences welfare differently across countries. Panel (b) in Figure 6 displays the welfare effects of i) the full IRA (blue bar), ii) the energy subsidy component (red bar), and iii) the equipment subsidy component (yellow bar), compared to the baseline scenario across countries.

The IRA, combining both energy and equipment subsidies, increases welfare in the United States by 0.02%, but reduces global welfare by -0.03%, with significant variation across countries. Two clear patterns arise; first, fossil fuel net exporters countries such as Middle East, South America, and Russia, are worse off, and fossil fuel net importers are better off. Second, status-quo equipment net exporters, such as China, India, and Southeast Asia, also worse off.[35]

The energy subsidy component in the US increases the equipment demand in the US, which is mostly met by the supply from the status-quo net exporters of equipment. This increases those countries' welfare due to terms of trade effect, and learning-by-doing further boosts their gain as increasing the production reinforces the status-quo comparative advantage. 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. The US welfare gains and global welfare losses primarily stem from the terms of trade

[34]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.

[35]This can be seen in the changes 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, both 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.

effect, amplified by the learning-by-doing again. Overall, the equipment subsidy component reduces the global welfare by 0.02% but increases US welfare by 0.06%.

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

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

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

It is also important to note that the total budgetary cost of the IRA is higher than the combined cost of the energy and equipment subsidies when considered separately. This is due to the complementary nature of the subsidies: the energy subsidy stimulates domestic equipment production when the equipment subsidy is in place, as domestic demand is largely met by domestic supply. Meanwhile, the equipment subsidy lowers the cost of equipment, supporting domestic renewable energy production.

To compare the efficiency of energy and equipment subsidies, I calculate the marginal value of public funds in terms of carbon reduction, following Finkelstein and Hendren (2020). The results imply that each additional $1 billion in subsidies reduces global carbon emissions by 0.0013% under the full IRA, 0.0004% under the energy subsidy alone, and 0.0015% under the equipment subsidy alone, indicating that the equipment subsidy is more efficient than the energy subsidy in

terms of global carbon reduction.

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%

6.3 Role of Equipment Trade in the Impact of IRA

In this analysis, equipment trade plays a critical role in driving the results. To quantify the impact of equipment trade on the effects 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 carbon and welfare impact of the IRA under the baseline model (panel (a)) and the model without trade in equipment (panel (b)). Not considering equipment trade leads to a different implications on 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%).

Without equipment trade, the impact of both subsidies is largely confined to the US. In particular, since the US cannot export, the US welfare gains from the equipment subsidy diminish due to i) smaller learning-by-doing in equipment production, and ii) no welfare gains from carbon reductions in other countries. When combined with the energy subsidy, this results in an overall welfare loss for the US.

The modest global welfare gain stems primarily from carbon reduction within the US. Additionally, without equipment trade, the welfare losses previously experienced by countries with a comparative advantage in equipment production vanish, as these countries are no longer adversely affected by the terms-of-trade impacts of the US equipment subsidy.

The impact of energy and equipment subsidies also shows notable differences between the baseline model and the model without equipment trade. In the model without equipment trade, the energy subsidy results in a smaller global carbon reduction (0.15%), a smaller US welfare loss (-0.02%), and a negligible global welfare gain (0.00%). Without trade, the energy subsidy becomes less efficient in reducing carbon emissions as equipment costs are higher. However, since equipment demand is met solely by domestic supply, the US benefits more from learning-by-doing, while other countries learns less compared to the baseline, resulting in a smaller US welfare loss and a smaller global welfare gain.

Without equipment trade, the equipment subsidy yields a smaller global carbon reduction (-0.13%), a lower US welfare gain (+0.04%), and a higher global welfare gain (+0.01%) compared to the baseline. In this case, the US cannot export its subsidized equipment to the global market, as shown by the peak US solar equipment market share dropping to 12.8% from 20.6% under the baseline. Consequently, the benefits of cheaper equipment are confined to the US. However, the absence of a terms-of-trade effect—since the US cannot export—leads to an improvement in global welfare.

In the baseline model with equipment trade, where the US becomes a net exporter under the IRA subsidies, two key effects occur: i) US equipment productivity grows further due to exports, and ii) the energy transition in other countries accelerates, leading to greater reductions in global carbon emissions. These effects are absent in the no equipment trade scenario, which leads to a negative US welfare gain in that case.

6.4 Optimal Subsidy

A natural question arises regarding the optimal (unilateral) subsidy for the US and globally. While deriving the analytical formula for optimal subsidies is beyond the scope of this paper, I compute the welfare effects for the US and globally across a range of subsidy ratios, from 0% to 50%, to explore potential outcomes.

Figure 7 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.

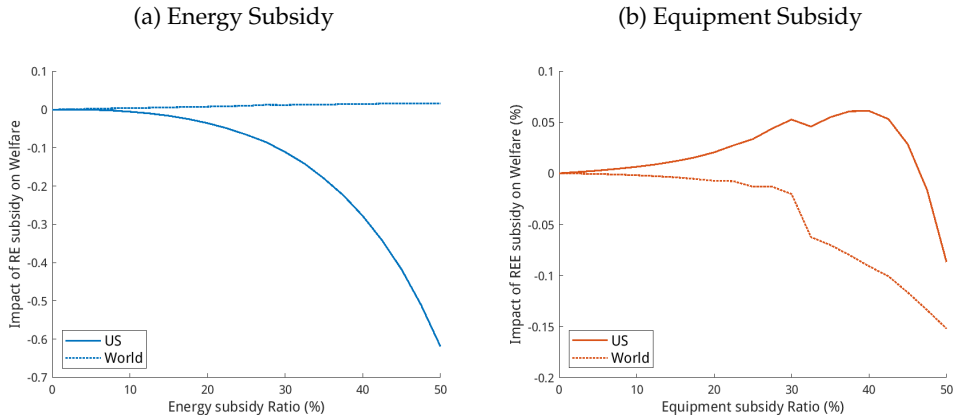
Compared to the optimal levels from the US perspective, the current IRA subsidy rates are too high for the energy subsidy and too low for the equipment subsidy. Table 9 summarizes the welfare and carbon impacts of the optimal subsidies for both the US and the world. The optimal subsidy for the US, consisting of no energy subsidy and a 40% equipment subsidy, reduces global carbon emissions by 0.63%, decreases global welfare by 0.10%, but increases US welfare by 0.07%. Compared to the current IRA, this optimal subsidy achieves greater carbon reductions and improves US welfare, albeit at the expense of global welfare.

In contrast, the subsidy rate that maximizes global welfare is 45% for the energy subsidy and 0% for the equipment subsidy. Under this scenario, global carbon emissions decrease by 0.63%, and global welfare increases by 0.02%, while US welfare declines by 0.45%. This result suggests that a unilateral optimal equipment subsidy by the US can reduce carbon emissions as effectively as an energy subsidy while simultaneously increasing US welfare.

As shown in panel (a) of Figure 7, the energy subsidy leads to a welfare loss for the US at any positive subsidy rate, with the global optimal energy subsidy being 45%. The intuition is straightforward: the renewable energy sector experiences decreasing returns to scale, and while the energy subsidy reduces carbon emissions within the US, the benefits of this reduction primarily accrue to other countries due to carbon leakage and increased demand for equipment, which is met by foreign suppliers.

On the other hand, as shown in panel (b) of Figure 7, the optimal equipment subsidy for the

Figure 7: 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.

US is 40%, while the global optimal equipment subsidy is 0%. The US equipment subsidy corrects the positive externalities within the country, boosting domestic productivity through learning-by-doing. However, this diminishes learning-by-doing in other countries as equipment production shifts to the US. As a result, while the 40% equipment subsidy is optimal for the US, it is too high from a global welfare 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.[36] 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.[37] Figure 8 illustrates the impact of the IRA (with and without tariffs) 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 US market share rises to 5% (red solid line), and the IRA combined with the solar tariff further boosts the market share to as much as 35% during the policy period (red dashed line) compared to the IRA without the solar tariff (blue dashed line). Imposing tariffs on solar equipment imports allows US-produced solar equipment to capture the domestic market more rapidly, leading to greater productivity gains through learning-by-doing and a higher global market share.

Panel (b) in Figure 8 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.

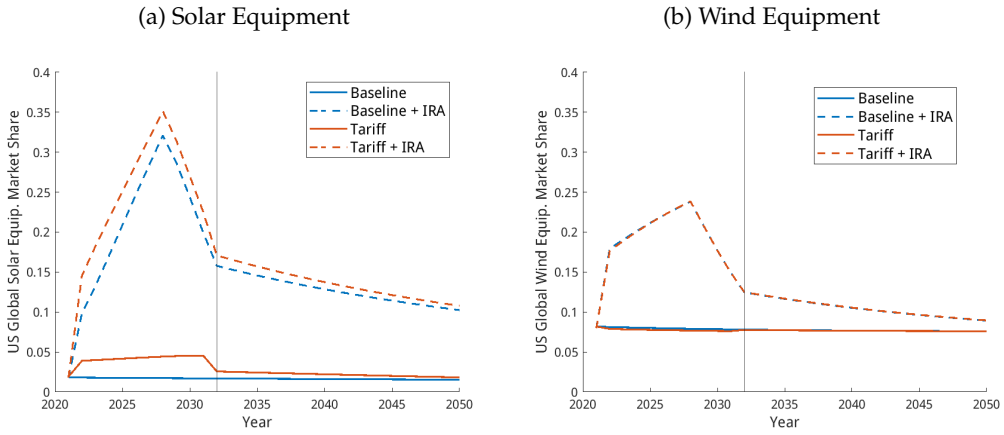
CO_2 Emissions and Welfare. Panel (b) in Table 10 summarizes the carbon and welfare impacts of the solar tariff and the IRA. Imposing a tariff on solar equipment (the first row of Panel (b) in Table 10) increases global carbon emissions by 0.01% and reduces both global and US welfare by 0.01%. This is primarily due to the delayed energy transition in the US as the price of equipment goes up, which also leads to smaller learning-by-doing effects in exporting countries, mainly in Southeast Asia.

The second row of Panel (b) in Table 10 shows the effects of combining the IRA with the solar tariff on carbon emissions and welfare. While it reduces global carbon emissions by 0.63%, global welfare decreases by 0.04% and US welfare increases by 0.01%, which are worse outcomes com-

[36] 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.

[37] The model with tariffs is provided in Appendix Section A.4.

Figure 8: 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.

pared to the baseline IRA scenario (-0.03% and 0.02%, respectively). The negative impact arises because, under the solar tariff, the US secures a larger market share despite its initially lower productivity relative to other equipment-exporting countries. This drives up equipment prices in the US, reducing domestic welfare and delaying the energy transition.

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.[38]

US Share in Global Renewable Energy Equipment Market. shows the evolution of the US global solar equipment market share. The US share increases to 6.4% by 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 decrease is due to heightened competition from China and the EU, which are also subsidizing their domestic solar equipment manufacturing.

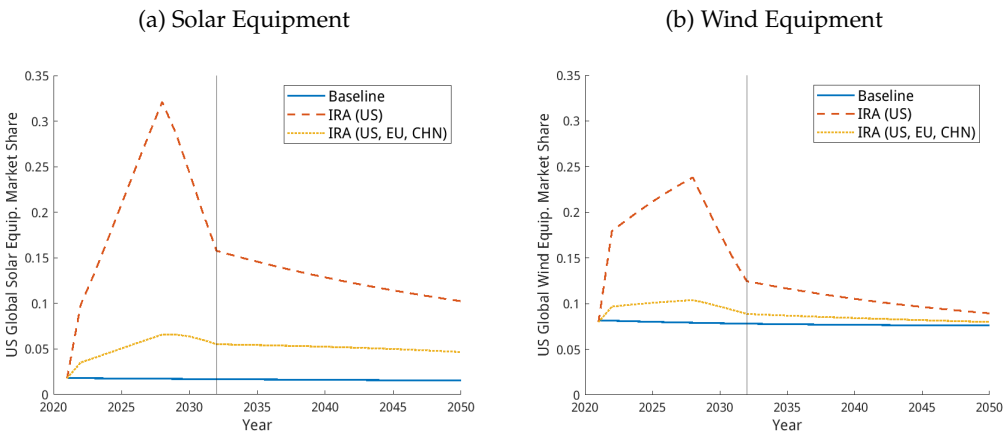
The US share in wind equipment follows a similar pattern. Panel (b) in Figure 9 illustrates the evolution of the US global wind equipment market share. The US share peaks at only 11% when the US, China, and the EU all implement subsidies (yellow dotted line), compared to 23% when only the US implements the policy (red dashed line). This reduction highlights the impact of increased competition from other regions also supporting their domestic industries.

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

The key finding is that multilateral green industrial policies lead to significantly larger reductions in carbon emissions, mitigate the effects of the US equipment subsidy, but still increase US

[38]While this extension does not directly analyze a non-cooperative Nash equilibrium or a globally optimal scenario, it offers valuable insights into the potential outcomes of multilateral policy coordination.

Figure 9: 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 represents the share under the baseline scenario, while the blue dotted (red dotted) line shows the share when only the US implements the IRA subsidy. The yellow dashed line indicates the share when the US, China, and the EU all implement the same subsidy. Panel (b) presents the evolution of the US global wind equipment market share under similar conditions.

welfare. Panel (c) in Table 10 shows a substantial aggregate reduction in carbon emissions of 3.16%, much larger than the reduction observed in the baseline IRA scenario where only the US implements the policy. However, global welfare decreases by 0.15%, a larger loss compared to the unilateral IRA case. At the same time, US welfare experiences a larger gain (0.04%).

This outcome is driven by two main factors. First, the carbon reduction effects of multilateral energy subsidies are additive. Since each country's energy subsidy primarily reduces its own carbon emissions, the cumulative impact grows as more countries adopt similar policies. Additionally, carbon leakage—where emissions reductions in one country lead to increases in others—is mitigated when major economies like China and the EU also implement energy subsidies.

Second, although the impact of the US equipment subsidy on its share of the global equipment market is muted when other major countries implement similar subsidies, the US still experiences a welfare gain, primarily due to the benefits of importing cheaper equipment subsidized by China. This improves the US's terms of trade, providing access to more affordable renewable energy technologies, thereby accelerating its energy transition and enhancing domestic welfare.[39]

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 not only the US carbon emissions but global carbon emissions by facilitating the energy transition in other countries, with a positive welfare

[39] I further discuss the impact of policy competitions on other countries in the Appendix Section C.4.

Table 10: Equilibrium Comparison

	Global CO_2	Global Welfare	US Welfare	Peak US Solar Equip. Share
(a) 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%
(b) IRA + Solar Tariff				
Tariff	0.01%	-0.01%	-0.01%	4.5%
IRA + Tariff	-0.63%	-0.03%	0.01%	35.1%
(c) US-CHN-EU Policy				
US-CHN-EU IRA	-3.16%	-0.15%	0.04%	6.6%

gain for the US but at the cost of global welfare due to terms of trade effect, and (ii) not considering equipment trade gives different implications on the impact of the IRA, as it predicts smaller carbon reduction effect, and opposite welfare implications.

The results reveal that equipment subsidy component in the IRA, compared to energy subsidy component, 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.

There are additional critical aspects of the energy transition on both the supply and demand sides, such as electric vehicles (EVs) and battery technologies. EVs represent a major shift in energy consumption, particularly in transportation, while advancements in battery technology are essential for efficient energy storage and managing the intermittency of renewable sources like solar and wind. These technologies could significantly affect the outcomes of policies like the IRA by reshaping energy markets and supply chains, especially for critical materials like lithium. Incorporating these elements into the model would provide a more comprehensive analysis of how industrial policies impact global carbon emissions and welfare distribution, but I leave this for future research.

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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:

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

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

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

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

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

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

n this section, I incorporate sectoral tariffs into 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, let the total trade cost inclusive of the tariff be denoted as $\kappa^j_{ni,t} \equiv d^j_{ni,t}(1+\tau^j_{ni,t})$. To include the tariff effect, equation (15) can be rewritten as follows:

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

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

To incorporate the tariff into the trade balance condition, the equation should reflect that tariffs affect the value of imports:

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

The household's total income should now include the revenue generated from tariffs:

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

Now we can define an equilibrium with tariff.

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).

Appendix B Data

B.1 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.[1] 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.

B.2 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

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

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	C31-C33	Manufacturing nec; repair and installation of machinery and equipment
Service	D -T	Other sectors

- 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.

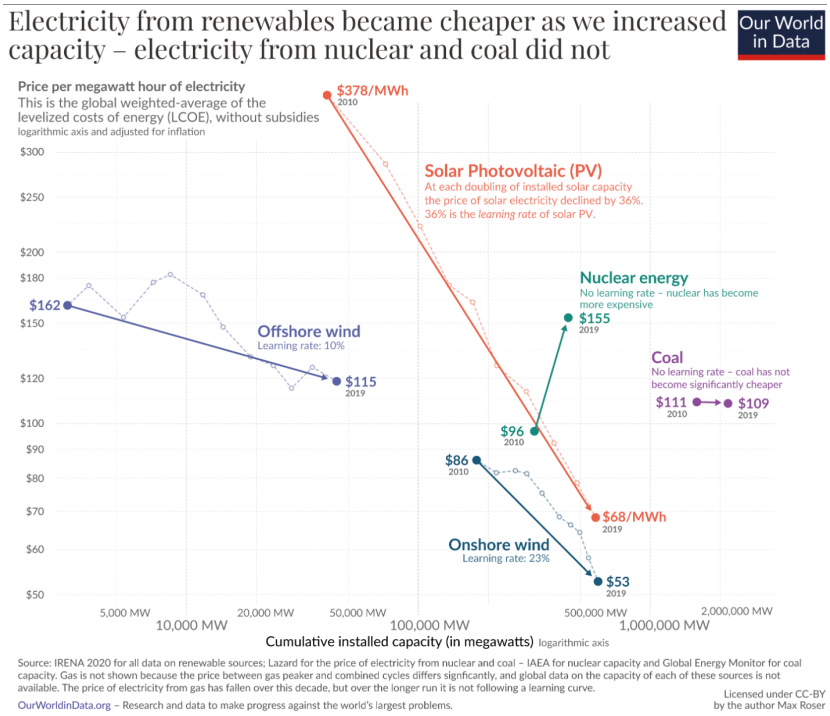
Time horizon I treat 2021 as the starting point of the model and collect from various data sources the information necessary for constructing this initial economy. While the model has infinite horizon, I report some of the results focusing on the years 2021–2050. I treat each period in the model as one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

B.3 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.

Figure B.1: Price of Electricity by Source



Source: Our World in Data

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.

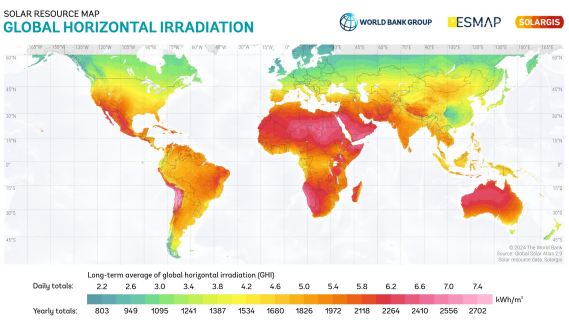
B.4 Renewable Potential

B.4.1 Geospatial Data for Renewable Potential

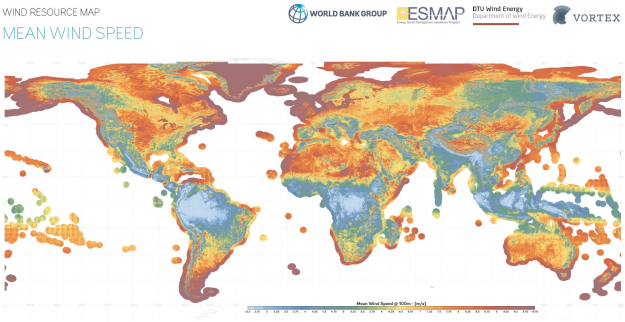
Although renewable energies are often considered 'renewable,' the amount of energy that can be generated in any given location depends on the region's renewable potential. Furthermore, even areas with high potential may not be suitable for installing renewable energy infrastructure. Oakleaf et al. (2019) introduced the Development Potential Index (DPI) at a 1 km resolution, utilizing spatial multi-criteria decision analysis within geographic information systems. They first identified sector-specific land constraints that could restrict development, such as appropriate land cover and slope. Then, they developed spatially explicit criteria—continuously scaled factors that

Figure B.2: Renewable Potentials

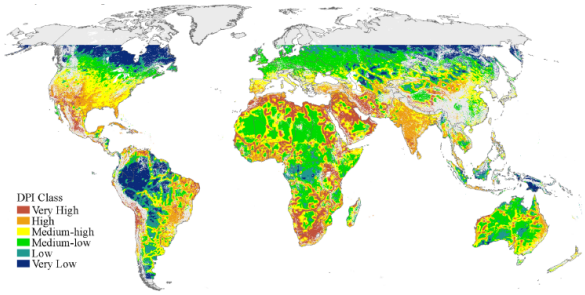
(a) Solar Potential



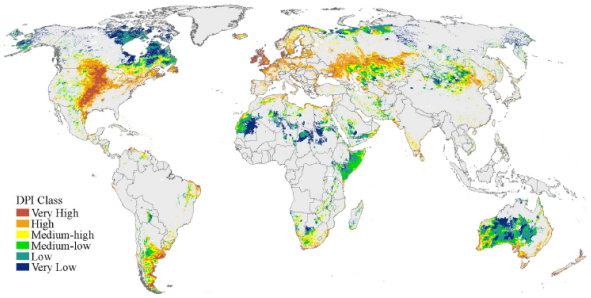
(b) Wind Potential



(c) DPI (Solar)



(d) DPI (Wind)



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. Panel (c) and (d) displays the Development Potential Index (DPI) of solar and wind, respectively. Source: Panel (a): Global Solar Atlas, panel (b): Global Wind Atlas, panel (c) and (d): Oakleaf et al. (2019).

improved the suitability of a region for development. These criteria accounted for both renewable potential and development feasibility, considering factors such as proximity to major roads, railroads, ports, power plants, the electrical grid, and demand centers.

Figure B.2 shows the global distribution of renewable energy potentials, specifically solar and wind, across the entire globe (panel (a) and (b)), using data from the Global Solar and Wind Atlas, as well as across regions that consider the feasibility of development (panel (c) and (d)), based on Oakleaf et al. (2019). In all panels, regions shown in red have higher potential, while regions colored blue have lower potential. There is significant heterogeneity not only between countries but also within each country.

Two patterns emerge: First, within-country heterogeneity in renewable energy potentials increases when development feasibility is factored in, and second, the feasible areas for installing renewable energy equipment are quite limited—especially for wind energy, which has a smaller feasible area compared to solar energy.

B.4.2 Alternative Method to Calibrate DRS

In this section, I present an alternative method for calibrating decreasing returns to scale in renewable energy production by combining solar and wind farm location data with renewable potential data over time. While the renewable potential at each location remains fixed, the locations of solar

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

Countries	A_n^s	A_n^w	**DRS** (ξ_n^s)	**DRS** (ξ_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

and wind farms change 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 regions indicating lower potential. The middle panel displays the locations of solar farms in 2011, while the bottom panel combines the solar farm locations from 2021 with the solar potential data. By using the annual additions of renewable power farms provided in the dataset, I can track the yearly changes 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.

$$\log(A_{n,t}^j) = \xi^{j,ALT} \log(K_{n,t}^j) + FE_n^j + \varepsilon_{n,t}^j$$

Table B.3 presents the correlation between major countries' potential for additional solar and wind power farm locations and cumulative installations, after controlling for country fixed effects.[2] The results show that: (i) both solar and wind potential decrease with additional installations, and (ii) wind potential declines faster than solar potential, which is consistent with the direct measure used in the main specification based on the DPI. Moreover, the scale of the decrease is relatively similar, though the DPI measure indicates a slightly faster decreasing return to scale for solar and a slower one for wind.

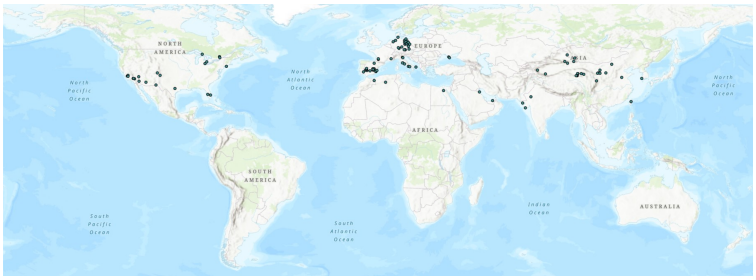
[2]Figure B.4 illustrates the correlation between major countries' potential for additional solar and wind power farm locations and cumulative installations.

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

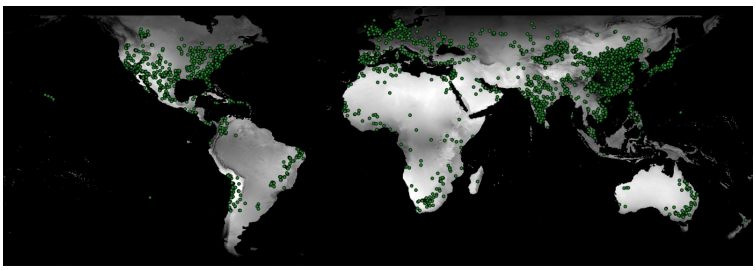
(a) Solar Potential



(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.

Appendix C Additional Results

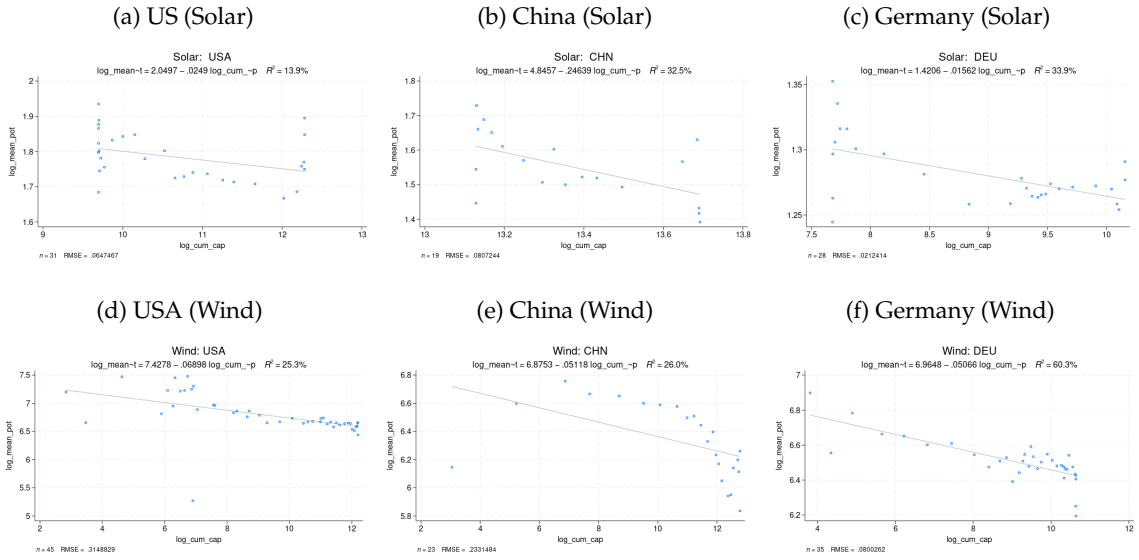
C.1 Comparative Statics

In this section, I perform two comparative statics analyses to examine the roles of learning-by-doing and trade in renewable energy equipment during the energy transition.

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

One of the key components of the model is learning-by-doing in the production of renewable energy equipment. To assess its impact, I eliminate 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,

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.

Table B.3: Additional Evidence of DRS

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

Standard errors in parentheses

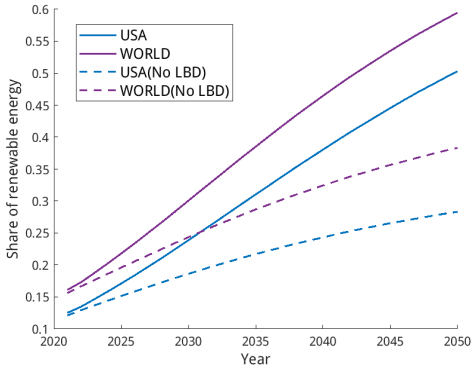
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EU, and China from 2021 to 2050, both with and without learning-by-doing. In the model incorporating learning-by-doing, the share of renewable energy in primary energy use is projected 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 36% in the US and 25% globally.

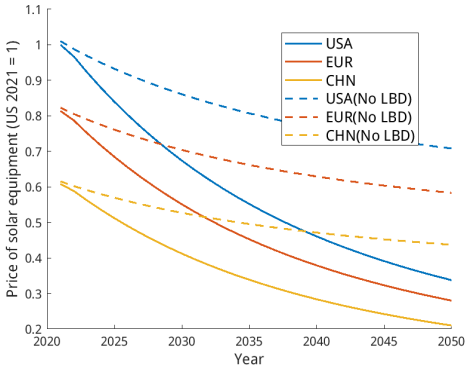
To understand why this occurs, Panel (b) displays the price of solar energy equipment in the US, EU, and China. Without learning-by-doing in equipment production, the price index for equipment declines much more slowly in each country due to the absence of productivity growth. This slower decline in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

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

(a) Share of Renewable Energy



(b) Price of solar equipment



Note: Panel (a) shows the evolution of the share of renewable energy in total primary energy use from 2021 to 2050 in the US (blue line) and globally (purple line). Panel (b) illustrates the evolution of the price index for solar energy equipment over the same period in the US (blue line), EU (red line), and China (yellow line). The outcomes under the baseline scenario with learning-by-doing are represented by solid lines, while the outcomes without learning-by-doing are shown with dashed lines.

C.1.2 Role of renewable energy equipment trade

To assess the role of renewable energy equipment trade in the transition, I analyze three scenarios: free trade with no trade costs, the baseline scenario with calibrated trade costs, and a scenario with no trade.

In the free trade scenario, I set the trade cost for renewable energy equipment to one for all country pairs, i.e., $d^j_{in,t} = 1$ for $j \in S, W$. In the no trade scenario, I eliminate trade in renewable energy equipment by setting 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 the current calibration, free trade, and no trade scenarios. In the free trade scenario, represented by the dotted line, the share of renewable energy in primary energy use reaches 68% in the US and 66% globally. In contrast, without trade, the share of renewable energy in primary energy use only reaches 38% in the US and 40% globally (dashed lines). These outcomes are driven by the equipment price trends shown in Panel (b).

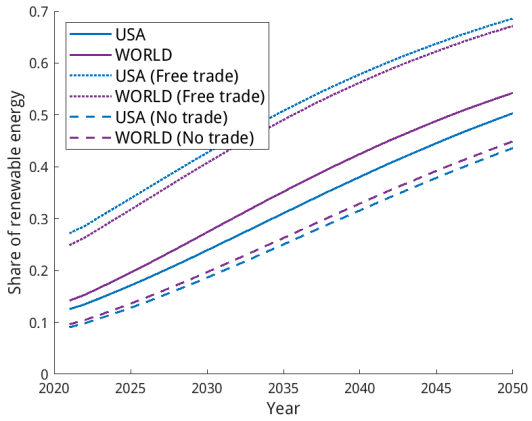
Panel (b) shows the evolution of the price index for solar energy equipment from 2021 to 2050 in the US, EU, and China under each scenario. The price index for solar energy equipment under the free trade scenario (dotted line) is the lowest, facilitating the transition in each country, as shown by the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

C.2 Extending Policy Periods

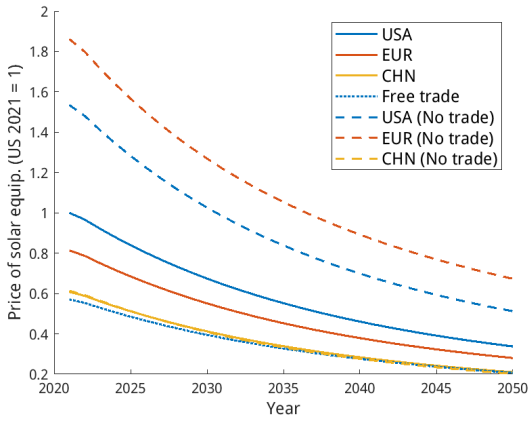
Another potential policy adjustment is extending the duration of the policy period. In this section, I extend the policy period from 10 years (2022-2031) to 20 years (2022-2041). Table C.1 compares

Figure C.2: Role of renewable energy equipment trade

(a) Share of Renewable Energy



(b) Price of solar equipment



Note: Panel (a) shows the evolution of the share of renewable energy in total primary energy use from 2021 to 2050 in the US (blue line) and globally (purple line). Panel (b) displays the evolution of the price index for solar energy equipment from 2021 to 2050 in the US (blue line), EU (red line), and China (yellow line). The outcomes under the baseline scenario with calibrated trade costs are represented by solid lines, the outcomes under free trade in renewable energy equipment are shown with dotted lines, and the outcomes under no trade in renewable energy equipment are depicted by dashed lines.

the equilibrium outcomes under the baseline IRA and the extended IRA. Extending the policy period amplifies the effects on carbon reductions, welfare, and the US share of the equipment market, but it does not alter the qualitative results. However, even with the extended policy period, the impact of the subsidies remains temporary. In the steady state, the US share of the global equipment market reaches only 0.1% for solar equipment and 5.4% for wind equipment.

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%

C.3 Additional Results on IRA under Trade Policy

Figure E.6 illustrates the effects of the IRA combined with the solar tariff on accumulated carbon emissions (Panel (a)) and welfare (Panel (b)) compared to the corresponding subsidy scenarios without the tariff, across different countries.

Energy Subsidy + Tariff. When combined with the energy subsidy, the solar tariff leads to

higher US carbon emissions compared to using the energy subsidy alone. This is because the tariff raises the price of solar equipment in the US, making the energy subsidy less effective in accelerating the domestic energy transition. Additionally, the combination of the energy subsidy and tariff increases global carbon emissions in the long run, as countries like China and Southeast Asia lose learning-by-doing experience due to reduced exports, slowing their transition to renewable energy.

Equipment Subsidy + Tariff. In contrast, when the solar tariff is combined with the equipment subsidy, US carbon emissions rise in the short run due to higher equipment prices, but global carbon emissions decline further in the long run. The key difference lies in the US becoming a net exporter of solar equipment under this policy. The tariff, combined with the equipment subsidy, boosts the US's global market share in solar equipment, allowing it to export more and facilitate the global energy transition.

Impact on Non-US Countries. The impact of these combined policies on welfare and emissions varies across countries. Figure E.6 shows that while the combination of the IRA and solar tariff with an equipment subsidy reduces global carbon emissions more effectively, combining the energy subsidy with the tariff results in higher emissions in Southeast Asia due to hindered productivity growth from learning-by-doing. Welfare losses are most pronounced in countries directly affected by the tariff, such as China, Southeast Asia, and the US. However, some countries, like Korea and Mexico, benefit as they gain market share in solar equipment previously supplied by Chinese imports.

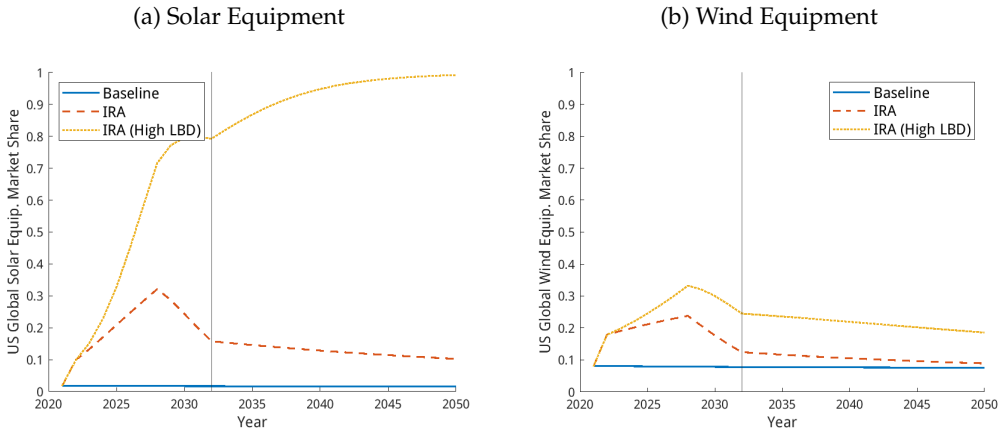
C.4 Additional Results on US-CHN-EU Policy Competition

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

In terms of carbon emissions, as shown in panel (a) of Figure E.7, this multilateral policy scenario results in a substantial aggregate reduction of 3.16%, which is significantly larger than the 0.60% reduction observed in the baseline IRA scenario where only the US implements the policy. While the energy subsidies lead to significant carbon emission reductions mainly in China, the EU, and the US, with limited spillover to other countries, the equipment subsidy component in each policy further amplifies the global reduction in carbon emissions, contributing an additional 1.73% decrease.

In Panel (b), I observe significant welfare losses in China, primarily due to the large scale of equipment subsidies provided. These welfare losses stem from the fact that China already holds 82% of the global solar equipment market share, leaving little room for additional gains through further subsidization. Although the equipment subsidy accelerates the global energy transition by reducing fossil fuel demand, this leads to welfare losses for fossil fuel-exporting countries, such as the Middle East, Russia, and South America. On the other hand, net fossil fuel importers, like Japan and Korea, benefit from the reduced demand for fossil fuels.

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.

C.5 Robustness Check

The impact of the IRA primarily depends on three key sets of parameters: (i) the elasticity of substitution between renewable energy and fossil fuels, η_e, (ii) the trade elasticities of equipment (θ^S and θ^W), and (iii) the rates of learning-by-doing in equipment production, ν_D^S and ν_D^W. In this section, I analyze how variations in these parameters influence the outcomes of the IRA.

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 ψ to 5, compared to the baseline value of $\psi = 3.08$.

Panel (b) in Table C.2 summarizes the results for $\psi = 5$. The results from the baseline specification remain qualitatively robust: the IRA leads to global welfare losses, and the equipment subsidy reduces global carbon emissions more effectively than the energy subsidy. Additionally, the equipment subsidy decreases other countries' welfare while boosting US welfare.

With a higher elasticity of substitution, subsidies become more effective in replacing fossil fuels with renewable energy, thus magnifying the impact of subsidies on reducing global carbon emissions. This results in greater welfare gains from the energy subsidy, both for the US and globally. However, the increased elasticity of substitution raises equipment demand, causing the equipment subsidy to generate higher welfare gains for the US while imposing welfare losses on other countries due to the terms-of-trade 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 illustrates the impact of enhanced 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 equipment market by 2030. This accelerates productivity gains from learning-by-doing

in the US, boosting global welfare by enabling the installation of cheaper US-produced solar equipment. For wind equipment, the effect is less pronounced. Although the higher learning rate increases the peak US market share compared to the baseline IRA case, the share still declines after the policy period due to lower trade elasticity, similar to the baseline scenario.

Panel (c) in Table C.2 summarizes the results under higher learning-by-doing rates. Overall, the IRA improves US welfare by 1.96%, primarily due to gains from equipment subsidies. Notably, the impact of the subsidies is no longer purely transitory. In the steady state, the US continues to dominate the solar equipment market, which has a long-term positive effect on US welfare and a negative effect on global welfare.

Higher learning-by-doing accelerates the energy transition but also leads to higher carbon emissions, driven by the income effect combined with the low elasticity of substitution between renewables and fossil fuels. While the faster transition to renewable energy reduces energy prices and increases overall economic production, this leads to higher emissions, resulting in a backfire effect on global welfare.

Trade Elasticities of equipment (θ^S and θ^W). Another important set of parameters is the trade elasticities of equipment. To assess how changes in trade elasticities impact the results, I calibrate the trade elasticity for solar energy equipment using the value for electronics (10.60) and for wind energy equipment using the value for the machinery sector (1.52) from Caliendo and Parro (2015).

Panel (d) in Table C.2 compares the results under different trade elasticities for solar and wind equipment. Higher trade elasticity in equipment amplifies the impact of subsidies, leading to a greater global market share. With $\theta^S = 10.6$, the US dominates the solar equipment market during the policy period and retains a substantial share even after the IRA expires, driven by accumulated productivity gains from increased production. The beggar-thy-neighbor effect of the equipment subsidy is minimal compared to the positive spillovers; the 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 arises 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: $A^j_{n,t}, \sigma^j_n, \alpha, d^j_{in,t}, \tau^j_{in,t}, \mu^j_n, \gamma^j_{n,t}, \gamma^{L,j}_{n,t}, \gamma^{M,j'j}_{n,t}, \gamma^{j',j}_{n,t}, \eta^j \ \ \forall j, n, t$

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

$$I^k_{n,t} \quad = \quad \varphi^k_{n,t} K^k_{n,t}. \tag{D.1}$$

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

Table C.2: Robustness Check

	Global CO_2	Global Welfare	US Welfare	Peak US Solar Equip. Share
(a) 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%
(b) 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%
(c) 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%
(d) 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%

(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 $k \in \Omega_K$.

(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 $\{\varphi^k_{n,t}\}^{T,N}_{t=1,n=1}$, $\mathbf{k}^k_2$ is determined by (20) and (D.1). That is,

$$K^k_{n,2} = \chi_k\left(\varphi^k_{n,1}K^k_{n,1}\right)^{\alpha}(K^k_{n,1})^{1-\alpha} + (1-\delta)K^k_{n,1}$$

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

4. Plug the values to each $K^k_{n,t}$ in the Euler Equation to compute the excess demand $Z^k_{n,t}$ for 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.

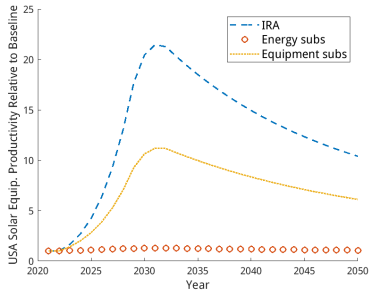
$$\{\varphi^{k,NEW}_{n,t}\}^{T,N}_{t=1,n=1} = \varphi^k_{n,t} + \psi Z^k_{n,t}(\{\varphi^k_{n,t}\}^T_{t=1}) \tag{D.4}$$

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

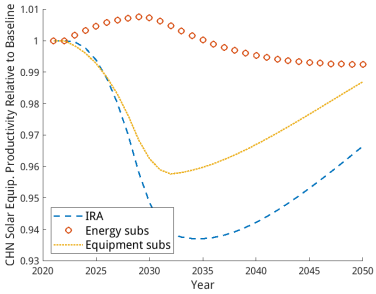
Appendix E Additional Figures

Figure E.1: Equipment Productivity

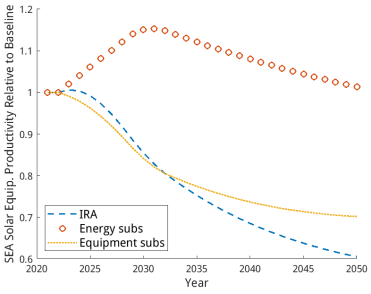
(a) US (solar equipment)



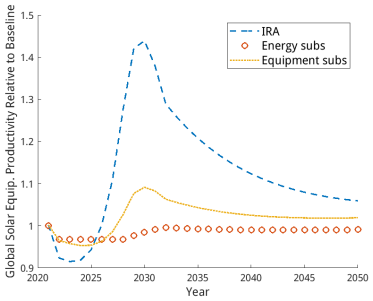
(b) China (solar equipment)



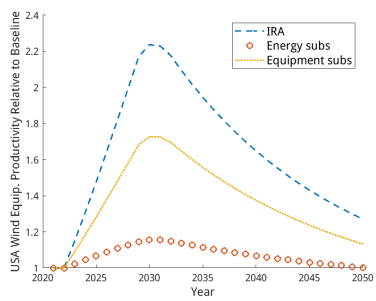
(c) Southeast Asia (solar equipment)



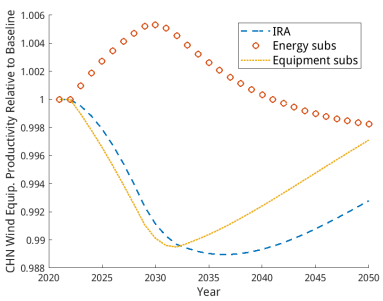
(d) Global (solar equipment)



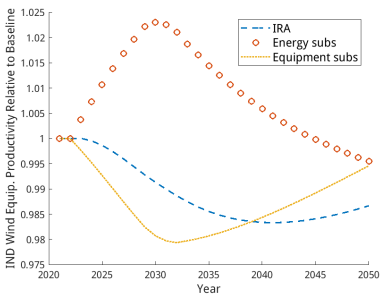
(e) US (wind equipment)



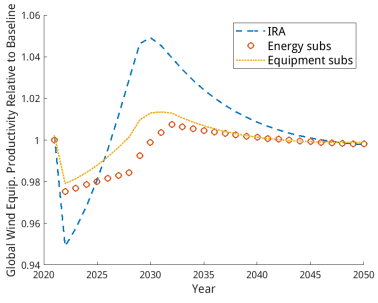
(f) China (wind equipment)



(g) India (wind equipment)



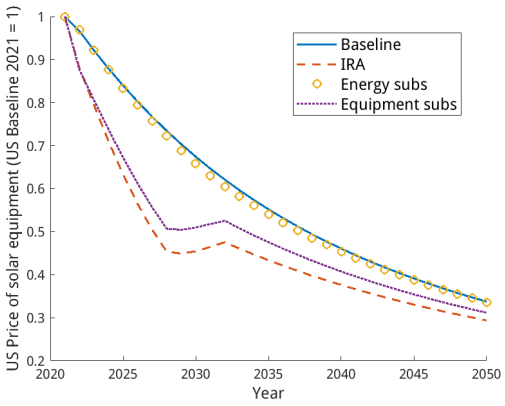
(h) Global (wind equipment)



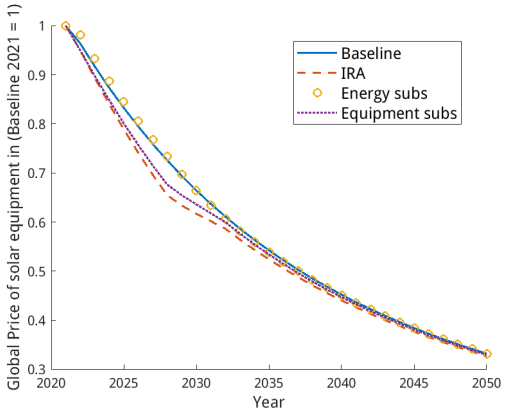
Note: Each panel plots the effect of subsidies on equipment productivity relative to the productivity under baseline. Impact of IRA is plotted by blue dashed line, energy subsidy by red circles, and equipment subsidy by yellow dotted line.

Figure E.2: Equipment Price

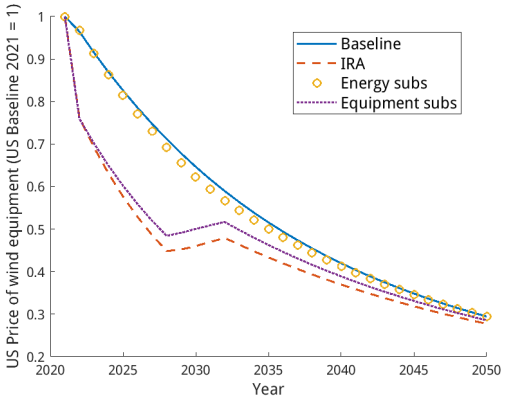
(a) US Solar Equipment Price



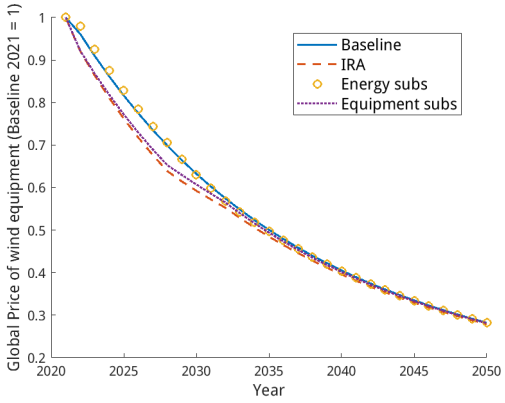
(b) Global Solar Equipment Price



(c) US Wind Equipment Price



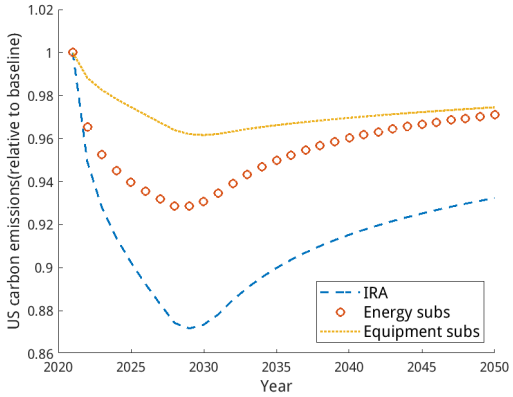
(d) Global Wind Equipment Price



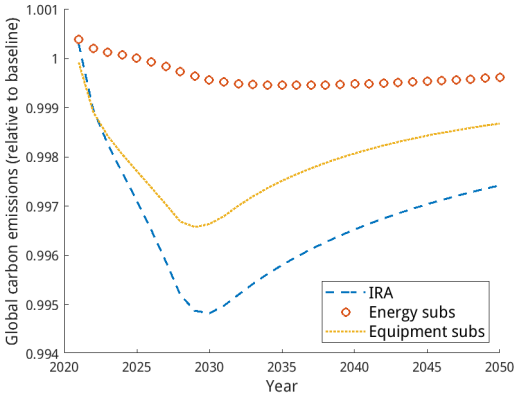
Note: Each panel plots the effect of subsidies on equipment price, in the US (panel (a) and (c)) and the aggregated global (panel (b) and (d)). Baseline price is plotted by blue solid line, price under IRA is plotted by red dashed line, energy subsidy by yellow circles, and equipment subsidy by purple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

Figure E.3: Change in Carbon Emissions

(a) US



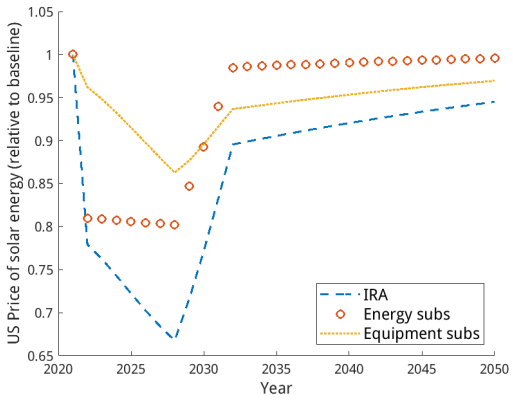
(b) Global (excluding US)



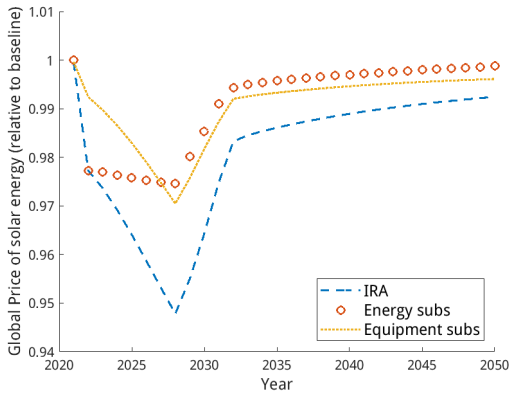
Note: This figure plots the relative change in the US (panel (a)) and non-US global (panel (b)) carbon emissions under IRA (blue dashed line), energy subsidy (red circles), and equipment subsidy (yellow dotted line).

Figure E.4: Renewable Energy Price

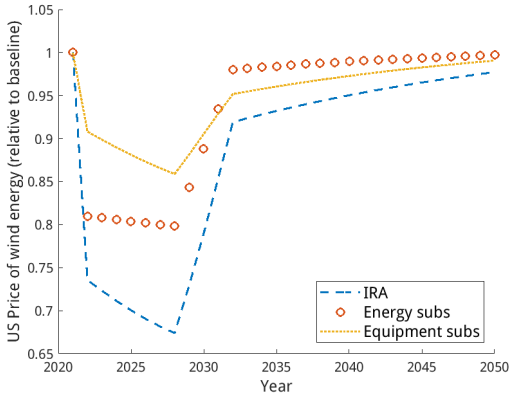
(a) US Solar Energy Price



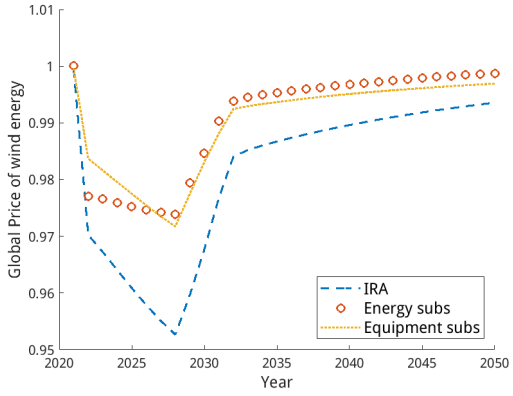
(b) Global Solar Energy Price



(c) US Wind Energy Price



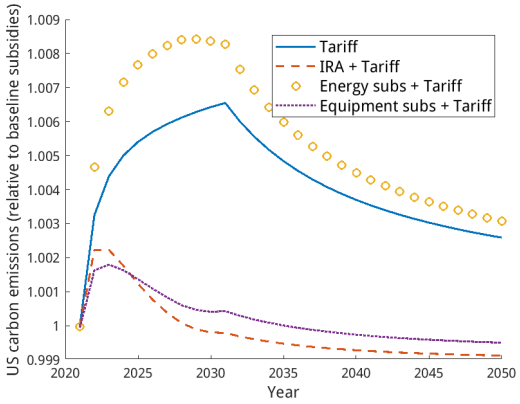
(d) Global Wind Energy Price



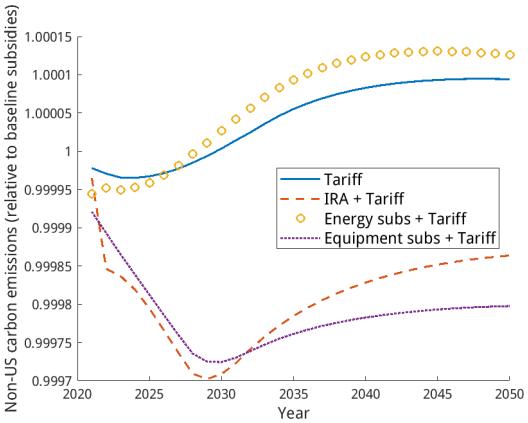
Note: Each panel plots the effect of subsidies on solar and wind energy price, in the US (panel (a) and (c)) and the aggregated global (panel (b) and (d)). The prices are relative to the baseline prices in *each time period*. Prices under IRA are plotted with blue dashed lines, energy subsidy with red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

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

(a) US

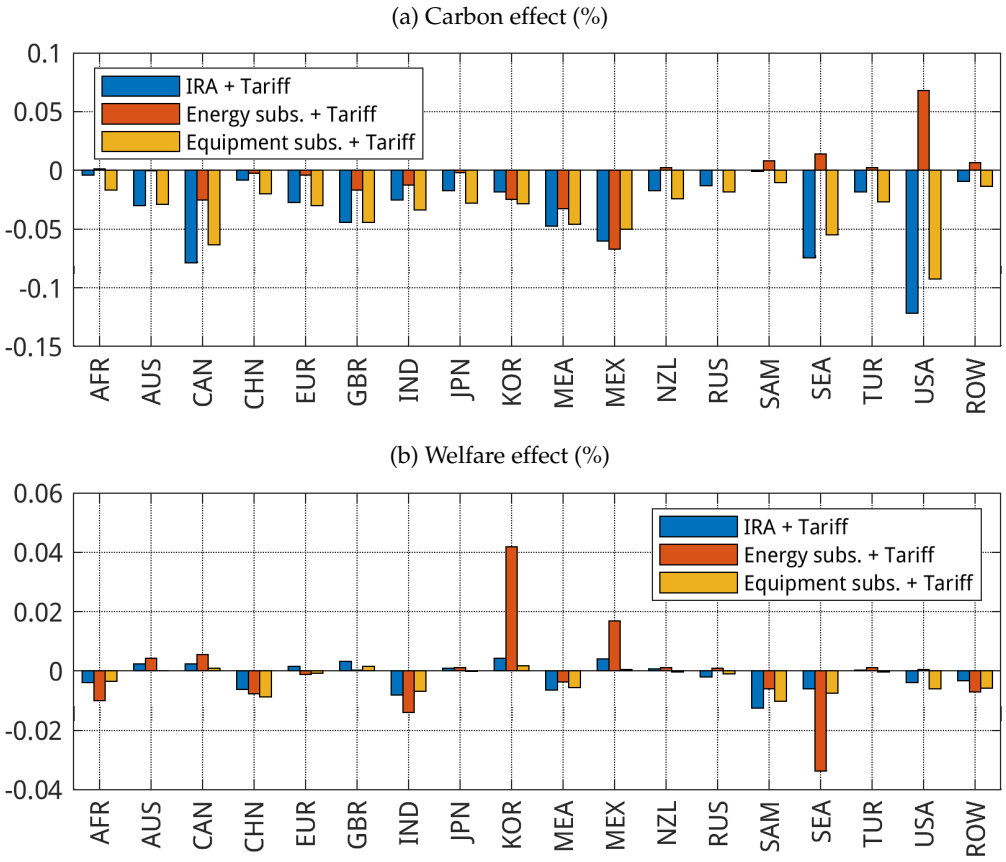


(b) Global (excluding US)



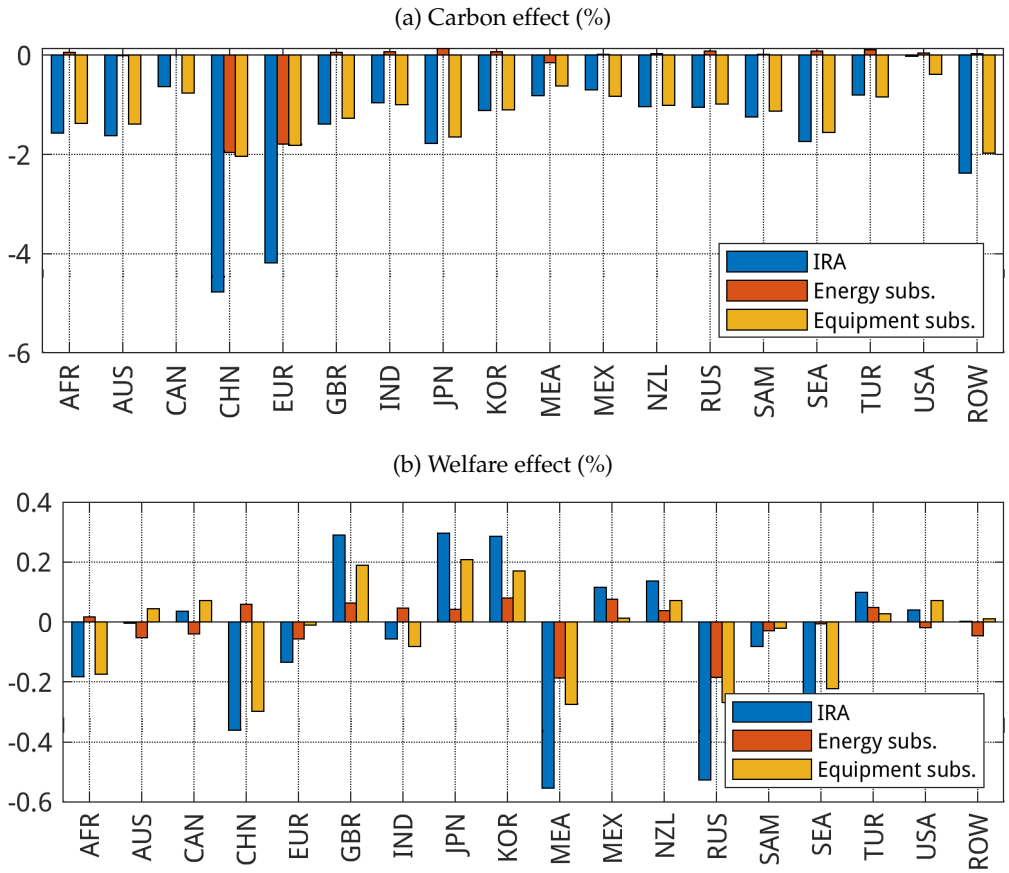
Note: This figure plots the relative change in the US (panel (a)) and non-US global (panel (b)) carbon emissions under solar tariff (blue solid line), solar tariff combined with IRA (red dashed line), energy subsidy (yellow circles), and equipment subsidy (purple dotted line), relative to corresponding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

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



Note: Panel (a) plot the effect of IRA under US imposing solar equipment tariff on global accumulated carbon emissions by 2100 relative to the corresponding subsidies without the tariff. Panel (b) plot the effect of IRA with solar equipment tariff on welfare for residents across countries.

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



Note: The figures plot the global accumulated carbon emissions by 2100 (panel (a)) and the welfare (panel (b)) across countries when the US, China, and EU implement identical green industrial policies to IRA relative to the baseline scenario.