Green Industrial Policy in a Globalized Economy [*†]

Sungwan Hong
University of Pittsburgh

June 2026

Abstract

This paper studies green industrial policy when clean-energy equipment is traded internationally but electricity generation is local. I develop a dynamic multi-country general-equilibrium trade model with solar and wind equipment, learning-by-doing, and a global carbon externality. The two policy margins act through different channels: subsidizing renewable *deployment* raises demand for largely imported equipment, shifting production and learning abroad, whereas subsidizing equipment *manufacturing* expands home production but lets the cost declines it induces diffuse to all producers. Green industrial policy is therefore a problem of *assignment*: the country with the strongest national incentive to subsidize need not be the one whose support generates the largest global gains. The equipment subsidy the U.S. would choose on its own lowers world real GDP and yields the U.S. only small gains; deployment support does the reverse, raising world welfare with no unilateral gain to the U.S.; and China, whose equipment support would help the world most, would lose by providing it. Coordinating deployment in importing markets with equipment support at the production hub, once carbon is priced, makes every participant better off.

JEL: F13, F18, O25, Q42, Q54, Q56

Keywords: Green Industrial Policy, Inflation Reduction Act, Energy Transition, renewable-energy equipment trade

[*]I am grateful to Fernando Parro, Jingting Fan, and Stephen Yeaple for their guidance. I appreciate suggestions and comments from Kai-Jie Wu, Seula Kim, Yan Bai, Xiang Ding, Sharat Ganapati, Costas Arkolakis, Haruka Takayama, David Hemous, Konstantin Kucheryavyy, Johannes Boehm, Eugenie Dugoua, David Atkin, George Alessandria, Allan Hsiao, and seminar and conference participants. I am especially grateful to Jevan Cherniwchan and Dongkyu Yang for valuable discussions. All errors are mine.

[†]Correspondence by email: sungwan.hong@pitt.edu

1 Introduction

Green industrial policy involves two design choices, not one: which margin to subsidize, and where to locate support. A subsidy can be attached to downstream *deployment* of clean energy, or to upstream *manufacturing* of clean inputs; support can also be located in a large deployment market, such as the United States or Europe, or in an incumbent equipment producer, such as China. The U.S. Inflation Reduction Act (IRA) provides a salient benchmark because it combines demand-side subsidies for renewable-energy production with supply-side support for domestic manufacturing of renewable-energy equipment—henceforth, the *deployment subsidy* and the *equipment subsidy*.[1] Although these instruments are implemented at the national level, equipment production is embedded in global supply chains, so two policies that raise renewable capacity by the same amount can direct income, production, and learning to entirely different countries.

The open-economy incidence of these policies hinges on a basic asymmetry: renewable electricity is rarely traded across borders, whereas its equipment—solar panels and wind turbines—is heavily traded and concentrated in a few producers. The U.S. and EU meet about 85% and 95% of domestic solar-equipment demand with imports, respectively, while China produces roughly 80% of global supply. These facts make green industrial policy a policy-assignment problem: the country with the strongest national incentive to subsidize a margin need not be the one whose support generates the largest global spillovers, so the location of support, not only its size, determines who gains at home and abroad. Equipment is a small share of world output, but its leverage is not: as the upstream input whose cost, through learning-by-doing, sets the future global price of abatement, and as the channel through which a national subsidy transmits to other countries, it shapes emissions and the incidence of policy far out of proportion to its size. Most quantitative evaluations abstract from this traded-equipment margin and the associated cross-border incidence (Arkolakis and Walsh, 2023; Bistline et al., 2023; Casey et al., 2023; Donald, 2024; Gentile, 2024).

This paper compares the domestic and global consequences of these subsidy instruments and locations in an open economy, using the IRA as a quantitatively relevant benchmark. I build a multi-country dynamic general equilibrium model with international input–output linkages à la Caliendo and Parro (2015) in which (i) solar and wind equipment are traded capital goods that accumulate over time; (ii) electricity is produced with installed renewable-energy equipment and fossil inputs in a nested constant-elasticity-of-substitution (CES) energy block; (iii) equipment productivities evolve endogenously via external learning-by-doing (LBD); and (iv) CO_2 emissions generate a global externality. Policy enters as ad valorem output support to renewable electricity (the deployment subsidy) or to equipment manufacturing (the equipment subsidy), allowing a direct comparison of their transmission channels and incidence, as well as counterfactual policy assignments across major de-

[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.

ployment markets and equipment producers.

Two features organize the open-economy incidence of green industrial policy. First, renewable electricity is effectively non-tradable while equipment is heavily traded and the U.S. is a net importer: a *deployment subsidy* loads onto a domestic renewable–fossil wedge but meets much of the induced equipment demand through imports, so terms-of-trade and world-price effects shape cross-border incidence, whereas an *equipment subsidy* operates on traded margins, expanding domestic manufacturing and lowering the world equipment price. Second, because equipment productivity evolves through learning-by-doing, today's geography of production shapes the future global cost of clean inputs. Together these features make incidence depend on a country's net equipment-trade position, so the same subsidy yields different national returns for a large importer, a potential entrant, or an incumbent hub.

Whether a subsidy raises or lowers world welfare follows from comparative advantage in equipment production. Because equipment is produced most cheaply by a few incumbents, a subsidy that pushes production toward that low-cost location raises world real GDP, while one that pulls production toward a high-cost producer lowers it. A deployment subsidy sources its induced capacity from the cheapest suppliers and so moves with comparative advantage; an equipment subsidy in a high-cost importer works against it, expanding the global surplus less than it raises that importer's own welfare, while the same subsidy in the low-cost incumbent reinforces the efficient allocation. This is why the location of support, not the choice of instrument, signs its world return.

The geography of learning sharpens this. Because most of the cost decline a manufacturing subsidy finances diffuses across borders—I estimate a local share near 0.16 for solar—an importer that subsidizes to build a domestic base captures little of the gain, while the low-cost incumbent that could deliver it has no private reason to act. The efficient location for equipment support and the willing one come apart; coordination, once carbon is priced, can bring them back together.

These channels imply opposite cross-country incidence: equipment exporters gain from foreign deployment subsidies but lose under foreign equipment subsidies, while net importers benefit from the latter. Because the climate benefit is shared but the real-income component can move in opposite directions, welfare differs by country—so whether the IRA or its components are net beneficial for a given country, or for the world, is a quantitative question.

The model is disciplined by country–sector data from input–output tables and trade flows, augmented with geospatial measures of renewable potential (solar irradiance and wind resource) that anchor cross-country absolute advantage and within-country decreasing returns. The central dynamic margin is equipment learning: using trade-share-implied productivity movements and cumulative output, I discipline the solar and wind learning elasticities and, crucially, the *local content* of that learning—the share of the cost decline that stays with the producing country. The estimated local share is small for solar (about one-sixth, so learning is mostly a global spillover) and larger for wind. I also estimate the solar–wind substitution elasticity to discipline the energy mix. Together,

these primitives govern the transition speed in each country: faster where renewable potential, substitutability, and learning are stronger, and slower where they are weaker.

With the model disciplined by data, I quantify how emissions, welfare, and aggregate efficiency depend on which margin is subsidized and where. Welfare is a consumption-equivalent variation that combines a real-income component with a climate component valued at a social cost of carbon; I report *world real GDP*—the GDP-weighted change in real income—separately, as a measure of aggregate efficiency that excludes the carbon channel.

Main quantitative findings. First, the IRA cuts emissions and raises world welfare but delivers no national gain to the U.S.: it lowers global CO_2 by 0.443% and raises world welfare by 0.030%, yet leaves U.S. welfare slightly negative (-0.060%). The two instruments reach the world differently. The deployment subsidy sources its induced capacity from the lowest-cost producers, moving *with* comparative advantage: it raises world welfare and cuts emissions at little national cost. The equipment subsidy does the opposite—by steering production toward the high-cost U.S., it lowers world real GDP and adds little to world welfare.

Second, the equipment subsidy earns the U.S. essentially no national return: the learning it finances is mostly global, so a domestic subsidy pays for an advantage that largely accrues to competitors. A U.S. equipment subsidy at IRA scale leaves U.S. welfare slightly negative (-0.014%); even the U.S.-optimal equipment subsidy rate is only about a third of the IRA's, and the national gain there remains negligible.

Third, the location that *should* subsidize manufacturing has no private reason to. Because China is the low-cost producer, a Chinese equipment subsidy reinforces the efficient allocation: it raises world welfare ($+0.075\%$), cuts global emissions most, and delivers a large real-income gain to the U.S. ($+0.105\%$) as a net importer of cheaper equipment. But it lowers China's own real income (-0.067%), so the incumbent would not act unilaterally—the assignment problem in its sharpest form.

Finally, coordination resolves the misalignment once carbon is priced. Pairing deployment support in large importing markets with manufacturing support at the production hub places each instrument where it does the most good. A package combining U.S. and EU deployment support with Chinese equipment support cuts global CO_2 by 0.30% and makes every participant better off. These magnitudes depend on equipment trade, the locality of learning, trade elasticities, fiscal incidence, and welfare weights.

Related Literature. First, this paper relates to the industrial-policy literature in open economies, from classical analyses (Baldwin, 1969; Bardhan, 1971; Ethier, 1982; Krugman, 1987) to recent quantitative trade evaluations (Goldberg et al., 2024; Lashkaripour and Lugovskyy, 2023; Ju et al., 2024; Bartelme et al., 2025; Choi and Levchenko, 2025). It adds to this literature by analyzing the global welfare implications of unilateral green industrial policies in a dynamic open-economy framework that combines a *global* carbon externality with production-linked learning in renewable-

equipment manufacturing, allowing carbon benefits and real-income incidence to diverge across countries.

Second, this paper contributes to the general-equilibrium analysis of clean-energy subsidy design—including IRA provisions—by contrasting *deployment* subsidies with *equipment*-manufacturing support in a dynamic *open-economy* setting.[2,3] Such analyses are typically closed-economy (Donald, 2024; Gentile, 2024; Casey et al., 2023; Bistline et al., 2023); the closest open-economy work, Arkolakis and Walsh (2023), develops a dynamic spatial model with a detailed electricity grid but evaluates the deployment subsidy alone, abstracting from equipment trade. Equipment trade makes the *location* of support decisive: it is what turns subsidy design into an assignment problem and gives deployment and equipment support their opposite cross-country incidence, through traded-input prices, terms of trade, and the reallocation of learning.[4] Finally, causal evaluations of Chinese solar industrial policy (Banares-Sanchez et al., 2026) identify large within-country responses; I complement them by quantifying the *global* incidence once clean equipment is traded and learning is mostly global.

Third, the paper builds on quantitative trade models with input–output linkages and multi-sector, multi-country structure, and on the environmental trade literature that emphasizes leakage, terms-of-trade, and coordination. The model adopts gravity-based discipline for trade elasticities and sectoral structure (Eaton and Kortum, 2002; Caliendo and Parro, 2015; Eaton et al., 2016), embeds an explicit energy nest, and features traded renewable-energy equipment with dynamic costs. Taken together, these elements allow standard general-equilibrium channels to interact with energy transition and the geography of upstream clean-technology goods production, connecting to recent work on trade and the environment (Shapiro, 2021; Kortum and Weisbach, 2021; Xiang, 2023; Cruz and Rossi-Hansberg, 2024; Caliendo et al., 2024; Garcia-Lembergman et al., 2023; Farrokhi and Lashkaripour, 2025; Hsiao, 2024). Unlike trade-and-environment models centered on the carbon embodied in traded goods or on emissions leakage, this paper concerns trade in the *capital goods* that determine the future cost of abatement.

Fourth, the paper connects to work on directed technical change and clean innovation (Acemoglu et al., 2012; Aghion et al., 2015). The premise that policy can durably lower clean-technology costs is common to both, but where that literature studies the *direction* and incentives of innovation, I take cost declines as production-linked learning-by-doing and ask how its *geography*—where production, and hence learning, locates—shapes the open-economy incidence of green industrial policy. It is the location of learning, not the pace of innovation, that signs the national return to a subsidy and divides

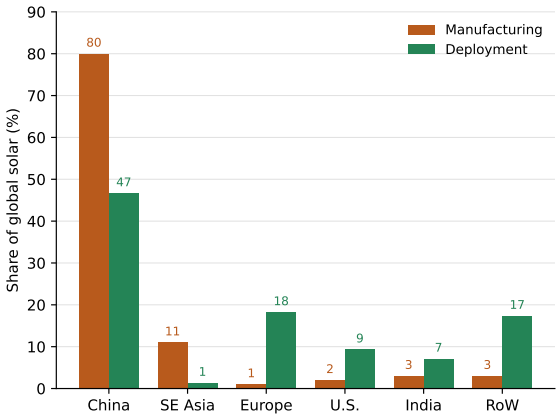
[2] For empirical evidence on within-country effects of deployment (renewable-output) subsidies, see Aldy et al. (2023); Gerarden (2023); De Groote and Verboven (2019); Gugler et al. (2021); Hitaj and Löschel (2019).

[3] Bollinger et al. (2024) study the impact of solar tariffs within the U.S. and explore the counterfactual effects of solar-equipment subsidies. I differ by focusing on the comparative global effects of deployment and equipment subsidies using a dynamic general-equilibrium model that incorporates learning-by-doing in both solar and wind.

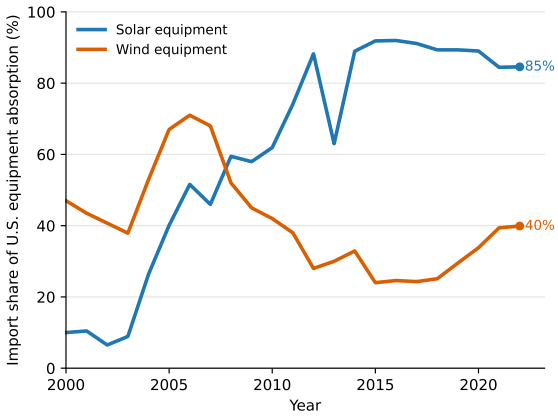
[4] Relatedly, Shin (2024) studies climate-policy incidence through factor-reallocation frictions; I instead emphasize dynamic equipment trade.

Figure 1: Renewable-Equipment Production, Deployment, and U.S. Import Reliance

(a) Where solar equipment is made vs. deployed, 2022



(b) U.S. import penetration



Note: Panel (a) compares regional shares of global solar-equipment manufacturing (amber) and deployment (green); manufacturing shares are 2022 production-origin shares (China ≈80%) and deployment shares are based on solar capacity additions. Panel (b) reports U.S. solar-module import penetration and a component-weighted U.S. wind-equipment import-exposure proxy, 2000–2022. See Appendix B.3 for sources.

its gains across trading partners.

2 Background

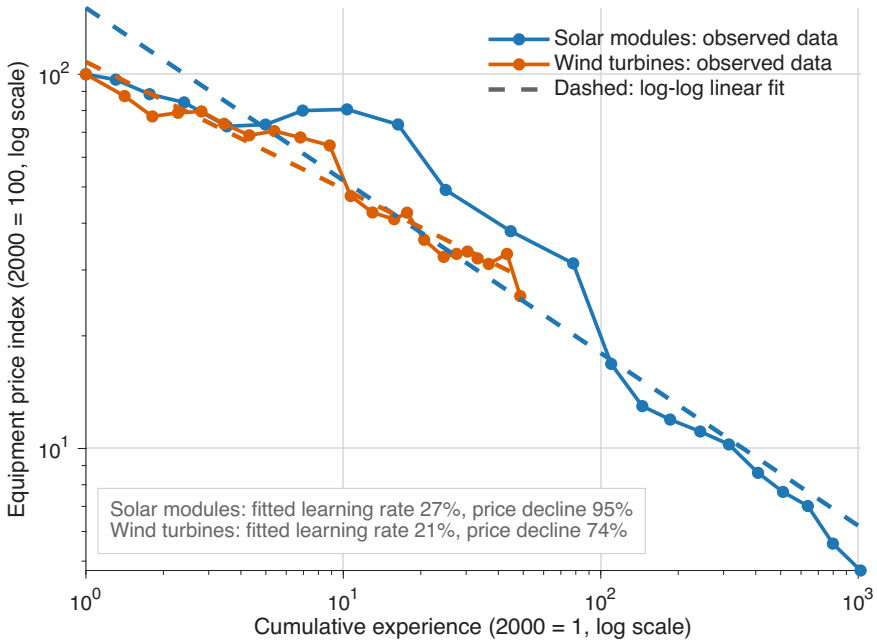
2.1 Production, Deployment, and Trade in Renewable-energy Equipment

I document two facts about the geography of renewable-energy equipment.[5] Although renewable electricity is generated locally, the equipment used to build that capacity is (i) produced in a few concentrated supply chains that are largely separate from where it is deployed, and (ii) increasingly supplied to the United States through imports.

Panel (a) of Figure 1 contrasts where solar equipment is *manufactured* with where it is *deployed*. The two diverge sharply: China and Southeast Asia together produce about 91% of global solar equipment but account for only about 58% of deployment, whereas Europe, the United States, and the rest of the world deploy far more than they manufacture—the United States installs roughly 8% of global capacity while producing about 2%. Because equipment is tradable, this gap is bridged by large cross-border flows. Panel (b) traces the U.S. side of that bridge: the imported share of U.S. solar-equipment absorption rose from about 10% in 2000 to 85% in 2022, while a separate component-weighted proxy for U.S. wind-equipment import exposure stands at about 40%. Production is thus concentrated where deployment is not, so the geography of manufacturing—and hence of learning-by-doing—differs from the geography of use. This separation is what makes equipment

[5] For details on the data used in this section, see Appendix B.3.

Figure 2: Equipment Prices and Cumulative Experience



Note: Prices are indexed to 100 in 2000. Solar experience is cumulative global PV module production; wind experience is cumulative global installed wind capacity. Dashed lines are fitted log–log relationships.

trade, and the location of the learning it carries, central to how green industrial policy operates and to who gains from it.

2.2 Equipment Cost Declines and Learning-by-Doing

The cost of renewable electricity is driven primarily by the cost of equipment. Figure 2 plots equipment price indexes against cumulative experience. Solar module prices fell by 95% between 2000 and 2021, while wind turbine prices fell by 74%. A simple log–log fit implies price declines per doubling of cumulative experience of about 27% for solar modules and 21% for wind turbines.[6]

Because equipment production is concentrated in a few countries while deployment is widespread (Figure 1, panel (a)), the geography of learning is central to subsidy design. If learning is localized—tied to a country's own production—then policies that redirect manufacturing toward domestic producers generate persistent dynamic gains at home. If learning is global—driven by world cumulative output regardless of geographic origin—then the location of production matters less for future costs. The estimation evidence in Appendix B.4 helps discipline the plausible range of this local tacit share.

Together, these facts establish the two features at the heart of the paper. One is static: the capital goods are produced in a few locations and traded widely, while the electricity they generate is local.

[6]This figure is descriptive. The quantitative model uses the estimates in Appendix B.4 to discipline the total learning elasticity ν_{tot} and the local tacit share λ_L.

The other is dynamic: producing the equipment lowers its future cost through learning-by-doing, and how local that learning is determines whether moving production also moves those gains—or leaves them shared across all producers. The next section develops the model in which subsidy incidence depends on production location, equipment cost shares, and the geography of learning.

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 structure extends Caliendo and Parro (2015) with detailed energy production, while the dynamic block adds capital accumulation and external learning-by-doing in equipment production.

The model has two parts linked by two state variables. The world is solved as a sequence of within-period ("static") equilibria, connected across periods by laws of motion ("dynamic") for the installed stock of renewable-energy equipment in each country and for the productivity of that equipment. The analysis rests on three ingredients. First, solar and wind *equipment* is a tradable capital good, produced under Eaton–Kortum gravity, shipped across borders, and accumulated into a national stock. Second, electricity is generated from installed equipment together with fossil inputs through a nested-CES energy block, so the returns to equipment depend on the local resource base and on fossil prices. Third, equipment productivity rises through learning-by-doing that is external to the firm and only partly appropriable locally—the channel through which today's deployment lowers tomorrow's cost. Carbon emissions are a global externality. I present the static equilibrium first and then the laws of motion that connect successive periods.

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 model divides the economy into energy and non-energy sectors, further categorizing them into sub-sectors. 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 sectors include 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.[7]

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

Two objects are predetermined within each period and evolve only across periods: the installed stock of renewable-energy equipment $K^k_{n,t}$ and its productivity $A^k_{n,t}$. Both are taken as given in the within-period equilibrium of Section 3.3 and follow laws of motion—including the learning-by-doing process for equipment productivity—specified in Section 3.4.

3.2 Household

In each region n, the representative household is endowed with an initial stock of labor L_n and capital stocks $K^k_{n,1}$ for $k \in \Omega_K$. Labor is supplied inelastically and is mobile across sectors within each region. The representative household makes consumption ($C^j_{n,t}$) 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 μ^j_n with disutility from carbon emissions factored into the utility function:

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

The second term in square brackets 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 the household cannot directly choose.

The household's saving choice trades off consumption today against the accumulation of claims that finance consumption tomorrow, determining the supply of savings and the return that prices capital accumulation. Its static demands enter the within-period equilibrium below; the consumption–saving margin drives the dynamics of Section 3.4.

3.3 Static Equilibrium

Holding the equipment stock and its productivity fixed, I describe the within-period equilibrium—household demand, sectoral production, Eaton–Kortum trade shares, the nested-CES energy block, and market clearing—taking each in turn. I begin with production.

[7] While both solar and wind equipment production is concentrated at the country level, this does not necessarily imply that individual firms possess market power. For example, major wind equipment producers such as Gamesa, Vestas, and Nordex reported negative profit margins (EBITDA) in 2022. (U.S. Department of Energy (2023))

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. All goods are tradable in the model except renewable electricity. Once capital goods—solar and wind equipment, fossil-fuel capital goods, and non-energy capital goods—are produced, they are traded internationally and, when installed, they accumulate as capital stocks through investment. These capital stocks then serve as inputs into future production.

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

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

The production efficiency $z_n^j(\omega^j)$ is country- and sector-specific, capturing heterogeneity in solar and wind potential across countries. I assume within-country decreasing returns $\xi_n^j < 1$, which captures site-quality heterogeneity; I calibrate ξ_n^j using geospatial resource–supply curves in Section 4.2. The intuition is that as a country increases solar or wind equipment installations, areas with higher potential are utilized first, and additional installations are placed in locations with relatively lower potential *within* the country.

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

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

Due to the decreasing returns to scale, the unit cost of producing renewable energy rises as the stock of installed renewable-energy 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-energy equipment.

Fossil fuel energy production. Fossil fuel sector combines labor, fossil fuel capital, and intermediates in country n at time t:

$$y_{n,t}^f(\omega^f) \quad = \quad z_n^f(\omega^f)(L_{n,t}^f(\omega^f))^{\gamma_n^{L,f}}(K_{n,t}^F(\omega^f))^{\gamma_n^{F,f}} \prod_{j' \in \Omega_K^*} \left(M_{n,t}^{j'f}(\omega^f)\right)^{\gamma_{n,t}^{M,j'f}} \tag{4}$$

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

$$c^{f}_{n,t} = B^{f}_{n,t}(w_{n,t})^{\gamma^{L,f}_{n}}(r_{n,t})^{\gamma^{F,f}_{n}} \prod_{j'\in\Omega^{*}_{K}} \left(P^{j'}_{n,t}\right)^{\gamma^{M,j'f}_{n,t}} \tag{5}$$

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:

$$y^{r}_{n,t}(\omega^r) = \left[[\eta_r]^{\frac{1}{\rho}}[y^{s}_{n,t}(\omega^s)]^{\frac{\rho-1}{\rho}} + [1-\eta_r]^{\frac{1}{\rho}}[y^{w}_{n,t}(\omega^w)]^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{6}$$

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:

$$e_{n,t}(\omega^e) = \left[[\eta_e]^{\frac{1}{\psi}}[y^{r}_{n,t}(\omega^r)]^{\frac{\psi-1}{\psi}} + [1-\eta_e]^{\frac{1}{\psi}}[y^{f}_{n,t}(\omega^f)]^{\frac{\psi-1}{\psi}}\right]^{\frac{\psi}{\psi-1}}, \tag{7}$$

where η_e is a level shifter and ψ captures substitution elasticity between renewable energy and fossil fuel energy. These two nests capture distinct margins. The inner elasticity ρ summarizes how far annual solar and wind generation substitute; because their availability is imperfectly correlated, the two are imperfect substitutes ($\rho < 1$, gross complements). Because the model is annual, ρ captures this substitutability in reduced form and abstracts from the sub-annual dispatch and storage that govern intermittency proper. The outer elasticity ψ governs how far the renewable bundle as a whole displaces fossil generation as its relative cost falls.

Carbon emissions. Carbon emissions are proportional to fossil use and accumulate over time; there is no abatement technology, so decarbonization occurs only via a higher renewable share in the energy nest. Because a ton of CO_2 imposes the same marginal damage worldwide, no individual country internalizes the full social cost of its emissions; this environmental externality is distinct from the learning externality below, and the two together render the laissez-faire allocation inefficient.

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

Non-energy sectors production. Production technology for non-energy sectors, $j \in \Omega_E^*$, combines labor, non-energy capital $K_{n,t}^D$, and intermediates in country n at time t:

$$y_{n,t}^j(\omega^j) = z_{n,t}^j(\omega^j)(L_{n,t}^j(\omega^j))^{\gamma_n^{L,j}}(K_{n,t}^D(\omega^j))^{\gamma_n^{D,j}}\prod_{j'\in\Omega_K^*}\left(M_{n,t}^{j'j}(\omega^j)\right)^{\gamma_{n,t}^{M,j'j}}. \tag{8}$$

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

$$c_{n,t}^j = B_{n,t}^j(w_{n,t})^{\gamma_n^{L,j}}(r_{n,t})^{\gamma_n^{D,j}}\prod_{j'\in\Omega_K^*}\left(P_{n,t}^{j'}\right)^{\gamma_{n,t}^{M,j'j}} \quad \text{for } j\in\Omega_E^*, \tag{9}$$

where $B_{n,t}^j$ is a function of share parameters.[9]

For the equipment sectors, productivity $z_{n,t}^j$ for $j \in \Omega_{REE}$, is endogenously determined by learning-by-doing, with the exact specification provided in a later section (Section 3.4).

Composite intermediate goods. Composite intermediate goods in sector j are produced by aggregating a continuum of varieties using a standard Dixit–Stiglitz aggregator. The implied variety demand and sectoral price index are standard and reproduced in Appendix A.1. I retain only the notation $P_{n,t}^j$ in the main text.

Trade costs and prices (with production subsidies). Trade in tradable sectors faces iceberg costs: to deliver one unit of a sector-j variety from origin i to destination n, $\kappa_{ni}^j \geq 1$ units must be shipped, with $\kappa_{ii}^j = 1$. Policy enters as an origin-based ad valorem *production* subsidy $s_{i,t}^j \in [0,1)$, which scales down the producer's effective unit cost by a factor $(1-s_{i,t}^j)$.[10] Thus the purchaser price in destination n for variety ω^j is the minimum delivered cost across origins: $p_{n,t}^j(\omega^j) = \min_i\left\{\frac{c_{i,t}^j\kappa_{ni}^j(1-s_{i,t}^j)}{z_{i,t}^j(\omega^j)}\right\}$. I refer to $s_{n,t}^j$ applied to renewable-electricity sectors $j \in \Omega_{RE}$ (non-tradable) as the *deployment subsidy*, and to $s_{n,t}^k$ applied to tradable equipment sectors $k \in \Omega_{REE}$ as the *equipment subsidy*.

Following Eaton and Kortum (2002), productivities are Fréchet: $\Pr\left[z_{n,t}^j(\omega^j)\leq z\right] = \exp\{-A_{n,t}^j z^{-\theta^j}\}$, where $A_{n,t}^j$ is a country–sector technology level and θ^j governs dispersion.[11] In the quantitative exercises, time variation in $A_{n,t}^j$ is driven by learning-by-doing in the renewable-energy equipment sectors (Section 3.4), $j \in \Omega_{REE}$; for all other sectors, $A_{n,t}^j$ is time-invariant.

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

[10] Equivalently, the subsidy creates a wedge between the producer-side resource cost and the purchaser price.

[11] Following Caliendo and Parro (2015), I assume productivity draws are i.i.d. across varieties, sectors, and countries, and assume $1+\theta^j > \sigma^j$.

The implied sectoral price index in country n is

$$P_{n,t}^{j} = \left[\sum_{i} \left(c_{i,t}^{j} (1 - s_{i,t}^{j}) \kappa_{ni}^{j} \right)^{-\theta^{j}} A_{i,t}^{j} \right]^{-1/\theta^{j}}. \tag{10}$$

All sectors are tradable except renewable electricity: $\kappa_{ni}^{s} = \kappa_{ni}^{w} = \infty$ for $i \neq n$. Hence for $j \in \Omega_{RE}$ the price index simplifies to $P_{n,t}^{j} = c_{n,t}^{j}(1 - s_{n,t}^{j})(A_{n,t}^{j})^{-1/\theta^{j}}$, so other countries' deployment subsidies have no direct effect on renewable-electricity prices in n. By contrast, because equipment is tradable, an equipment subsidy in one country affects foreign equipment prices through (10) and reallocates trade shares.

Deployment subsidy transmission. Because renewable electricity is non-tradable, the deployment subsidy mainly operates on the domestic energy margin. In the nested CES energy block, the share of fossil fuel input in producing goods in sector j, $\gamma_{n,t}^{M,fj}$, is endogenously determined by

$$\gamma_{n,t}^{M,fj} = \gamma_{n,t}^{M,Ej} \left[1 + \frac{\eta_e}{1 - \eta_e} \left(\frac{P_{n,t}^{f}}{P_{n,t}^{r}} \right)^{\psi - 1} \right]^{-1}, \tag{11}$$

where $\gamma_{n,t}^{M,Ej}$ is the cost share of the composite energy input, $P_{n,t}^{f}$ is the fossil-energy price, and $P_{n,t}^{r}$ is the price of the renewable composite.[12] A deployment subsidy lowers the domestic renewable price $P_{n,t}^{r}$, narrowing the renewable–fossil wedge. When $\psi > 1$, this increases the renewable share and reduces domestic emissions. This domestic action also generates two international spillovers: (i) lower domestic fossil use depresses the world fossil price, inducing leakage abroad; and (ii) higher domestic deployment raises demand for tradable equipment, putting upward pressure on the global equipment price and potentially slowing the transition elsewhere.

Trade share. Trade flows are the fraction of country n's expenditure on sector j goods that is sourced from country i. Under Fréchet draws, the bilateral expenditure share $\pi_{ni,t}^{j}$—the share of country n's spending on sector j goods sourced from i at time t—is

$$\pi_{ni,t}^{j} = \frac{\left(c_{i,t}^{j} (1 - s_{i,t}^{j}) \, \kappa_{ni,t}^{j} \right)^{-\theta^{j}} A_{i,t}^{j}}{\sum_{m} \left(c_{m,t}^{j} (1 - s_{m,t}^{j}) \, \kappa_{nm,t}^{j} \right)^{-\theta^{j}} A_{m,t}^{j}}. \tag{12}$$

Because an equipment subsidy in exporter i lowers its delivered cost, the bilateral share $\pi_{ni,t}^{k}$ for any foreign buyer $m \neq n$ increases—i.e., $\partial \pi_{ni,t}^{k} / \partial s_{i,t}^{k} > 0$ by equation (12)—which raises shipments from i to n and thus increases exporter i's output in sector k. With country-specific learning-by-doing (introduced later in equation (19)), this accelerates i's future productivity growth and lowers its costs, which passes through into lower delivered equipment price indices $P_{n,t+\ell}^{k}$ abroad and, via cheaper

[12] Analogous expressions for other energy-input shares follow directly from the same CES aggregator; see Appendix A.2.

installations, lower renewable energy prices $P^r_{n,t+\ell}$ over time. By contrast, a renewable-deployment subsidy $s^r_{i,t}$ acts on a non-tradable good in our setting, so this cross-border reallocation channel is absent.

Lastly, from equation (12) the magnitude of the effect scales with the trade elasticity θ^k: higher θ^k amplifies the response of global market shares to a given price change induced by $s^k_{i,t}$.

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,

$$Y^j_{n,t} = \sum_{m=1}^{N} \frac{\pi^j_{mn,t}}{1 - s^j_{n,t}} X^j_{m,t}. \tag{13}$$

Equation (13) 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 $X^{F,k}_{n,t} = P^k_{n,t} I^k_{n,t}$ 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:

$$X^j_{n,t} = \sum_{j' \in \Omega} \gamma^{M,j'j}_n \gamma^{j'}_n Y^{j'}_{n,t} + X^{F,j}_{n,t}. \tag{14}$$

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

$$w_{n,t} L_{n,t} = \sum_{j \in \Omega} \gamma^{L,j}_n Y^j_{n,t}. \tag{15}$$

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

$$\sum_{k \in \Omega_K} r_{n,t} K^k_{n,t} = Y^s_{n,t} + Y^w_{n,t} + \gamma^{F,f}_n Y^f_{n,t} + \sum_{j \in \Omega^*_E} \gamma^{D,j}_n Y^j_{n,t}. \tag{16}$$

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 (14), the

trade-balance condition is

$$\sum_{j\in\Omega}\sum_{n=1}^{N}\frac{\pi^{j}_{in,t}}{1-s^{j}_{i,t}}X^{j}_{i,t}-D_{i,t}=\sum_{j\in\Omega}\sum_{i=1}^{N}\frac{\pi^{j}_{ni,t}}{1-s^{j}_{n,t}}X^{j}_{n,t}. \tag{17}$$

The left-hand side of equation (17) 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 subsidies, across all sectors j. I assume trade is balanced at the global level: the total trade deficits across all countries sum to zero, $\sum_i D_{i,t} = 0$, 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.

These conditions pin down all within-period prices, quantities, and trade flows, taking the equipment stock and its productivity as given. I now let those two objects evolve across periods.

3.4 Dynamics: Laws of Motion

Two objects evolve from period to period: equipment productivity, through learning-by-doing, and the installed capital stock, through investment net of depreciation.

Dynamic external economies in equipment production. Equipment learning has two components. A common global frontier captures codified process improvements, R&D-driven gains, common economies of scale, and technology embodied in tradable manufacturing equipment—turnkey production lines, supplier deepening, and standardized inputs—that diffuse across producers. A local component captures origin-specific tacit manufacturing capability—production know-how, organizational capital, idiosyncratic plant scale, and supplier networks tied to a particular national industry. The distinction follows the codified–tacit knowledge framework of Polanyi (1966) and Cohen and Levinthal (1990): codified knowledge moves freely across borders, while tacit knowledge is sticky to its production location.[13] The total elasticity ν^{k}_{tot} is therefore a reduced-form experience elasticity that bundles tacit learning, R&D-driven improvement, and economies of scale, net of exogenous input prices; λ^{k}_{L} splits this bundle into a locally-appropriable share and a global-spillover share.[14]

For the transition model, I write this externality in baseline-normalized form. Let $Q^{k}_{n,t}$ denote the real production-experience stock of country n in equipment sector k, initialized at a strictly positive

[13] This formulation generalizes the country-sector externality used in earlier versions of this paper. I abstract from cross-technology spillovers between solar and wind equipment; see Donald (2024) for an analysis of that margin.

[14] How global the frontier is depends on how far the manufacturing technology is embodied in tradable, standardized capital. Solar cell and module lines are largely purchasable turnkey, so process and scale gains diffuse rapidly across producers—hence a small λ^{S}_{L}. Wind-turbine production is more bespoke and regionally assembled, so more of its learning is origin-specific—hence a larger λ^{W}_{L}.

pre-sample value $Q^k_{n,0}$. The stock evolves according to

$$Q^k_{n,t+1} = \mu Q^k_{n,t} + y^{k,\text{real}}_{n,t}, \qquad k \in \Omega_{REE}, \tag{18}$$

where $\mu \in (0,1)$ governs the persistence of experience. Learning is driven by real equipment output, not subsidy-grossed nominal revenue. I measure real output as the physical quantity of origin-n equipment absorbed across all destinations,

$$y^{k,\text{real}}_{n,t} = \sum_m x^k_{mn,t},$$

equivalently nominal producer sales deflated by the producer-side equipment price. Let $Q^k_{W,t} \equiv \sum_i Q^k_{i,t}$ denote the global cumulative production stock. Equipment productivity is then

$$A^k_{n,t} = A^k_{n,0} \left(\frac{Q^k_{W,t}}{Q^k_{W,0}} \right)^{(1-\lambda^k_L)\nu^k_{\text{tot}}} \left(\frac{Q^k_{n,t}}{Q^k_{n,0}} \right)^{\lambda^k_L \nu^k_{\text{tot}}}, \qquad k \in \Omega_{REE}, \tag{19}$$

where $A^k_{n,0}$ is the initial EK Fréchet location parameter recovered from the baseline trade inversion, ν^k_{tot} is the total learning elasticity in the Fréchet location parameter, and $\lambda^k_L \in [0,1]$ is the local tacit share. Because the EK price index scales with A^{-1/θ^k}, the corresponding all-else-equal elasticity of the equipment price index with respect to cumulative experience is $\nu^k_{\text{tot}}/\theta^k$. The local tacit share governs how much of this Fréchet-location improvement is tied to where production occurs and therefore determines manufacturing-location rents and persistent national competitive advantage. The baseline-normalization keeps the calibrated initial productivity levels intact and avoids a zero-experience problem at $t = 1$.

Equation (19) is a Marshallian externality at the country-sector level: individual equipment producers are competitive and take $A^k_{n,t}$ as given, while aggregate cumulative production—both globally and within their country—feeds back into next-period productivity.[15] The baseline uses the global frontier stock $Q^k_{W,t}$, which includes own production; replacing it with $Q^k_{-n,t} = \sum_{i \neq n} Q^k_{i,t}$ would isolate foreign spillovers. The specification nests two extreme benchmarks. When $\lambda^k_L = 0$ (purely global frontier learning), origin shares are irrelevant for future productivity and the model reduces to a Lucas–Stokey-style global learning externality (Lucas, 1988; Stokey, 1988; Arkolakis and Walsh, 2023). Any $\lambda^k_L > 0$ produces a differential dynamic advantage between subsidized and unsubsidized

[15] External economies of scale of this kind can generate multiple equilibria in a static trade model with *contemporaneous* spillovers, and the conditions for a unique, well-behaved equilibrium are characterized by Kucheryavyy et al. (2023). That issue does not arise here: because $A^k_{n,t}$ is predetermined—it depends on *past* cumulative production through equation (18), not on contemporaneous output—each within-period equilibrium is a standard Eaton–Kortum gravity equilibrium with fixed productivities and is therefore unique. The increasing-returns nature of learning can in principle support multiple long-run steady states (history-dependent specialization); I solve the perfect-foresight transition from the calibrated initial allocation over a finite horizon rather than selecting among such steady states.

origins; the special case $\lambda_L^k = 1$ (purely local tacit learning) is the limit in which only domestic production feeds national productivity and the equipment subsidy concentrates all dynamic gains at home. For intermediate values, both channels operate. The two-component decomposition is closely related to the codified–tacit knowledge distinction in the technology-diffusion literature (Comin and Hobijn, 2010; Verdolini and Galeotti, 2011; Costantini et al., 2017) and to firm-level evidence on peer effects and local spillovers in clean-energy industries (Bollinger and Gillingham, 2012; van Benthem, 2015; Covert and Sweeney, 2024).

Capital accumulation. Capital evolves with convex installation costs as

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

where $\chi_k > 0$ scales installation efficiency, $\alpha \in (0,1)$ governs adjustment costs—so installation efficiency declines in $I_{n,t}^k / K_{n,t}^k$ (Eaton et al., 2016; Ravikumar et al., 2019)—and δ^k is depreciation. Investment equals purchases of capital good k by the representative household: $I_{n,t}^k = x_{n,t}^k$.

Household optimality. The household's within-period budget constraint is

$$\sum_{h \in \Omega_K^*} P_{n,t}^h C_{n,t}^h = w_{n,t} L_{n,t} + \sum_{k \in \Omega_K} r_{n,t}^k K_{n,t}^k - \sum_{j \in \Omega} \frac{s_{n,t}^j}{1 - s_{n,t}^j} \sum_{m=1}^{N} \pi_{mn,t}^j X_{m,t}^j + D_{n,t} - \sum_{k \in \Omega_K} P_{n,t}^k I_{n,t}^k \quad \equiv \quad E_{n,t},$$

where the left-hand side is expenditure on non-capital consumption goods. The right-hand side collects labor income $w_{n,t} L_{n,t}$, capital income $\sum_k r_{n,t}^k K_{n,t}^k$, subtracts the government's subsidy outlays in n (the term with $s_{n,t}^j$), adds trade deficit $D_{n,t}$, and subtracts investment spending. Thus $E_{n,t}$ denotes disposable expenditure available for consumption in period t.

Given prices and $E_{n,t}$, the household's within-period allocation across $h \in \Omega_K^*$ satisfies

$$P_{n,t}^h C_{n,t}^h \;=\; \mu_n^h \, E_{n,t}. \qquad h \in \Omega_K^*, \tag{21}$$

To characterize investment, define period utility as

$$u_t(C_{n,t}) \equiv \log C_{n,t} + \log\!\left(\tfrac{1}{1 + SCC_t (Z_t - Z_0)} \right), \quad C_{n,t} \equiv \prod_{j \in \Omega_K^*} (C_{n,t}^j)^{\mu_n^j},$$

and let $P_{n,t}$ denote the corresponding consumption price index, $P_{n,t} \equiv \prod_{j \in \Omega_K^*}^{J} \left(\frac{P_{n,t}^j}{\mu_n^j} \right)^{\mu_n^j}$. The capital-

accumulation equation (20) implies the Euler condition, for each $k \in \Omega_K$:[16]

$$\frac{u_t'(C_{n,t})}{u_{t+1}'(C_{n,t+1})} \frac{P_{n,t+1}}{P_{n,t}} \frac{p_{n,t}^k}{\chi_k} \left(\frac{I_{n,t}^k}{K_{n,t}^k}\right)^{1-\alpha} = \beta\alpha \left[r_{n,t+1}^k + \frac{(1-\alpha)\, p_{n,t+1}^k I_{n,t+1}^k}{\alpha K_{n,t+1}^k} + \frac{(1-\delta^k)\, p_{n,t+1}^k}{\alpha \chi_k} \left(\frac{I_{n,t+1}^k}{K_{n,t+1}^k}\right)^{1-\alpha} \right]. \tag{22}$$

The left-hand side is the marginal cost at t of delivering an additional unit of effective capital at $t+1$; the right-hand side is the discounted marginal payoff at $t+1$ (the rental return plus continuation value from capital and adjustment). An equipment subsidy reduces the equipment cost $p_{n,t}^k$, lowering the marginal cost of investment and therefore raising desired investment in renewable-energy equipment relative to other capital goods. Combined with the capital law of motion (equation (20)), this implies higher installation along the transition path and faster accumulation of renewable-energy equipment capital. Both instruments raise installed renewable capacity but enter this condition at different points: the deployment subsidy raises the marginal return to generation (the rental term $r_{n,t+1}^k$), while the equipment subsidy lowers the cost of acquiring capacity (the price $p_{n,t}^k$). The substantive question is therefore not whether each expands renewables but how the two compare in cost and in where the resulting rents accrue.

Steady state. In steady state, productivities A_n^k and capital stocks K_n^k are constant. The Euler equations (22) and the accumulation law (20) pin down (i) the investment–capital ratio for each k and (ii) the ratio of rental payments to investment spending:

$$\frac{I_n^k}{K_n^k} = \left(\frac{\delta^k}{\chi_k}\right)^{1/\alpha}, \qquad \frac{r_n^k K_n^k}{p_n^k I_n^k} = \frac{1-\beta+\beta\,\delta^k\alpha}{\beta\,\delta^k\alpha},$$

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

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:

$$W_n = \sum_{t=1}^{\infty} \beta^{t-1} \log\left(\frac{E_{n,t}}{P_{n,t}} \frac{1}{(1+SCC_t(Z_t - Z_0))}\right). \tag{23}$$

3.5 Sequential Equilibrium

Definition 1 summarizes the equilibrium conditions.

Definition 1. ***A sequential equilibrium of the model*** *is a set of prices* $\left\{w_{n,t}, P_{n,t}^j, r_{n,t}^k\right\}_{n=1,j=1,k=1,t=1}^{N,J,K,T}$ *and allocations of goods and labor* $\left\{\pi_{ni,t}^j, L_{n,t}^j\right\}_{n=1,i=1,j=1,t=1}^{N,N,J,T}$ *that satisfies the static equilibrium conditions: production (equations (2)-(9)), trade shares (12), local prices (10), labor and market*

[16] If $\alpha = 1$ and $\chi_k = 1$, this collapses to $\frac{u_t'(C_{n,t})}{u_{t+1}'(C_{n,t+1})} \frac{P_{n,t+1}}{P_{n,t}} P_{n,t}^k = \beta\left[r_{n,t+1}^k + (1-\delta^k)P_{n,t+1}^k\right]$.

clearing conditions (equations (15) *and* (16)*), and trade balance (17), and dynamic conditions: law of motion of capitals (20), and Euler equation (22).*

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

3.6 From Mechanisms to Quantification

The two subsidies act on different margins. Working through the price system (10)–(12) and the capital dynamics (20)–(22), the deployment subsidy concentrates abatement at home but pushes up the world equipment price, a negative spillover abroad. The equipment subsidy does the opposite: by reallocating production toward the U.S. it pushes the price down—a positive spillover. Whether it also moves future productivity to the U.S. through learning-by-doing (19), or instead cuts costs for all producers as a global spillover, depends on how local the learning is. The net effect on U.S. welfare, world welfare, and emissions is therefore ambiguous, depending on the trade elasticities θ^j, the renewable–fossil substitution ψ, the learning parameters ν^k_{tot} and λ^k_L, and renewable potential A^r_n. The rest of the paper quantifies it.

4 Calibration and Model Validation

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. Appendix B.2 shows the list of countries. For sectors, I aggregate into 10 categories: 3 energy sectors, 3 energy equipment sectors, and 4 additional sectors (Agriculture & Mining, Non-Durable Manufacturing, Durable Manufacturing, and Services).

4.2 Parameters in Renewable Energy Production

Data. I use three datasets: (i) geospatial resource potentials from the Global Solar and Wind Atlases (measured in kWh/m^2); (ii) renewable power-plant locations from the Global Solar and Wind Power Trackers, which catalogue utility-scale projects (capacity $\geq$ 10 MW) and cover roughly 70% of installed global capacity up to year 2021; and (iii) the Development Potential Index (DPI) of Oakleaf et al. (2019), which summarizes siting feasibility (physical and social constraints).[17]

Measuring the absolute-advantage parameter, A^r_n. A^r_n captures cross-country heterogeneity in renewable potential. To avoid overweighting infeasible sites in country averages of the Atlases, I compute $A^r_{n,1}$ from an *atlas–tracker matched* sample: the average resource potential at the locations

[17] Details are documented in Appendix B.5.1.

of solar and wind plants installed by 2021 (the initial calibration year). Panel (a) of Figure B.7 reports the cross-country distribution.[18]

Measuring decreasing returns, ξ_n^r. Within-country heterogeneity implies progressively lower-quality sites as deployment expands. Using DPI-weighted potential distributions, I construct each country's "resource supply curve" (best-to-marginal sites) and estimate its local slope around observed deployment, which I map into $\xi_n^r < 1$ via the elasticity of unit cost with respect to installed capacity in (3). Lower ξ_n^r steepens marginal cost growth, slowing the transition and raising the value of equipment efficiency gains. Panel (b) of Figure B.7 shows estimates; the means are $\overline{\xi}^s = 0.965$ (sd 0.004) and $\overline{\xi}^w = 0.954$ (sd 0.007), indicating stronger DRS and greater dispersion for wind.

In Appendix B.5.2, I also compute decreasing returns from an alternative source of variation: the relationship between renewable potential and the installed renewable capital stock. The result (Table B.4) shows that the change in capital stocks is also strongly negatively correlated with change in the renewable potential, confirming the decreasing returns to scale.

4.3 Estimating CES in Energy Production

Energy production in the model is a two–level CES. I estimate the *inner-nest* elasticity between solar and wind, ρ, directly from the model-implied log–log relationship

$$\log\left(\frac{y^s_{n,t}}{y^w_{n,t}}\right) = -\rho \log\left(\frac{p^s_{n,t}}{p^w_{n,t}}\right) + FE_n + FE_t + \varepsilon_{n,t}, \tag{24}$$

where FE_n and FE_t denote country and year fixed effects. Country fixed effects absorb time-invariant cross-country heterogeneity (e.g., average site quality), while year fixed effects flexibly capture common time-varying factors such as global technological progress, input-price movements, and other shocks shared across countries. Equation (24) corresponds to the demand system dual to the inner CES aggregator in equation (6).

Relative prices and quantities are jointly determined, so OLS is biased by simultaneity. To address this, I instrument $\log(p^s_{n,t}/p^w_{n,t})$ with wind subsidies that vary across country–year. The instrument is relevant because, under decreasing returns to scale, subsidies shift unit costs and therefore the relative price. The exclusion restriction is that wind subsidies affect the solar–wind output ratio only through the relative price $\log(p^s/p^w)$.[19]

Data. The data on solar and wind energy output (y^s, y^w) 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 for solar and wind (sourced from IRENA) with wind deployment subsidies (from OECD) for the years 2010-2021.

[18] Further details on the dataset are provided in Appendix B.5.2.

[19] Institutionally, feed-in tariffs/premia and production tax credits are set by policy processes with lags and are not mechanically tied to short-run demand conditions. Moreover, wind subsidies are frequently part of broader, long-term renewable energy strategies rather than reactive policies to short-term demand fluctuations.

Table 1: Estimates for Substitution Elasticity (Inner Nest)

	Dependent Variable: $\ln(y^s_{n,t}/y^w_{n,t})$			
	(1)	(2)	(3)	(4)
$\ln(p^s_{n,t}/p^w_{n,t})$	-1.067	-1.173	-0.332	-0.645
	(0.211)	(0.356)	(0.413)	(0.554)
Model F	25.56	56.19	54.00	
1st-stage F				52.46
N	144	144	144	144
Country FE		✓	✓	✓
Year FE			✓	✓
IV				✓

Note: The unit of observation is country-year. Standard errors are clustered at the country level and reported in parentheses.

Results. Table 1 reports estimates. OLS suggests an elastic response to relative prices; adding FE_n and FE_t attenuates the slope as expected. The preferred IV with country and year fixed effects delivers $\hat{\rho} = 0.645 < 1$, rejecting the perfect-substitutability benchmark often imposed in the literature. Because $\hat{\rho} < 1$, solar and wind energy are gross complements rather than substitutes: a rise in the relative price of one source does not crowd it out in favor of the other. This complementarity reflects the intermittency of both sources (Gentile (2024)): their production profiles do not align hour by hour. Solar output concentrates around midday and collapses after sunset (and on overcast winter days), whereas wind generation often peaks overnight and during shoulder seasons. This ρ pins down how quickly the renewable composite rebalances internally in response to relative cost shocks (e.g., targeted subsidies, equipment price movements) and, through the outer nest, how those shocks propagate to the fossil share via equation (11).

Outer nest. For substitution between the renewable composite and fossil, I set $\psi = 3.08$ from Jo (2025), within the range reported by Papageorgiou et al. (2017) and Wiskich (2023). Intuitively, renewables mostly supply on-grid electricity, while fossil inputs have broader end uses (e.g., internal combustion engines), rationalizing $\psi < \infty$.[20]

4.4 Equipment Learning Rates

The dynamic externality in equation (19) has two equipment-learning parameters: the total experience elasticity ν^k_{tot}, governing how fast the world equipment frontier falls with cumulative production, and the local tacit share λ^k_L, governing how much of that improvement is appropriable by the producing country. I identify them from two distinct moments—a world experience curve for ν^k_{tot} and a structural-gravity capability for λ^k_L—because they measure different objects (world cost de-

[20] Robustness to higher $\psi = 5$ is reported in Appendix C.9; the instrument ranking and the real-income incidence are unchanged—the larger welfare gains there reflect the bigger shared carbon benefit—though the share response in (11) scales proportionally.

cline versus own-country competitiveness). The full estimation, instruments, and robustness are in Appendix B.4; here I summarize the design and the resulting calibration.

Total elasticity. Because the equipment price index inherits the Eaton–Kortum structure, $P^k \propto A^{-1/\theta^k}$, the elasticity of the world price with respect to world cumulative output is $\nu^k_{\text{tot}}/\theta^k$, so the implied learning rate—the percent price decline per doubling of cumulative production—is

$$LR^k = 1 - 2^{-\nu^k_{\text{tot}}/\theta^k}. \tag{25}$$

Regressing the log world price on log world cumulative production, while controlling for the dominant traded input (polysilicon for solar, steel for wind) so that input-cost cycles are not mistaken for learning, yields $\nu^S_{\text{tot}} = 1.91$ for solar; the naive slope is inflated by the 2004–08 polysilicon shortage. This is statistically indistinguishable from the benchmark $\nu^S_{\text{tot}} = 2.00$ I adopt; evaluating (25) at the two elasticities gives $LR^S = 21.8\%$ at the estimated $\nu^S_{\text{tot}} = 1.91$ and $LR^S = 22.7\%$ at the adopted $\nu^S_{\text{tot}} = 2.00$, and the slope is robust to controls for the post-2010 surge in deployment and Chinese manufacturing subsidies (Appendix B.4, Table B.2). The wind price series is too short and trend-collinear to pin its slope, so I calibrate $\nu^W_{\text{tot}} = 1.00$ ($LR^W = 14.6\%$); both lie in the central range of the experience-curve literature (Nemet, 2006; Fraunhofer Institute for Solar Energy Systems, 2025; National Renewable Energy Laboratory, 2025; Wiser et al., 2024).

Local share. The total elasticity is silent on *where* learning accrues. I measure each country's equipment productivity by an exporter-by-year *capability* $\hat{S}^k_{n,t}$—the exporter fixed effect of a structural-gravity equation estimated on the full bilateral trade matrix (the exporter term of equation (12)). Regressing this capability on own cumulative production,

$$\log \hat{S}^k_{n,t} = \left(\lambda^k_L \nu^k_{\text{tot}}\right) \log Q^k_{n,t} + \delta^k_n + \delta^k_t + \varepsilon^k_{n,t}, \tag{26}$$

identifies the local component as the slope on own experience: the year effects δ^k_t absorb the common global frontier, leaving the part of productivity tied to a country's *own* accumulation. For solar the slope is 0.30, so $\lambda^S_L = 0.30/1.91 \approx 0.16$—about five-sixths of solar learning is a global frontier and one-sixth is locally appropriable. The estimate is robust to dropping China and to a leave-out global control, and, because own production is endogenous to subsidies, I instrument it with the staggered onset of destination feed-in-tariff programs, which yields a similar elasticity (Appendix B.4).[21]

Wind. For wind, a thinner manufacturer-level panel gives a larger own-country elasticity (≈ 0.6), so I adopt a conservative $\lambda^W_L = 0.50$ and read it as directional. The cross-technology comparison is what matters: light, modular, heavily traded solar modules learn predominantly globally, while

[21] A second, model-consistent route corroborates this. Regressing the EK-inverted *absolute* (frontier-preserving) equipment productivity—recovered as $(\text{price}/\text{input cost})^{-\theta}$ scaled by the domestic share—on own and leave-out-global cumulative production recovers a total elasticity near 2.0 (consistent with the world experience curve) and attributes most of it to the global term, implying a comparably small local share (around 0.15). The local share is imprecisely identified—own and global cumulative output are highly correlated—but both routes point to predominantly global learning.

heavier, regionally assembled wind turbines retain a larger locally-appropriable share—the codified-versus-tacit contrast of Section 3.4.

Relation to prior estimates. Country-level learning differs from the global experience rates common in the literature (Arkolakis and Walsh, 2023), where the aggregate fit is driven by China because most output originates there. The decomposition is consistent with that evidence—a dominant global frontier ($1-\lambda_L^S = 0.84$ for solar) plus a smaller locally-appropriable component—and with patent evidence that codified knowledge crosses borders (Bahar et al., 2014). The leaky solar share is the conservative benchmark for the paper's central result: it is the case least favorable to a durable U.S. manufacturing advantage, so the equipment-subsidy returns reported below are, if anything, understated relative to a more local reading.

Calibration. The benchmark sets $\nu_{\text{tot}} = (2.00, 1.00)$ and $\lambda_L = (0.16, 0.50)$ (Table 3). For solar this means $(1-\lambda_L^S)\nu_{\text{tot}}^S = 1.68$ operates through the global frontier and only 0.32 is local-tacit. The local share is the parameter the central policy result turns on: it is what makes an equipment subsidy build a *durable* national advantage rather than a fleeting one. I treat the no-learning, fully global ($\lambda_L = 0$), and pure-local ($\lambda_L = 1$) cases as robustness bounds (Appendix C.9) rather than the baseline.

4.5 Trade Elasticities

Trade elasticities (θ^j) discipline how strongly delivered-price changes from policies reallocate expenditure across suppliers within each sector. I calibrate θ^j to product- or sector-level estimates.

Renewable-energy equipment sectors. For solar and wind equipment, because the equipment sectors are broader than single HS6 products, I use pooled ICIO sector-level elasticities from Fontagné et al. (2022): for solar equipment, $\theta^S = 5.38$; for wind equipment, $\theta^W = 4.38$. The relatively higher θ^S versus θ^W implies that an equal ad-valorem equipment subsidy generates a larger shift in global market shares in solar equipment than in wind, magnifying the trade-share channel and the learning-by-doing amplification discussed in Section 3.6.

Other tradable sectors. For broader aggregates I adopt estimates from multi-sector Eaton–Kortum calibrations: agriculture 8.11, durable manufacturing 5.26, non-durables 4.55, services 4.55, and fossil fuels 15.08, matched from Parro (2013) and Caliendo and Parro (2015).

Non-tradable energy (solar, wind). Although solar and wind *energy* are non-tradable ($\kappa = \infty$ across borders), θ^j still governs within-country variety dispersion in the sectoral price index. I set $\theta^s = \theta^w = 4.55$ which is the average elasticity in Caliendo and Parro (2015).

4.6 Other Parameter Values and Initial Values

Shares 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 con-

Table 2: Trade Elasticities (θ^j)

Sectors	**Trade Elasticity** (θ^j)
Solar Energy	4.55
Wind Energy	4.55
Fossil Fuel	15.08
Solar Equipment	5.38
Wind Equipment	4.38
Agriculture and Mining	8.11
Non-Durable Manufacturing	4.55
Durable Manufacturing	5.26
Service	4.55

sumption. For each sector, input shares are measured as payments to labor, capital, and intermediates divided by gross output. A challenge is that the dataset does not separately report labor vs. capital value added. Following Greenwood et al. (1997), I assume a capital share of 0.3 in value added to split the total. For the final-goods consumption share μ_n^j, I subtract intermediate expenditures from total expenditures in sector j and divide by total absorption.

Depreciation rates (δ_k). Following Arkolakis and Walsh (2023), I set the annual depreciation rates to $\delta_S = \delta_W = 0.03$, $\delta_F = 0.02$, and $\delta_D = 0.07$.

Capital adjustment cost (α) and investment efficiency (χ_k). Following Ravikumar et al. (2019), I set $\alpha = 0.76$ and $\chi_k = (\delta_k)^{1-\alpha}$.[22] Under this formulation, there are no adjustment costs in the steady state when investment just replaces depreciation.

Trade costs (κ_{ni}^j). To calibrate iceberg trade costs, I invert bilateral trade data under symmetric costs, $\kappa_{ni}^j = \kappa_{in}^j$, following Head and Ries (2001):

$$\kappa_{ni}^j = \left(\frac{X_{ni,t}^j \, X_{in,t}^j}{X_{nn,t}^j \, X_{ii,t}^j} \right)^{-\frac{1}{2\theta^j}}.$$

This uses the trade elasticity θ^j from Section 4.5 and observed bilateral expenditures $X_{ni,t}^j$ where $t = 2021$.

Initial sector–region productivity (A). For all sectors except renewable energies, I recover initial productivities by inverting the model using equation (B.1). For solar and wind energy, I use the calibrated values based on renewable resource data in Section 4.2. A sector-specific level shifter in renewable energy aligns this sector's productivity with others to match the observed global share of renewables in primary energy consumption.

[22] $\alpha = 0.76$ corresponds to the annualized adjustment-cost parameter in Eaton et al. (2016).

Discount factor (β). Each model period is a year; I set $\beta = 0.96$.

Damage parameter (SCC_t). I calibrate a time-varying social cost of carbon path consistent with EPA (2023): \$175/tCO_2e in 2022, \$206 in 2030, \$283 in 2050, and \$382 in 2080. I set $SCC_t = \$382$ for $t > 2080$. This dollar-per-ton path is mapped into the emissions disutility term in equation (1).[23]

Initial labor and capital stocks (L, K). Initial labor is the total number of employed workers from the Penn World Table (variable `emp`). The construction of initial capital stocks by asset type is detailed in Appendix B.6.

Table 3 summarizes parameter values and their sources or calibration methods.

4.7 Model Validation

Panel (a) of Table 4 lists the moments targeted in calibration. I match trade shares (the import share in domestic absorption) for all tradable sectors, while assuming the renewable energy sectors are non-tradable.[24] For example, the model exactly matches China's shares of global solar and wind equipment production—80% and 65%, respectively. I also calibrate a level shifter in renewable energy production so that the model replicates the global *average* renewable share in primary energy consumption (15%) in Energy Institute (2024).[25]

I then assess the model against non-targeted moments. I first compare the equipment share of global GDP in 2021, which scales the budget impact of subsidies and the policy multipliers. The first row of Panel (b) in Table 4 shows a small gap between model and data.

A second non-targeted moment is the solar-plus-wind share of electricity by country/region, whose drivers—country-specific renewable potential and the DRS parameter—are measured outside the model. For 2022, the correlation between model outcomes and the Ember/OWD data across regions is 0.91. Panel (a) of Figure 3 plots model against data.

To validate the model's dynamics—how policy shapes equipment production over time—I examine whether the IRA simulation reproduces the observed rise in the U.S. domestic share of solar-module supply, $\pi^S_{US,US}$. Panel (b) of Figure 3 plots the model (solid blue), with policies active from 2023 (Section 45X's first effective year), against an empirical series defined as U.S. PV module production divided by U.S. PV installations for 2022–2025 (red dashed); the band reflects measurement uncertainty in module production.[26] Through 2023 the model tracks the data closely, with the IRA's

[23] Country-heterogeneous social costs of carbon can be incorporated; Appendix B.7 outlines the implementation. Appendix C.9 reports sensitivity of the results with heterogeneous $SCC_{n,t}$.

[24] Cross-border electricity trade is common within the interconnected EU market. In the quantification, I aggregate EU member states into a single region, so those intra-EU flows are internal to that region. The "non-tradable" assumption applies to electricity across model regions (e.g., EU vs. U.S.), not within the aggregated EU market.

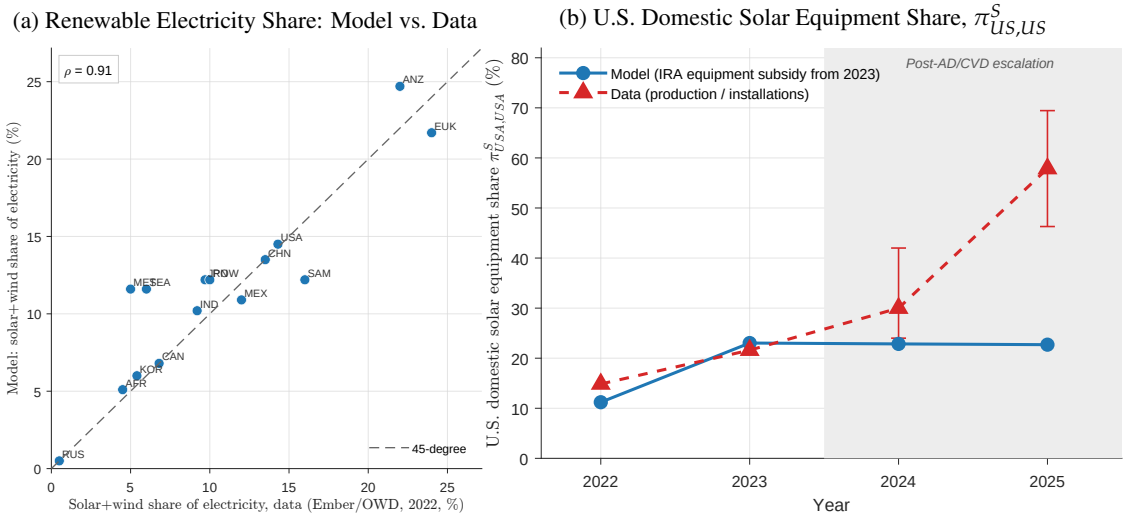
[25] Because OECD-IO does not separately identify renewable energy sectors, I use Energy Institute (2024) via Our World in Data to measure the fossil vs. renewable split in primary energy.

[26] U.S. module production from NREL Solar Industry Updates (National Renewable Energy Laboratory, 2025) and SEIA/Wood Mackenzie *U.S. Solar Market Insight* reports: approximately 3 GW (2022), 7 GW (2023), 12–21 GW (2024),

Table 3: 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	0.645	Estimation
ψ	(Upper nest) CES elasticity of substitution	3.08	Jo (2025)
μ	Forgetting rate in learning-by-doing	0.99	Arkolakis and Walsh (2023)
		(solar, wind)	
ν_{tot}	Total LBD experience elasticity	(2.00, 1.00)	Calibration (§4.4)
λ_L	Local tacit share of learning	(0.16, 0.50)	App. B.4
(Other Parameters)			
A	Region-sectoral productivity	Region-sector specific	Renewable Potentials: see manuscript Other sectors: Model inversion using equation (B.1)
θ^j	Trade elasticities	Sector-specific	Parro (2013), 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	0.96	
SCC_t	Damage parameter	Time-specific	Match social cost of carbon path of EPA (2023)
κ	Trade cost	Region-sector-pair specific	Head and Ries (2001)
(Capital)			
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)

Figure 3: Model Validation



Notes: Panel (a) plots the renewable electricity share in the Ember/OWD 2022 data (x-axis) against model outcomes (y-axis); the 45-degree line is shown. Panel (b) plots the model (solid blue) against the data (red dashed) for the U.S. domestic solar-equipment share, $\pi^S_{US,US}$, from 2022 to 2025; the shaded region marks the post-2023 escalation of antidumping and countervailing-duty measures on imported solar (see footnote for data).

equipment-manufacturing support lifting the U.S. domestic share from about 11% to roughly 23%. After 2023 the data rise sharply—reaching about 58% by 2025—while the model's subsidy-driven share plateaus near 23%. This post-2023 divergence coincides with the escalation of antidumping and countervailing-duty (AD/CVD) measures on imported solar cells and modules (shaded region), a trade-protection channel that lies outside the model's subsidy-and-learning mechanism. The validation thus isolates the IRA's subsidy contribution to reshoring, which the model reproduces through 2023; the further surge reflects trade barriers, which I analyze separately in Section 6.

5 Policy Instruments, Incidence, and Assignment

Green industrial policy for clean energy works through two instruments—a *deployment subsidy* on renewable-electricity output and an *equipment subsidy* on domestic manufacturing—that operate through opposing channels in an open economy and carry distinct climate consequences. This section studies how each channel works and who gains from it. The deployment subsidy works through existing global sourcing patterns: by stimulating domestic deployment (and thus domestic abatement) that is largely met by imports from low-cost incumbents, it concentrates emissions reductions

and 20–30 GW (2025). Installations from the SEIA/WoodMac *Year in Review* reports: 20.2 GW (2022), 32.4 GW (2023), 50 GW (2024), and 43.2 GW (2025). The 2024 range reflects measurement uncertainty between NREL's reported H1 2024 production of 4.2 GW and the SEIA/WoodMac statement that full-year 2024 production tripled relative to 2023. The 2025 range reflects facility ramping as module capacity reached 65.5 GW year-end. These are module-assembly shares; deeper cell/wafer domestic content is smaller because U.S. silicon cell production resumed only in Q3 2024.

Table 4: Model Validation

Moment	Model	Data
(a) Matched moments		
China share in global solar equipment production	80%	80%
China share in global wind equipment production	65%	65%
Global renewable share in primary energy	15%	15%
(b) Non-targeted moments		
Equipment share in global GDP (2022)	0.16%	0.12%
Solar+wind electricity share by country/region (2022)	See Figure 3 Panel (a)	
U.S. domestic solar equipment share under the IRA	See Figure 3 Panel (b)	

at home while sending part of the equipment demand abroad. In contrast, the equipment subsidy seeks to shift production to the U.S.: it lowers world equipment prices—diffusing cheaper deployment abroad—and raises U.S. cumulative output, though the learning this generates is mostly a global spillover (Section 4.4) and so buys the U.S. little durable cost advantage. Because these channels move national welfare, global welfare, and the location of abatement in different directions, the policy problem is one of *assignment*—which instrument, at what rate, and in which country. I use the IRA, which couples both instruments at empirically observed rates, as the concrete benchmark for quantifying these channels: I decompose it into its components and then vary the instrument and the location of support.

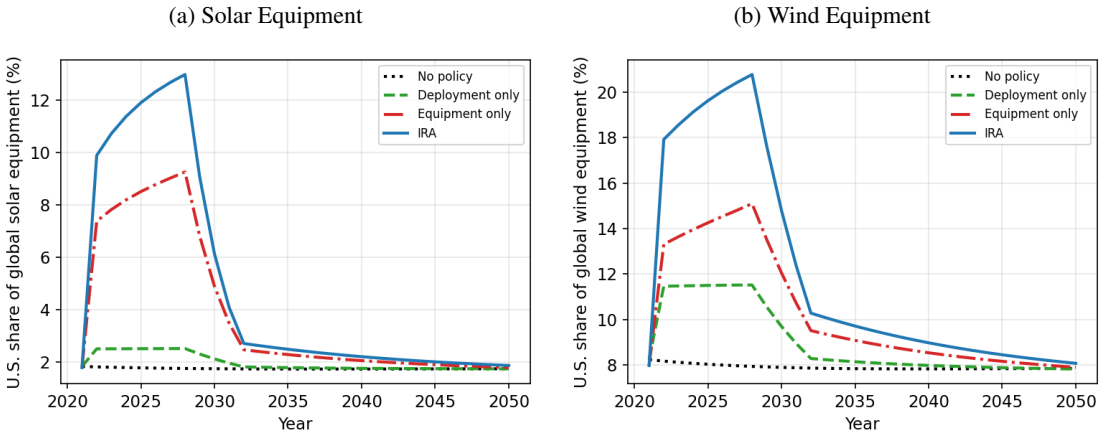
Policy scenarios. Relative to the no-policy baseline, I study four sets of experiments: (i) the two instruments in isolation—a *deployment-only* and an *equipment-only* subsidy—and their combination in the *IRA* as legislated; (ii) a grid of unilateral U.S. policies that varies the rate and mix of the two instruments, used in Section 5.2 to characterize the U.S.-optimal policy; (iii) relocating equipment support from the U.S. to *China*, the incumbent production hub; and (iv) *coordinated* packages pairing deployment support in large importing markets with equipment support in China.

Mapping the IRA to the model. The IRA disciplines the instrument rates: I set ad-valorem subsidies of 20 percent on renewable-electricity output (the production tax credit) and 30 percent on equipment manufacturing (the Section 45X credit), with both rates phased out over 2029–2031.[27]

Welfare decomposition and fiscal cost. I evaluate welfare using the function defined in (1), replacing the infinite horizon with a finite sum through 2100 focusing on the transition rather than very

[27]The 20% deployment rate maps the 2022 Production Tax Credit of \$0.0275/kWh against the average U.S. retail electricity price of \$0.1236/kWh (EIA, 2023); producers may elect the PTC or the Investment Tax Credit, and I treat the flow-based PTC as the operative instrument (Appendix B.1). The 30% equipment rate maps the 45X schedule of about \$0.14/W against the 2022 average domestic module price of \$0.44/W; wind components, also eligible under 45X, map to a comparable rate. In 2029–2031 the rates decline to 75%, 50%, and 25% of their initial levels.

Figure 4: U.S. Production Share in Global Renewable-Equipment Supply



Note: This figure shows the evolution of the U.S. share of the global equipment market. Panel (a) illustrates the 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 deployment 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 U.S. production share in global wind equipment market under each scenario.

long–run steady states.[28] Changes in welfare in country n can be decomposed as:

$$d\ln W_n = \underbrace{d\ln\left(\frac{E_n}{P_n}\right)}_{\Delta\text{real income}} - \underbrace{d\ln(1+SCC_t(Z_t-Z_0))}_{\Delta\text{carbon disutility}}, \tag{27}$$

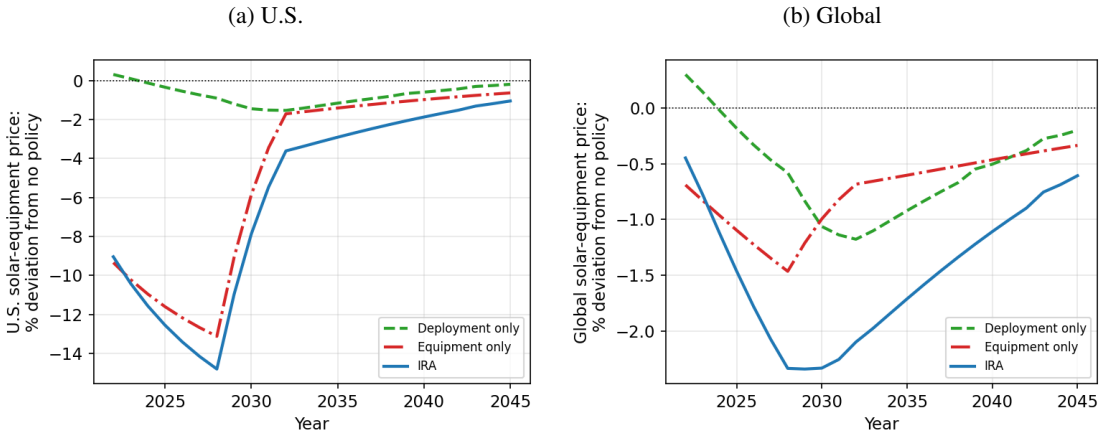
where the first term captures movements in real income (including general-equilibrium price and factor-income effects and the fiscal cost of subsidies) and the second term captures the change in disutility from cumulative emissions. Under the calibration, the present-value IRA subsidy outlay over 2022–2031 is approximately $610 billion ($785 billion undiscounted). These magnitudes are comparable to estimates in the literature (see Appendix C.2).

5.1 The Two Instruments: Mechanisms and Incidence

U.S. production share in global renewable-equipment supply. Figure 4 plots the U.S. production share in global renewable-energy equipment, decomposing the IRA into its components; the two instruments act on opposite margins. The *deployment subsidy* stimulates domestic equipment *demand*, but because equipment is tradable that demand is largely met by imports, so it lifts the U.S. solar-equipment share by only about 0.7 percentage point at its peak and puts mild upward pressure on the world equipment price. The *equipment subsidy* instead lowers U.S. unit costs and expands domestic *supply*: it raises the U.S. global solar-equipment share from about 2% to 9.2% at the peak, with

[28] I measure welfare changes using consumption-equivalent variation (CEV); see Appendix A.3 for the derivation.

Figure 5: Price of Solar Energy Equipment



Notes: Evolution of solar-equipment prices, 2021–2050. Panel (a) shows the U.S.; panel (b) shows the global (installation-weighted) index. Lines denote baseline (solid), IRA (dashed), deployment subsidy (circles), and equipment subsidy (dotted). Wind-equipment price levels (index) are reported in Appendix Figure C.1.

learning-by-doing amplifying the gain and the larger world supply lowering the global equipment price (Figure 5). The full IRA combines the two and pushes the U.S. solar share to a peak of about 13.0%.

Wind (panel (b)) shows the same qualitative pattern but a muted equipment-subsidy response: the U.S. wind-equipment share rises from about 8% to 15% under the equipment subsidy, with an IRA peak near 21%. Two calibrated forces shape the equipment-subsidy response in wind. First, the equipment trade elasticity is lower for wind ($\theta^W = 4.38$ versus $\theta^S = 5.38$), so an equal ad-valorem subsidy reallocates global market shares less than in solar. Second, the experience elasticity is smaller ($\nu^W_{\text{tot}} = 1.00$ versus $\nu^S_{\text{tot}} = 2.00$), so learning-by-doing amplifies the induced cost decline less. On the other hand, the U.S. begins from a higher wind base (8% versus 2%), reflecting greater competitiveness in the heavier, more regionally-assembled wind supply chain; it therefore captures a larger share of the *deployment*-subsidy-induced demand in wind than in solar.

After the subsidies expire in 2031, learning-induced productivity gains hold the U.S. share above baseline for a time, but the advantage gradually erodes and the share returns toward its initial level—the policy's competitive effects are ultimately transitory.[29]

Equipment prices. Figure 5 traces the channel through which these policies reach the rest of the world: the price of solar equipment. The two instruments move it very differently. The equipment subsidy, by lowering domestic unit costs directly, cuts the U.S. price sharply—by about 13% at the height of the subsidy window (panel a)—but compresses the *global* price far less (around 1.5%; panel b), because the U.S. is a small producer and the cost reduction it finances is mostly shared worldwide

[29] In Appendix C.9 I extend the policy horizon to 20 years; even then the long-run U.S. share remains limited, indicating that the U.S. would struggle to sustain competitiveness in this sector absent subsidies.

Table 5: Welfare and CO_2 Outcomes by Instrument

	Global CO_2 (%)	U.S. Welfare (%)	Global Welfare (%)	World Real GDP (%)
Deployment subsidy	-0.195	-0.007	0.030	-0.005
Equipment subsidy	-0.165	-0.014	0.003	-0.007
IRA	-0.443	-0.060	0.030	-0.028

Notes: Reported values are cumulative through 2100. *Global Welfare* includes the real-income and SCC-valued carbon components and is aggregated with working-age-population weights (each person's welfare counted equally), using baseline-year shares. *World Real GDP* is the change in real income aggregated with baseline-GDP weights, excluding the carbon component—a measure of aggregate (Kaldor–Hicks) efficiency. Both world aggregates include the U.S.

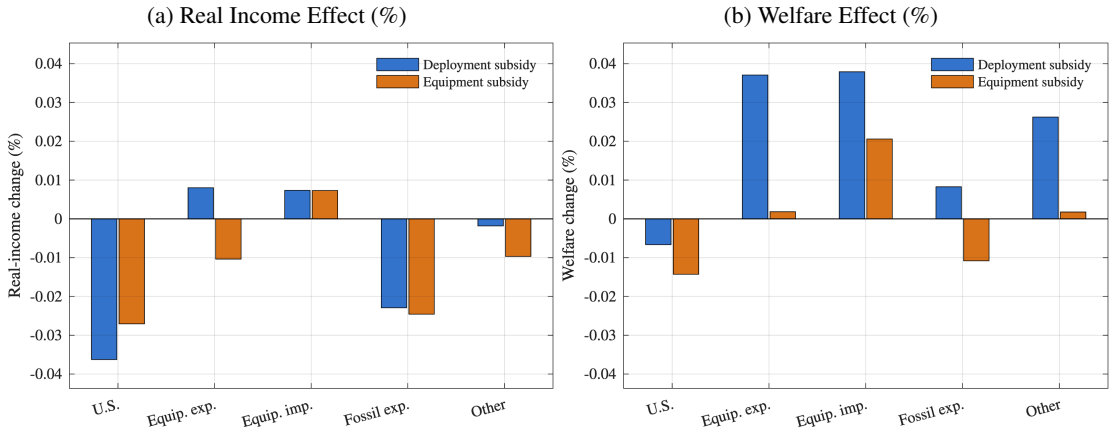
through learning. The deployment subsidy does the reverse: it barely moves the U.S. price, since the new demand is met largely by imports, and it initially *raises* the global price as that demand outruns supply before induced learning pulls it down. The IRA combines the two and depresses both indices most, lowering the global price by about 2.3% around 2030. After the subsidies expire in 2031 the gaps unwind and both indices climb back toward baseline, echoing the transitory market-share gains above; the lasting effect on world equipment prices is small.

Global carbon outcomes. I first report aggregate reductions in global CO_2 relative to the no-policy baseline; details on the cross-country incidence of abatement appear in Appendix C.3. The first column of Table 5 shows that the deployment subsidy lowers global CO_2 by 0.195% by 2100, with abatement concentrated in the U.S. The equipment subsidy yields a comparable, marginally smaller decline (0.165%): it lowers world equipment prices and diffuses abatement abroad, but because it reallocates production toward the high-cost U.S. and the learning it induces is mostly a global spillover, its net cost-reducing effect is muted. The two single-instrument abatements are close, and I do not rest any conclusion on their ordering. Combining both instruments, the IRA produces the largest decrease—0.443% by 2100.

Real-income effects. I next decompose welfare into its real-income and carbon components, following equation (27). Figure 6 reports the change by country group under each instrument, and Table 5 the global aggregates; selected country decompositions appear in Appendix Table C.1.

Figure 6, Panel (a), shows that real-income incidence sorts by trade position. The U.S. (shown separately) now loses slightly in real income under *both* instruments: the deployment subsidy's demand push passes through into higher import bills, and the equipment subsidy lowers domestic unit costs but secures no durable advantage, because the learning it finances is overwhelmingly a *global* spillover (Section 4.4); expanding high-cost U.S. production at the IRA's scale then makes the country slightly worse off in real income. Net equipment exporters show the mirror image: worse off under the equipment subsidy, which displaces their production, but better off under the deployment subsidy, which lifts foreign demand for their equipment. Net equipment importers gain under both instruments—more under the equipment subsidy, whose larger world supply lowers global equipment prices and hence their deployment costs. Fossil-fuel exporters lose under both policies as global

Figure 6: Real-Income and Welfare Effects of Subsidies, by Country Group



Notes: Each panel reports percent changes relative to the no-policy baseline, discounted and cumulated to 2100, aggregated by country group (working-age-population–weighted within each group; the U.S. is shown on its own). Within each group, the left bar is the effect of the deployment subsidy and the right bar the effect of the equipment subsidy. Panel (a) shows the real-income component; Panel (b) adds the SCC-valued carbon component to obtain welfare. Country groups (left to right): the U.S.; net equipment exporters (CHN, IND, SEA); net equipment importers (CAN, MEX, EU, GBR, JPN, KOR, AUS, NZL); fossil-fuel exporters (MEA, RUS, SAM); and other (AFR, TUR, RoW).

fossil demand weakens.[30] In aggregate efficiency terms—the GDP-weighted change in world real GDP, which strips out the carbon component—both U.S. instruments are mildly negative: steering deployment or production through the high-cost U.S. is a small drag on world output.

Welfare: adding the carbon component. Panel (b) of Figure 6 adds the climate component to real-income effects, lifting every group's bars upward. The carbon channel adds about 0.029 percentage points to U.S. welfare under the deployment subsidy and 0.013 under the equipment subsidy. The aggregates in Table 5 sharpen the contrast: the deployment subsidy raises global welfare while leaving U.S. welfare essentially flat, whereas the equipment subsidy adds little to world welfare and leaves the U.S. slightly negative. The central point is that the equipment subsidy at the IRA's scale earns the U.S. no positive national return (point estimate $\approx -0.014\%$).

Combined policy (IRA). Bringing the two instruments together, the IRA couples a demand push from the deployment subsidy with a supply shift from the equipment subsidy. Table 5 reports the headline effects: global CO_2 falls by 0.443% by 2100 and global welfare rises ($+0.030\%$), but U.S. welfare does *not*—it is modestly negative (-0.060%). The IRA thus delivers no national welfare gain of the kind often ascribed to it: because the equipment subsidy's learning leaks abroad, stacking it onto the deployment subsidy adds fiscal cost without a commensurate domestic return.

The combined policy's real-income incidence is clearly negative for the U.S. (-0.110%), for the reasons just given. Incumbent equipment exporters face adverse real-income effects as produc-

[30] Canada and Mexico are informative exceptions. Canada exports fossil fuels but also supplies intermediates for U.S. equipment production; Mexico is a net fossil-fuel importer from the U.S. and imports U.S. equipment. Both benefit more from the equipment subsidy via lower world equipment prices and cross-border supply linkages, while the deployment subsidy has different implications across them given their distinct fossil and intermediate trade positions.

tion shifts toward the U.S., and fossil-fuel exporters lose as fossil demand falls; many net equipment importers gain from cheaper equipment, but not enough to offset a fall in world real GDP (about -0.028%). The package is therefore hard to justify on real-income grounds—nationally or globally—and turns positive for the world only once the carbon benefit is added. For the U.S., even the carbon benefit leaves welfare slightly negative.

5.2 Unilateral versus Global Assignment

Unilateral incentives of a large equipment importer. The IRA fixes both rates at their legislated values, so it shows what the observed bundle does, not what a country acting in its own interest would choose. I therefore characterize the instrument mix that unilateral U.S. welfare favors, evaluating U.S. and global welfare over a grid of deployment- and equipment-subsidy rates; Figure C.3 summarizes the surface, with a full characterization in Appendix C.5. A self-interested U.S. would choose no deployment subsidy and only a small equipment subsidy of about 10%, worth a negligible $+0.002\%$; larger rates turn costly, the IRA's 30% leaving the U.S. at -0.014%. Tilting toward manufacturing support, the direction a national-competitiveness rationale would recommend, does not pay.

Why manufacturing support earns the importer no national return. The instruments differ in incidence. A marginal dollar of *deployment* support is spent disproportionately on foreign-made equipment, so it raises domestic deployment and abatement but bids up the world equipment price and leaks abroad as a terms-of-trade loss. A marginal dollar of *equipment* support is spent at home—it lowers domestic unit costs and shifts sourcing toward U.S. suppliers. The usual rationale for the second instrument is that it builds a durable production advantage: by raising cumulative domestic output it should capitalize future cost declines inside the U.S. That rationale does not survive the estimated geography of learning. With only about one-sixth of the cost decline from cumulative production staying with the producer (Section 4.4), a U.S. equipment subsidy finances productivity gains that diffuse to all producers—China most of all, as the dominant supplier—while the U.S. alone bears the fiscal and sourcing distortions. The importer cannot manufacture a comparative advantage that learning will not let it keep.

The assignment problem hinges on location. The instrument the *world* prefers is clear: the deployment subsidy raises global welfare ($+0.030\%$) while leaving U.S. welfare essentially flat (-0.007%). A U.S. equipment subsidy raises neither—it adds little to the world ($+0.003\%$) and, at the IRA's rate, leaves the U.S. slightly negative (-0.014%). The deeper point is not which instrument is chosen but *where* the support lands. Because learning diffuses, an equipment subsidy is close to a global public good: its world return turns on whether it moves production toward or away from the low-cost location. Applied at the high-cost importer it does little; applied at the low-cost incumbent it does a great deal—and, as the next section shows, that is precisely where the national and global interests

diverge. Green industrial policy thus faces a genuine *assignment* problem of location: where support is applied, not merely which margin or how much, determines who gains.

The geography of learning, not the rate, caps the U.S. return. Because the learning a U.S. equipment subsidy finances mostly diffuses abroad—the local share is near 0.16 (Section 4.4)—the U.S. captures too little to profit at any rate. The return would be sizable only if learning were far more local: about $+0.108\%$ at a local share of one, against -0.041% under frictionless global learning (as in Arkolakis and Walsh (2023)), with a positive return requiring a share above about 0.28. And because the U.S. is a high-cost producer, even its optimal subsidy steers output to an inefficient location, so it lowers world real GDP as well.

5.3 Coordination and the Social Cost of Carbon

Comparative advantage and world welfare. Whether an instrument raises or lowers world welfare depends on whether it moves equipment production toward or away from its low-cost location. In the calibration, equipment is produced most cheaply by a few incumbents (China and Southeast Asia). The deployment subsidy raises domestic demand that is largely met by imports from these incumbents, so the new capacity is sourced efficiently and world welfare rises ($+0.030\%$). A U.S. equipment subsidy does the opposite: because the U.S. is a high-cost producer, it shifts output away from cheaper incumbents and reduces the gains from specialization, so world real GDP falls (-0.007%) and the policy adds almost nothing to world welfare even after the carbon benefit ($+0.003\%$); and because the learning it would capture mostly diffuses abroad, it adds nothing for the U.S. either (-0.014%). The location of equipment support, not the choice of instrument, is what signs its world return.

Relocating the equipment subsidy to China sharpens the point. There the subsidy expands output where production is already cheapest, so world real GDP rises ($+0.055\%$) instead of falling (Table 6). Equipment support is globally valuable or nearly neutral depending on where it is applied, and the place where it is most valuable has the least reason to act. The low-cost incumbent loses real income at any rate by discounting an export base it already supplies, so it would not subsidize. The high-cost importer would—its privately optimal rate is positive, if only just—but its subsidy does nothing for the world. Incentive and value point in opposite directions: the country that gains from acting is not the one the world needs to act.

Equipment support at the incumbent production hub. Table 6 relocates the equipment subsidy to China, the incumbent production hub. The result is a large positive global spillover that China itself does not want. A 30% China equipment subsidy cuts global CO_2 by 1.405%—the largest abatement of any single-instrument experiment—and raises world welfare by 0.075%. The real-income incidence, however, is sharply asymmetric: China's own real income falls (-0.067%) while the U.S., a net importer, gains ($+0.105\%$). Because China already supplies the bulk of world equipment, the

Table 6: Equipment Support at the Incumbent Production Hub

China equipment subsidy	Fiscal cost	China real income	U.S. real income	World welfare	World real GDP	Global CO_2
5%	\$136bn	−0.004	+0.008	+0.002	+0.005	−0.096
30%	\$1,463bn	−0.067	+0.105	+0.075	+0.055	−1.405

Notes: Reported values are percentage changes relative to the no-policy baseline, cumulative through 2100. Welfare includes the real-income component and the SCC-valued carbon component. World welfare is aggregated using baseline working-age-population weights; *World real GDP* is the change in real income aggregated with baseline-GDP weights, excluding the carbon component (aggregate efficiency). *China real income* and *U.S. real income* are the respective countries' own real-income changes. *Fiscal cost* is the present-value subsidy outlay over 2022–2031.

subsidy discounts a large export base it already serves rather than building new capacity, and the price cut passes through to importers as a near-pure terms-of-trade transfer.

Coordinated deployment and equipment support. China does not choose the equipment subsidy unilaterally in the calibrated model, but the result identifies a complementarity between deployment markets and equipment-production hubs. Deployment support in large importing markets raises demand for low-cost equipment, while equipment support in the incumbent production hub lowers the cost of serving that demand. Table 7 reports illustrative joint packages, some of which leave every participating region better off once carbon benefits are valued.

Reading Table 7 shows how pairing realigns incentives. Where China loses real income by subsidizing equipment alone (−0.004%), adding 10% U.S. deployment support raises demand for precisely the equipment China is cheapening and turns China's real income marginally positive (+0.001%)—a reason to participate it lacks unilaterally; with carbon valued, its welfare rises further (+0.020%) alongside the U.S. (+0.023%), and global CO_2 falls by 0.18%. Adding EU deployment support widens the demand base further: every participant gains (U.S. +0.037%, China +0.035%, EU +0.038%), world welfare reaches +0.024%, and abatement deepens to 0.30%.[31] The packages embody a comparative-advantage division of labor—the incumbent hub on supply-side (equipment) support, the large importers on demand-side (deployment) support—and the pairing lets China internalize, through stronger export demand, the spillover it cannot capture alone.

Self-enforcement and the social cost of carbon. Coordination and a carbon price together make these packages self-enforcing. Pairing repairs the hub's real-income loss—otherwise the misalignment of Section 5.2 would keep a hub like China from subsidizing alone—and the carbon benefit, largest in the deployment-paired packages that compress equipment prices most, lifts every participant into positive welfare. Under the calibrated EPA path (\$175/tCO_2e in 2022, rising to \$382 by 2080; EPA, 2023), the joint packages in Table 7 leave each region comfortably better off, though the

[31] The packages are individually rational against the no-policy baseline but do not eliminate the usual free-rider incentive: the EU's welfare is marginally higher when it benefits from the others' support without deploying itself (+0.044%) than when it adds its own deployment (+0.038%). What sustains its participation is the larger shared carbon benefit its deployment unlocks, not a private deployment return.

Table 7: Joint Deployment and Equipment-Support Packages

Policy package	Fiscal cost	Global CO_2	U.S. welfare	China welfare	China real income	EU welfare	World welfare
China equipment 5%	\$136bn	−0.096	+0.018	+0.003	−0.004	+0.030	+0.002
China equipment 5% + U.S. deployment 10%	\$246bn	−0.184	+0.023	+0.020	+0.001	+0.044	+0.015
China equipment 5% + U.S. and EU deployment 10%	\$412bn	−0.303	+0.037	+0.035	+0.003	+0.038	+0.024

Notes: Reported values are percentage changes relative to the no-policy baseline, cumulative through 2100. Welfare includes the real-income component and the SCC-valued carbon component. World welfare is aggregated using baseline working-age-population weights. *China real income* excludes the carbon component: it is negative when China subsidizes alone but turns positive once paired deployment lifts export demand for its equipment. *Fiscal cost* is the present-value subsidy outlay over 2022–2031.

Table 8: The IRA With and Without Equipment Trade

	Global CO_2 (%)	Global Welfare (%)	U.S. Welfare (%)
Baseline (equipment trade)	−0.443	0.030	−0.060
No equipment trade	−0.342	0.040	−0.049

Notes: Percent changes relative to the no-policy baseline of the corresponding economy—with equipment trade for the first row, autarky for the second—cumulative through 2100. The "no equipment trade" row imposes autarky in renewable-energy equipment and recalibrates the model to reproduce the same initial-year data under no trade.

real-income margins are thin: were the carbon benefit small and the export-demand boost to the hub weaker, the same packages might not be sustained.

5.4 The Role of Equipment Trade

The misalignment and coordination results above operate through a single channel: equipment is tradable, so support in one country diffuses—via world prices and the relocation of learning—to others. To isolate this channel, I re-run the IRA in a counterfactual that shuts down trade in renewable-energy equipment (equipment autarky), recalibrating the remaining parameters so the no-trade economy reproduces the same initial-year data, and compare aggregates to the open-economy baseline. The global component of learning is retained—each country's equipment productivity still rises with *world* cumulative output—so the counterfactual shuts down equipment *trade* without severing the cross-border diffusion of learning; it isolates the role of importing cheaper equipment, not the global spillover of cost reductions.

Equipment trade is the channel through which the IRA's effects cross borders. Shutting it down (Table 8) removes nearly a quarter of the global abatement—CO_2 falls by 0.34% under autarky versus 0.44% with trade—because the cheaper equipment the policy induces no longer diffuses to lower deployment costs abroad and accelerate foreign decarbonization. The welfare incidence shifts as well: the U.S. loses slightly less without trade (−0.049% vs. −0.060%), since the deployment

subsidy no longer leaks into imported equipment and worsens its terms of trade, while world welfare is marginally higher ($+0.040\%$ vs. $+0.030\%$) once the policy stops pulling equipment production toward the high-cost U.S. A model without equipment trade therefore mis-states both the IRA's emissions reduction and its cross-country incidence; the per-instrument decomposition is in Appendix C.6.

5.5 Robustness

I run two key robustness checks—one on the demand-side elasticities, one on the supply-side geography of learning.

On the demand side, raising renewable–fossil substitutability ($\psi = 5$) makes every instrument abate more, as subsidies displace fossil energy more readily; among the single instruments, deployment cuts more CO_2 than equipment (-1.36% versus -0.98%). The carbon-inclusive welfare numbers rise with the deeper abatement, but the real-income ordering across instruments is unchanged, so higher substitutability strengthens the climate channel without reshaping the industrial comparison. Lower equipment trade elasticities ($\theta = 2$) work in the same direction: weaker cross-border substitution mutes the terms-of-trade and learning-reallocation forces behind the industrial channel and leaves the carbon channel relatively stronger, tilting the comparison toward deployment support.

On the supply side, the assignment result of Section 5.2 runs through the global *diffusion* of learning. Shutting that channel off—so that only the estimated local component operates, with no cross-border spillover (Table C.3, Panel (c))—isolates its role for a U.S. equipment subsidy, and it changes little. Removing diffusion stops the subsidy from financing competitors' productivity, but it also weakens the U.S.'s own learning, so the two roughly offset and the U.S. return stays slightly negative (welfare -0.020%, against -0.014% at the estimate). The subsidy does little for the rest of the world either way: its effect on world welfare moves only from a slight $+0.003\%$ to essentially zero. The U.S. is a minor producer, so the learning a domestic subsidy adds to the global pool is small, and supporting equipment there does little for global costs however far learning travels—the location of support, not the reach of learning alone, governs the global return. The full set of exercises—substitutability, the locality of learning, longer policy horizons, lower trade elasticities, and a heterogeneous damage function—appears in Appendix C.9, Table C.3.

6 Extensions

In this section, I extend the counterfactual analysis along two dimensions. First, I pair the IRA with a trade policy that raises U.S. tariffs on imported solar equipment. Second, I allow for parallel IRA-style policies by other major economies (China and the EU). For comparability, all outcomes are summarized in Table 9.

6.1 Trade Policy and the IRA

Setup. I impose a 50% ad valorem tariff on solar equipment imported from China and Southeast Asia into the U.S. for 2022–2031 (hereafter, the *solar tariff*), mirroring recent U.S. policy.[32] The model with tariffs is described in Appendix A.4.

A tariff is the equipment subsidy in reverse. Both a tariff and an equipment subsidy aim to move equipment production to the U.S. and capture the learning tied to it; they differ only in how they do so. An equipment subsidy *lowers* the delivered cost of domestic output, reallocating production home while expanding deployment. A tariff *raises* the delivered cost of the cheaper foreign source, reallocating production home while contracting deployment. The motive is the same—manufacture a comparative advantage the U.S. does not yet hold—but the price effect is opposite, so for a climate objective that operates through installation the tariff is dominated: it slows deployment where the subsidy speeds it.

Trade policy in isolation. Used on its own, the tariff is costly on every margin. Because the tariff falls on the low-cost incumbents (China and Southeast Asia), it pulls production toward the high-cost location—the protectionist mirror of the assignment distortion in Section 5.2—and by taxing cheap imports it blocks the international diffusion of low-cost equipment that an equipment subsidy instead promotes. Relative to the no-policy baseline, the tariff alone raises global CO_2 by 0.04% and lowers world real GDP by 0.01%, global welfare by 0.01%, and U.S. welfare by 0.03% (Table 9, panel (b)). The modest gains from tariff revenue and extra domestic learning are outweighed by higher delivered prices, slower deployment, and delayed decarbonization, consistent with Lashkaripour and Lugovskyy (2023).[33]

Combining the solar tariff with the IRA. The realistic bundle pairs the tariff with the IRA (Section 301 duties alongside the subsidies). The tariff now does visible work on incidence: the IRA's deployment subsidy bids up demand that, without protection, leaks into imports, and the tariff keeps more of that induced demand on domestic producers, raising U.S. market share and the learning attached to it. Because the subsidies offset much of the tariff's static price distortion, the climate aggregate stays close to IRA alone (global CO_2 -0.43%). Yet the tariff is not a free addition even for the U.S.: it pushes U.S. welfare to -0.091%, *below* the -0.060% under the IRA alone, because the higher prices it imposes on a still-import-dependent market slow deployment and raise costs by more than the producer-share gain is worth. The tariff is best read as a distributional instrument—it redirects who captures the learning rents—rather than a climate or national-welfare instrument.

[32] In 2024 the U.S. announced higher Section 301 tariffs on Chinese solar cells (up to 50%). Several Chinese-affiliated manufacturers located in Southeast Asia account for a large share of U.S. solar imports and have faced preliminary duties.

[33] In quantitative trade models of this class the unilaterally optimal import tariff is generally positive, reflecting a terms-of-trade motive; the optimum is further shaped by international technology diffusion when learning crosses borders (Bai et al., 2024). The 50% rate studied here is far above any such optimum, and the climate externality lowers the optimal clean-equipment tariff further still—taxing renewable equipment raises its price and slows decarbonization, a social cost outside the standard terms-of-trade calculus (Farrokhi and Lashkaripour, 2025). The welfare losses reported here therefore reflect the large rate and the climate channel, not a claim that the optimal equipment tariff is zero.

6.2 Uncoordinated Proliferation

When the U.S., China, and the EU each adopt the full IRA bundle, global CO_2 falls by 3.86%—nearly nine times the unilateral IRA (-0.44%)—global welfare rises by 0.25%, and the U.S. gains $+0.41\%$ (Table 9, panel (c)). The equipment margin is the telling one. A U.S.-only equipment subsidy lowers world real GDP (-0.007%) and barely lifts world welfare ($+0.003\%$), but when the low-cost incumbent (China) and the EU subsidize equipment alongside the U.S., the multilateral equipment race turns positive on *both* margins ($+0.029\%$ world real GDP, $+0.069\%$ welfare, CO_2 -1.82%; Table C.2). The reason is compositional: a unilateral equipment subsidy concentrates capacity in a high-cost location and subtracts from world output, but once the low-cost producer subsidizes too, the expansion is no longer tilted toward the inefficient site, so the race stops eroding world output even as it deepens abatement and lifts the shared carbon benefit. The cross-country incidence, however, is unchanged: the U.S., a net importer, gains most ($+0.24\%$), buying cheaper subsidized equipment from China and the EU, while China still loses real income (-0.057%) even when subsidizing alongside the others—the same adverse incidence it bears acting alone—so the assignment misalignment of Section 5.2 survives multilateral proliferation.

Proliferation is still not coordination, however. Each bloc subsidizing *both* instruments replicates at home the high-cost-producer distortion of a unilateral equipment subsidy: every participant pays to expand equipment capacity it is not the cheapest to supply. The same abatement therefore costs more—fiscally and in forgone output—than under the comparative-advantage division of labor in the coordination analysis above, where each region supports only the margin on which it holds an advantage and equipment is left to the low-cost incumbent. The contrast sharpens the assignment point of Section 5.2: what matters for the global return is not how many countries subsidize, but whether the low-cost location is among those subsidizing equipment. Deployment-only and country-level results appear in Appendix C.8.

Table 9: Extensions: Tariffs and Parallel IRA-Style Policies

	Global CO_2 (%)	U.S. Welfare (%)	Global Welfare (%)	World Real GDP (%)
(a) Baseline IRA	-0.443	-0.060	0.030	-0.028
(b) Solar Tariff				
Tariff	0.041	-0.034	-0.013	-0.011
IRA + Tariff	-0.430	-0.091	0.019	-0.038
(c) U.S.–China–EU IRA	-3.860	0.407	0.249	0.006

Notes: Reported values are cumulative through 2100.

7 Conclusion

The transition to renewable energy relies heavily on trade in renewable-energy equipment, such as solar panels and wind turbines. Motivated by this observation, I develop a multi-country dynamic general-equilibrium trade model in which renewable-energy equipment is tradable and equipment learning-by-doing is partly local to the producing country. Applied to the IRA, accounting for equipment trade determines the distribution of gains: global CO_2 falls by 0.443%, U.S. welfare is slightly negative (-0.060%), and global welfare rises by 0.030%, with part of the environmental benefit operating through accelerated adoption abroad. Policy evaluation must therefore account for equipment tradability and the geographic locus of learning.

Comparing policy instruments highlights distinct roles. The equipment-subsidy component lowers domestic delivered costs, but because the learning it finances is mostly global—diffusing to competitors—it earns the U.S. no national return (U.S. welfare $\approx -0.014\%$); by steering production toward the high-cost U.S. it lowers world real GDP and adds little to world welfare. The deployment-subsidy component instead sources its induced capacity from the lowest-cost producers: it leaves U.S. welfare slightly negative through the terms-of-trade cost of imported equipment, yet raises world welfare and delivers the larger global abatement. Neither instrument, applied unilaterally by the U.S., yields a national welfare gain.

More broadly, the results show that green industrial policy is an assignment problem in a globalized equipment market. The direction of the global gains turns on comparative advantage: equipment support raises world welfare when located where production is already cheapest, and lowers it when located in a high-cost importer. A large equipment importer earns no national return from manufacturing support, because the learning it would finance is mostly global and diffuses to the incumbent suppliers it competes with. Conversely, support located in an incumbent equipment hub can generate global equipment-cost and carbon benefits while remaining unattractive to that producer because importers capture much of the price decline. Coordinated packages can partly align these margins once carbon benefits are valued, but this paper treats them as counterfactual incidence exercises rather than as a model of bargaining, enforcement, or global optimal policy.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, "The Environment and Directed Technical Change," *American Economic Review*, February 2012, *102* (1), 131–166.

Aghion, Philippe, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros, "Industrial policy and competition," *American Economic Journal: Macroeconomics*, 2015, *7* (4), 1–32.

Aldy, Joseph E., Todd D. Gerarden, and Richard L. Sweeney, "Investment versus Output Subsidies: Implications of Alternative Incentives for Wind Energy," *Journal of the Association of Environmental and Resource Economics*, 2023, *10* (4), 981–1018.

Alvarez, Fernando and Robert E. Jr. Lucas, "General equilibrium analysis of the Eaton–Kortum model of international trade," *Journal of Monetary Economics*, September 2007, *54* (6), 1726–1768.

Arkolakis, Costas and Conor Walsh, "Clean Growth," *Working Paper*, 2023.

Bahar, Dany, Konrad O. Stahl, and Soumyajit Chattopadhyay, "Direct International Knowledge Spillovers in Renewable-Energy Patents," *Energy Policy*, 2014. Working Paper.

Bai, Yan, Keyu Jin, Dan Lu, and Hanxi Wang, "Optimal Trade Policy with International Technology Diffusion," NBER Working Paper 32097, National Bureau of Economic Research 2024.

Baker, Erin, Meredith Fowlie, Derek Lemoine, and Stanley S. Reynolds, "The Economics of Solar Electricity," *Annual Review of Resource Economics*, 2013, *5*, 387–426.

Baldwin, Robert E., "The Case against Infant Industry Protection," *Journal of Political Economy*, 1969, *77* (3), 295–305.

Banares-Sanchez, Ignacio, Robin Burgess, David Laszlo, Pol Simpson, John Van Reenen, and Yifan Wang, "Ray of Hope? China and the Rise of Solar Energy," Working Paper 34893, National Bureau of Economic Research February 2026.

Bardhan, Pranab K., "On Optimum Subsidy to a Learning Industry: An Aspect of the Theory of Infant-Industry Protection," *International Economic Review*, 1971, *12* (1), 54–70.

Bartelme, Dominick, Arnaud Costinot, Dave Donaldson, and Andrés Rodríguez-Clare, "The Textbook Case for Industrial Policy: Theory Meets Data," *Journal of Political Economy*, 2025, *133* (5), 1527–1573.

Bistline, John, Neil Mehrotra, and Catherine Wolfram, "Economic Implications of the Climate Provisions of the Inflation Reduction Act," *Brookings Papers on Economic Activity*, 2023, *2023* (1), 77–182.

Boehm, Christoph E., Andrei A. Levchenko, and Nitya Pandalai-Nayar, "The Long and Short (Run) of Trade Elasticities," *American Economic Review*, April 2023, *113* (4), 861–905.

Bolinger, Mark, Ryan Wiser, and Eric O'Shaughnessy, "Levelized cost-based learning analysis of utility-scale wind and solar in the United States," *iScience*, 2022, *25* (6).

Bollinger, Bryan and Kenneth Gillingham, "Peer Effects in the Diffusion of Solar Photovoltaic Panels," *Marketing Science*, 2012, *31* (6), 900–912.

_ , _ , Drew Vollmer, and Daniel Xu, "Strategic Avoidance and the Welfare Impacts of Solar Panel Tariffs," *Working Paper*, 2024.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1), 1–44.

_ , Marcelo Dolabella, Mauricio Moreira, Matthew Murillo, and Fernando Parro, "Voluntary Emission Restraints in Developing Economies: The Role of Trade Policy," *Working Paper*, 2024.

Casey, Gregory, Woongchan Jeon, and Christian Traeger, "The Macroeconomics of Clean Energy Subsidies," *Working Paper*, 2023.

Choi, Jaedo and Andrei A. Levchenko, "The Long-Term Effects of Industrial Policy," *Journal of Monetary Economics*, June 2025, *152*, 103779.

Cohen, Wesley M. and Daniel A. Levinthal, "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 1990, *35* (1), 128–152.

Comin, Diego and Bart Hobijn, "An Exploration of Technology Diffusion," *American Economic Review*, 2010, *100* (5), 2031–2059.

Congressional Budget Office, "The Budget and Economic Outlook: 2024 to 2034," 2024.

Costantini, Valeria, Francesco Crespi, and Alessandro Palma, "Characterizing the Policy Mix and Its Impact on Eco-Innovation: A Patent Analysis of Energy-Efficient Technologies," *Research Policy*, 2017, *46* (4), 799–819.

Covert, Thomas R. and Richard L. Sweeney, "Winds of Change: Estimating Learning by Doing without Cost or Input Data," *Working Paper*, 2024.

Cruz, José-Luis and Esteban Rossi-Hansberg, "The Economic Geography of Global Warming," *The Review of Economic Studies*, March 2024, *91* (2), 899–939.

Donald, Eric, "Spillovers and the Direction of Innovation," *Working Paper*, 2024.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1779.

_ , _ , Brent Neiman, and John Romalis, "Trade and the Global Recession," *American Economic Review*, 2016, *106* (11), 3401–3438.

EIA, "State Electricity Profiles," 2023, *https://www.eia.gov/electricity/state/unitedstates/.*

Energy Institute, "Statistical Review of World Energy," 2024.

EPA, "Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances," 2023.

Ethier, Wilfred J., "National and International Returns to Scale in the Modern Theory of International Trade," *American Economic Review*, 1982, *72* (3), 389–405.

Farrokhi, Farid and Ahmad Lashkaripour, "Can Trade Policy Mitigate Climate Change?," *Econometrica*, September 2025, *93* (5), 1561–1599.

Fontagné, Lionel, Houssein Guimbard, and Gianluca Orefice, "Tariff-based product-level trade elasticities," *Journal of International Economics*, 2022, *137*, 103593.

Fraunhofer Institute for Solar Energy Systems, "Photovoltaics Report," Technical Report, Fraunhofer ISE 2025. Updated periodically.

Garcia-Lembergman, Ezequiel, Natalia Ramondo, Andrés Rodríguez-Clare, and Joseph S. Shapiro, "The Carbon Footprint of Multinational Production," *Working Paper*, 2023.

Gentile, Claudia, "Relying on Intermittency: Clean Energy, Storage, and Innovation in a Macro Climate Model," *Working Paper*, 2024.

Gerarden, Todd, "Demanding Innovation: The Impact of Consumer Subsidies on Solar Panel Production Costs," *Management Science*, 2023, *69* (12), 7151–7882.

Global Wind Energy Council, "Mission Critical: Building the Global Wind Energy Supply Chain for a 1.5C World," 2023.

Goldberg, Pinelopi K., Réka Juhász, Nathan J. Lane, Giulia Lo Forte, and Jeff Thurk, "Industrial Policy in the Global Semiconductor Sector," *NBER Working Paper*, 2024, *32651*.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, 1997, *87* (3), 342–362.

Groote, Olivier De and Frank Verboven, "Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems," *American Economic Review*, 2019, *109* (6), 2137–2172.

Gugler, Klaus, Adhurim Haxhimus, and Mario Liebensteiner, "Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables," *Journal of Environmental Economics and Management*, 2021, *106*, 102405.

Head, Keith and John Ries, "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade," *American Economic Review*, September 2001, *91* (4), 858–876.

Hitaj, Claudia and Andreas Löschel, "The impact of a feed-in tariff on wind power development in Germany," *Resource and Energy Economics*, 2019, *57*, 18–35.

Hsiao, Allan, "Coordination and Commitment in International Climate Action: Evidence from Palm Oil," *Working Paper*, 2024.

Jo, Ara, "Substitution between Clean and Dirty Energy with Biased Technical Change," *International Economic Review*, May 2025, *66* (2), 883–902.

Ju, Jiandong, Hong Ma, Zi Wang, and Xiaodong Zhu, "Trade Wars and Industrial Policy Competitions: Understanding the US-China Economic Conflicts," *Journal of Monetary Economics*, 2024, *141*, 42–58.

Kavlak, Goksin, James McNerney, and Jessika E. Trancik, "Evaluating the Causes of Cost Reduction in Photovoltaic Modules," *Energy Policy*, 2018, *123*, 700–710.

Kortum, Samuel E. and David A. Weisbach, "Optimal Unilateral Carbon Policy," *Working Paper*,

2021.

Krugman, Paul, "The Narrow Moving Band, the Dutch Disease, and the Competitive Consequences of Mrs. Thatcher," *Journal of Development Economics*, 1987, *27*, 41–55.

Kucheryavyy, Konstantin, Gary Lyn, and Andrés Rodríguez-Clare, "Grounded by Gravity: A Well-Behaved Trade Model with Industry-Level Economies of Scale," *American Economic Journal: Macroeconomics*, 2023, *15* (2), 372–412.

Lafond, François, Aimee Gotway Bailey, Jan David Bakker, Dylan Rebois, Rubina Zadourian, Patrick McSharry, and J. Doyne Farmer, "How Well Do Experience Curves Predict Technological Progress? A Method for Making Distributional Forecasts," *Technological Forecasting and Social Change*, 2018, *128*, 104–117.

Lashkaripour, Ahmad and Volodymyr Lugovskyy, "Profits, Scale Economies, and the Gains from Trade and Industrial Policy," *American Economic Review*, 2023, *113* (10), 2759–2808.

Lucas, Robert E., "On the Mechanics of Economic Development," *Journal of Monetary Economics*, 1988, *22* (1), 3–42.

National Renewable Energy Laboratory, "Spring 2025 Solar Industry Update," NREL Technical Report NREL/PR-7A40-95135 2025.

Nemet, Gregory F., "Beyond the Learning Curve: Factors Influencing Cost Reductions in Photovoltaics," *Energy Policy*, 2006, *34* (17), 3218–3232.

Oakleaf, James R., Christina M. Kennedy, Sharon Baruch-Mordo, James S. Gerber, Paul C. West, Justin A . Johnson, and Joseph Kiesecker, "Mapping Global Development Potential for Renewable Energy, Fossil Fuels, Mining and Agriculture Sectors," *Scientific Data*, 2019, *6* (101).

Papageorgiou, Chris, Marianne Saam, and Patrick Schulte, "Substitution Between Clean And Dirty Energy Inputs," *The Review of Economics and Statistics*, May 2017, *99* (2), 281–290.

Parro, Fernando, "Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 72–117.

Polanyi, Michael, *The Tacit Dimension*, New York: Doubleday, 1966.

Ravikumar, B., Ana Maria Santacreu, and Michael Sposi, "Capital Accumulation and Dynamic Gains From Trade," *Journal of International Economics*, 2019, *119*, 93–110.

Ricke, Katharine, Laurent Drouet, Ken Caldeira, and Massimo Tavoni, "Country-level social cost of carbon," *Nature Climate Change*, 2018, *8*, 895–900.

Rubin, Edward S., Inês M. L. Azevedo, Paulina Jaramillo, and Sonia Yeh, "A Review of Learning Rates for Electricity Supply Technologies," *Energy Policy*, 2015, *86*, 198–218.

Shapiro, Joseph S., "The Environmental Bias of Trade Policy," *The Quarterly Journal of Economics*, 2021, *136* (2), 831–886.

Shin, David D., "Climate Policies under Dynamic Factor Adjustment," *Working Paper*, 2024.

Stokey, Nancy L., "Learning by Doing and the Introduction of New Goods," *Journal of Political Economy*, 1988, *96* (4), 701–717.

U.S. Department of Energy, "Land-Based Wind Market Report: 2023 Edition," 2023.

van Benthem, Arthur A., "Energy Leapfrogging," *Journal of the Association of Environmental and Resource Economists*, 2015, *2* (1), 93–132.

Verdolini, Elena and Marzio Galeotti, "At Home and Abroad: An Empirical Analysis of Innovation and Diffusion in Energy Technologies," *Journal of Environmental Economics and Management*, 2011, *61* (2), 119–134.

Wiser, Ryan, Mark Bolinger, Ben Hoen, Dev Millstein, Joseph Rand, Galen Barbose, Naim Darghouth, Will Gorman, Seongeun Jeong, Andrew Mills, and Bentham Paulos, "Land-Based Wind Market Report: 2024 Edition," Annual Report, Lawrence Berkeley National Laboratory 2024.

Wiskich, Anthony, "Perfect So Far? Substitutability Between Wind & Solar and Dirty Electricity Generation," *Working Paper*, 2023.

Xiang, Wei, "Clean Growth and Environmental Policies in the Global Economy," *Working Paper*, 2023.

Online Appendix:
Green Industrial Policy in a Globalized Economy

Sungwan Hong
University of Pittsburgh

Appendix A Derivations **2**
A.1 Composite Intermediate Goods (Dixit–Stiglitz) . . . 2
A.2 Energy Cost Shares in Production and Expenditure Shares in Consumption . . . 2
A.3 Measuring Welfare: Consumption Equivalent Variation . . . 3
A.4 A Model with Tariff . . . 3

Appendix B Calibration: Data and Estimation **4**
B.1 Renewable Energy Provisions in the IRA . . . 4
B.2 Geographic and Time Coverage . . . 5
B.3 Data Used in Section 2.1 . . . 6
B.4 Estimating Learning Rate of Equipment Production . . . 7
B.5 Renewable Potential . . . 14
B.6 Measuring Initial Capital Stocks . . . 15
B.7 Calibrating the Damage Parameter . . . 16

Appendix C Additional Results **17**
C.1 Impact of Subsidies on Wind Equipment Price . . . 17
C.2 Estimated Fiscal Cost and Instrument Complementarities . . . 17
C.3 Who Reduces Carbon Emissions? . . . 18
C.4 Welfare Decomposition . . . 19
C.5 Optimal Subsidy . . . 19
C.6 Comparative Statics . . . 20
C.7 Additional Results on IRA under Trade Policy . . . 22
C.8 Additional Results on U.S.-China-EU Policy Competition . . . 22
C.9 Robustness Check . . . 23

Appendix A Derivations

A.1 Composite Intermediate Goods (Dixit–Stiglitz)

Composite producers in sector j aggregate a unit continuum of varieties $\omega^j \in [0,1]$ via

$$Q^j_{n,t} = \left[\int_0^1 f^j_{n,t}(\omega^j)^{\frac{\sigma^j-1}{\sigma^j}} \, d\omega^j \right]^{\frac{\sigma^j}{\sigma^j-1}},$$

where $\sigma^j > 1$ is the elasticity across varieties. Cost minimization yields variety demand

$$f^j_{n,t}(\omega^j) = \left(\frac{p^j_{n,t}(\omega^j)}{P^j_{n,t}} \right)^{-\sigma^j} Q^j_{n,t},$$

and the sectoral price index

$$P^j_{n,t} = \left[\int_0^1 p^j_{n,t}(\omega^j)^{1-\sigma^j} \, d\omega^j \right]^{\frac{1}{1-\sigma^j}}.$$

These expressions underpin the notation in the main text.

A.2 Energy Cost Shares in Production and Expenditure Shares in 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 endogenously determined.

$$\begin{aligned}
\gamma_n^{M,fj} &= [\gamma_n^{M,Ej}] \left[1 + \frac{\eta_e}{1-\eta_e} \left(\frac{P_n^f}{P_n^r} \right)^{\psi-1} \right]^{-1} \\
\gamma_n^{M,sj} &= [\gamma_n^{M,Ej}] \left[1 + \frac{1-\eta_e}{\eta_e} \left(\frac{P_n^r}{P_n^f} \right)^{\psi-1} \right]^{-1} \left[1 + \frac{1-\eta_r}{\eta_r} \left(\frac{P_n^s}{P_n^w} \right)^{\rho-1} \right]^{-1} \\
\gamma_n^{M,wj} &= [\gamma_n^{M,Ej}] \left[1 + \frac{1-\eta_e}{\eta_e} \left(\frac{P_n^r}{P_n^f} \right)^{\psi-1} \right]^{-1} \left[1 + \frac{\eta_r}{1-\eta_r} \left(\frac{P_n^w}{P_n^s} \right)^{\rho-1} \right]^{-1}
\end{aligned}$$

where $P^r_n y^r_n = P^s_n y^s_n + P^w_n y^w_n$ and $p^E_n y^E_n = P^f_n y^f_n + P^r_n y^r_n$

Similar formula can be derived for the expenditure share of each energy source in consumption:

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

A.3 Measuring Welfare: Consumption Equivalent Variation

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

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

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

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

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

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

A.4 A Model with Tariff

In this section, I incorporate sectoral tariffs into the baseline model.

I consider an ad-valorem tariff, $\tau_{ni,t}^j$ 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 $d_{ni,t}^j \equiv \kappa_{ni}^j(1+\tau_{ni,t}^j)$ in equation (10). To include the tariff effect, equation (13) can be rewritten as follows:

$$
Y_{n,t}^j = \sum_{m=1}^{N} \frac{\pi_{mn,t}^j}{(1+\tau_{mn,t}^j)(1-s_{m,t}^j)} X_{m,t}^j. \tag{A.1}
$$

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:

$$\sum_{j\in\Omega}\sum_{n=1}^{N}\frac{\pi^j_{in,t}}{(1+\tau^j_{in,t})(1-s^j_{i,t})}X^j_{i,t}-D_i=\sum_{j\in\Omega}\sum_{n=1}^{N}\frac{\pi^j_{ni,t}}{(1+\tau^j_{ni,t})(1-s^j_{n,t})}X^j_{n,t} \tag{A.2}$$

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

$$\begin{aligned}
&\sum_{j\in\Omega^*_K}P^j_{n,t}C^j_{n,t}\\
&=w_{n,t}L_{n,t}+\sum_{k'\in\Omega_K}r^{k'}_{n,t}K^{k'}_{n,t}-\sum_{j\in\Omega}s^j_{o,t}\sum_{o=1}^{N}\frac{\pi^j_{on,t}}{(1-s^j_{n,t})}X^j_{o,t}+\sum_{j\in\Omega}\tau^j_{ni,t}X^j_{n,t}\sum_{i=1}^{N}\frac{\pi^j_{ni,t}}{(1+\tau^j_{ni,t})(1-s^j_{n,t})}\\
&+\sum_{j\in\Omega_{RE}}\Pi^j_{n,t}+D_n-\sum_{k\in\Omega_K}P^k_{n,t}I^k_{n,t}\\
&\equiv E_{n,t}
\end{aligned} \tag{A.3}$$

Now I 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), (5), and (9), trade shares (12), local prices (10), labor and market clearing conditions ((15),(16)), and trade balance (A.2), and dynamic conditions: law of motion of capitals ((20), and Euler equation (22), where gross output satisfies* (A.1) *and household budget constraint satisfies* (A.3).

Appendix B Calibration: Data and Estimation

B.1 Renewable Energy Provisions in the IRA

In August 2022, the United States enacted the Inflation Reduction Act (IRA), the largest U.S. investment to date in clean energy and climate policy. The law provides roughly $369 billion for energy security and climate programs, including incentives for deploying renewable energy and for manufacturing clean-energy equipment (Congressional Budget Office, 2024). External analyses project that, taken together, these measures could reduce U.S. greenhouse-gas emissions to around 40% below 2005 levels by 2030.[1]

The IRA's clean-energy support operates through two main channels that map directly into the model. First, demand-side deployment incentives expand and extend the Production Tax Credit (PTC; IRC §45)—a per kWh credit for qualified generation—and the Investment Tax Credit (ITC;

[1] This is a modeled projection (e.g., from research groups and agencies), not a statutory target in the IRA.

IRC §48)—a credit for a share of project capital costs. These provisions apply to technologies including wind and solar (among others); this paper focuses on wind and solar.

Second, supply-side manufacturing incentives are delivered via the Advanced Manufacturing Production Credit (IRC §45X), which pays per-unit credits for domestic production of components across clean-energy supply chains. For solar, covered items include PV-grade polysilicon, wafers, cells, modules, and inverters; for wind, blades, nacelles, and towers are eligible; battery cells/modules and certain critical minerals are also covered. These provisions aim to shift production toward domestic suppliers by lowering marginal costs and accelerating learning-by-doing.

Where relevant, bonus credit rates tied to prevailing-wage and apprenticeship requirements, domestic content, and energy-community siting further increase effective subsidy rates, but the analysis in this paper abstracts from those compliance details and focuses on the core economic channels.

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
- Europe: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland
- Middle East Asia: Jordan, Israel, and Saudi Arabia.
- South America: Argentina, 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.

Table B.1: Sector Aggregation

Aggregated Industry	Code in OECD-IO	Industry in OECD-IO
Agriculture and Mining	A01_02	Agriculture, hunting, forestry
Agriculture and Mining	A03	Fishing and aquaculture
Agriculture and Mining	B07_08	Mining and quarrying, non-energy producing products
Agriculture and Mining	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

B.3 Data Used in Section 2.1

This section documents the data used in Section 2.1.

Panel (b) of Figure 1 (U.S. import penetration). For solar, I use the U.S. Energy Information Administration's *Monthly Solar Photovoltaic Module Shipments* to proxy domestic supply and compute import penetration as the share of imports in total U.S. supply.[2] For wind, I use the U.S. Department of Energy's *Land-Based Wind Market Report*, which reports domestic-content shares by major component (nacelle assembly, towers, blades/hubs). I aggregate these component shares using component value-cost weights to obtain a plant-level domestic-content measure and the implied import share.

Panel (a) of Figure 1 (production and deployment shares). Bilateral trade data come from UN Comtrade at the 6-digit HS level. For solar equipment I use HS `854140` (photosensitive semiconductor devices, including PV cells and modules, and LEDs). For wind equipment I use HS `850231` (wind-powered generating sets) and `850300` (parts of electric motors/generators). I also include `841290` (parts of engines and motors) to capture additional wind components. Solar-equipment manufacturing shares are 2022 production-origin shares from the IEA PVPS dataset and coincide with the manufacturing-origin shares used in the calibration. Deployment shares are based on 2022 regional solar capacity additions. For wind production in 2021, I apportion by each country's share of value added in the global wind supply chain using Global Wind Energy Council (2023).

Figure 2 (equipment prices). Solar equipment price time series is taken from the IEA PVPS module

[2] "Import penetration" is measured as the import share in total U.S. supply.

price series. For wind equipment, I use IRENA's global onshore wind cost index.

B.4 Estimating Learning Rate of Equipment Production

To calibrate learning-by-doing (LBD) in renewable-energy equipment, I estimate the elasticity of productivity with respect to cumulative domestic output. Guided by equation (19), the estimating equation is

$$\log A^j_{n,t} = \nu^j_D \log\Big(\sum_{s=1}^{t-1} \mu^s y^j_{n,t-s}\Big) + \nu^j_G \log\Big(\sum_{i\neq n}\sum_{s=1}^{t-1} \mu^s y^j_{i,t-s}\Big) + \nu^j_n + \varrho^j t + u^j_{n,t}, \qquad j \in \Omega_{REE},$$

where $y^j_{n,s}$ is the output of renewable-energy equipment j in country n at time s and μ is the forgetting rate, which I set $\mu = 0.99$ following Arkolakis and Walsh (2023). The term $(\sum_{i\neq n}\sum_{s=1}^{t-1} y^j_{i,s})$ captures the global cumulative output, excluding country n. Identification in this specification relies on within-country variation, while controlling for global spillover effects and common technological progress over time. Mapping to the model, the own-cumulative coefficient identifies the local component $\nu^j_D = \lambda^j_L \nu^j_{\text{tot}}$ and the cross-country coefficient the global component $\nu^j_G = (1-\lambda^j_L)\nu^j_{\text{tot}}$ of equation (19).

Recovering $A^j_{n,t}$ by inversion. To run this regression, I first need to recover the time-series data for renewable-energy equipment productivity across countries ($A^j_{n,t}$). I infer productivity paths $\{A^j_{n,t}\}$ using the trade share equation,

$$\pi^j_{nn,t} = A^j_{n,t}\left(\frac{c^j_{n,t}}{P^j_{n,t}}\right)^{-\theta^j}, \tag{B.1}$$

where $\pi^j_{nn,t}$ is the domestic expenditure share, $c^j_{n,t}$ the input cost bundle, $P^j_{n,t}$ the sectoral price index, and θ^j the trade elasticity. This inversion supplies the baseline initialization $A^k_{n,0}$ and a robustness measure; for the preferred estimation below I instead measure productivity by the structural-gravity exporter capability $\hat{S}^k_{n,t}$ (Moment 2), which uses the full bilateral trade matrix and avoids smoothing. Data construction is detailed in Appendix B.4.1: input costs $c^j_{n,t}$ combine wages, manufactured inputs, and services from Penn World Table 10.1; solar cumulative output uses International Energy Agency Photovoltaic Power Systems Programme (PVPS) module-production data with Comtrade trade flows; and wind country manufacturing output is built by mapping turbine-maker market shares (LBNL, GWEC) to manufacturer-headquarters countries and scaling by global installations—distinct from deployment, since the largest manufacturers install little domestically.

Results: two complementary moments. I discipline the two learning parameters from two distinct moments. A world experience curve identifies the total elasticity ν^k_{tot}; a structural-gravity capability identifies the local share λ^k_L. Because they measure different objects—world cost decline versus own-country competitiveness—a price curve loading on global progress and a trade moment loading on local production are the *expected* signatures of the decomposition, not conflicting estimates.

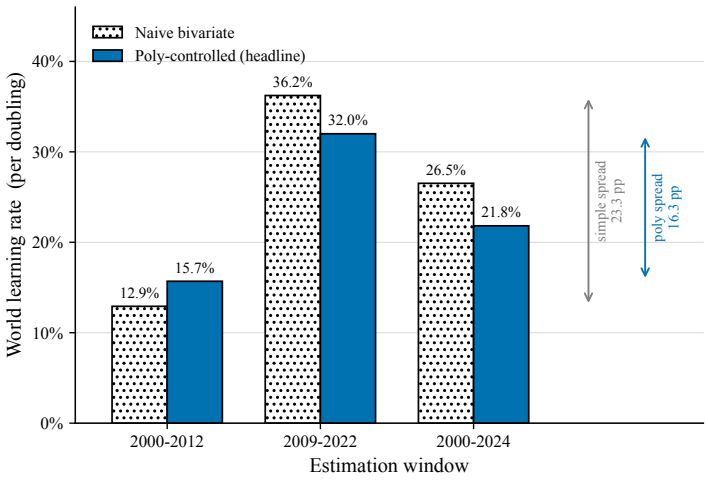


Figure B.1: Solar learning rate by estimation window: naive versus polysilicon-controlled. Controlling for the polysilicon price cycle stabilizes the implied learning rate across windows, indicating that the surviving slope reflects learning rather than the 2004–08 input-cost cycle.

Moment 1 (total elasticity). Regressing the log world equipment price on log world cumulative production, controlling for the dominant traded input (polysilicon for solar, steel for wind) so that input-cost cycles are not read as learning, gives a price slope b that maps into $\nu^k_{\text{tot}} = \theta^k|b|$ and $LR^k = 1 - 2^{-|b|}$. For solar the polysilicon-controlled slope yields $\nu^S_{\text{tot}} = 1.91$ (Newey–West s.e. 0.18; $LR^S = 21.8\%$); the polysilicon loading is positive and significant—the 2004–08 shortage-and-crash inflates the naive curve—and controlling for it shrinks the across-window swing in the implied learning rate from 23 to 16 percentage points, the signature that the surviving slope is learning rather than the input cycle. The estimate validates the external benchmark $\nu^S_{\text{tot}} = 2.00$, which lies inside the 95% confidence interval $[1.56, 2.26]$; Figure B.1 shows that the polysilicon control stabilizes the implied learning rate across estimation windows.

Robustness to subsidy confounding. Because deployment and Chinese manufacturing subsidies expanded sharply after 2010, one might worry that the post-2011 module-price collapse reflects subsidized overcapacity rather than learning, which would inflate ν^S_{tot}. The data do not bear this out (Table B.2). Adding China's share of world cumulative production leaves the slope essentially unchanged ($\nu^S_{\text{tot}} = 2.00$); a post-2011 indicator enters with a coefficient of $+0.02$—statistically indistinguishable from zero—so there is no structural break in the price–experience relationship beyond the learning curve itself; and dropping the 2011–2013 price-crash years entirely still yields $\nu^S_{\text{tot}} = 1.93$. Direct controls for cumulative deployment subsidies cannot be separated cleanly because they are nearly collinear with cumulative output—they enter with the wrong sign and mechanically inflate the slope. The economic logic is that subsidies act on the *quantity* of deployment—moving the industry further along a given experience curve—rather than on its *slope*; the per-doubling price decline that ν_{tot} measures is stable across the sample. The polysilicon-controlled

estimate is therefore robust to the subsidy concern, reinforcing the adopted $\nu^S_{\text{tot}} = 2.00$.

Table B.2: Solar total learning elasticity: robustness to subsidy/overcapacity controls

Specification	ν^S_{tot}	LR^S
Polysilicon-controlled (benchmark)	1.91	21.8%
+ China cumulative-output share	2.00	22.7%
+ post-2011 indicator	1.93	22.0%
drop 2011–2013 (price-crash years)	1.93	22.0%

Notes: World solar, 2000–2024; log world module price on log world cumulative production with the polysilicon control of Moment 1; $\nu^S_{\text{tot}} = \theta^S\,|b|$ with $\theta^S = 5.38$; Newey–West HAC (lag 2). Cumulative deployment-subsidy controls are omitted because they are nearly collinear with cumulative output (wrong-signed and slope-inflating), and so cannot be separated on this short world series.

Moment 2 (local share). I measure equipment productivity $A^k_{n,t}$ by an exporter-by-year *capability* $\hat{S}^k_{n,t}$ estimated from the full bilateral trade matrix by Poisson pseudo-maximum-likelihood gravity with importer-by-year and country-pair fixed effects—the exporter term of the trade-share equation (12), the model's own equilibrium object, rather than the smoothed domestic-share inversion of equation (B.1) used to initialize $A^k_{n,0}$; Figure B.2 plots the resulting capability paths. The importer-by-year effects normalize away the common annual frontier, so regressing $\hat{S}^k_{n,t}$ on log own cumulative production (with exporter and year fixed effects) identifies the local component $\lambda^k_L \nu^k_{\text{tot}}$. For solar the own-country elasticity is 0.30 (s.e. 0.07), so $\lambda^S_L = 0.30/1.91 \approx 0.16$; it is robust to dropping China, to a leave-out-global control (itself insignificant, consistent with the frontier being normalized away), and across the 2000–2023 window, and the fixed-effect ladder *rises* as controls are added (0.10→0.17→0.30), inconsistent with a mechanical-persistence artifact.

Because own cumulative output is endogenous to production subsidies, I instrument it with a staggered feed-in-tariff policy shift-share—initial (2000–2004) export exposure interacted with the staggered onset of destination feed-in-tariff programs (Germany 2004, Spain 2007, Italy 2011, China 2011, Japan 2012)—whose idiosyncratic timing survives the year fixed effects that absorb the common global demand wave. The first-stage Kleibergen–Paap F is 8.3 (against 0.9 for a naive demand shift-share that the year effects absorb), and the instrumented elasticity $\nu^S_D \in [0.29, 0.37]$ brackets the fixed-effect estimate, so subsidy-endogeneity does not appear to bias it materially.

I further corroborate the local channel with the 2018 "531" episode: when China abruptly cut its domestic deployment subsidy, Chinese capability *accelerated* (pre-2018 slope +0.05/yr versus +0.12/yr after, with no negative break) and its world export share rose from 31% to 42%—capability surviving the withdrawal of domestic demand support is consistent with an irreversible learning stock (Figure B.3).[3]

[3]Capability is measured as an efficient structural-gravity fixed-effect estimate, with no smoothing. One reason country-level learning differs from the global rates in Arkolakis and Walsh (2023) is that the global-aggregate fit is driven by China; Bahar et al. (2014) document substantial cross-border diffusion in renewable-energy patents, supporting a dominant global frontier.

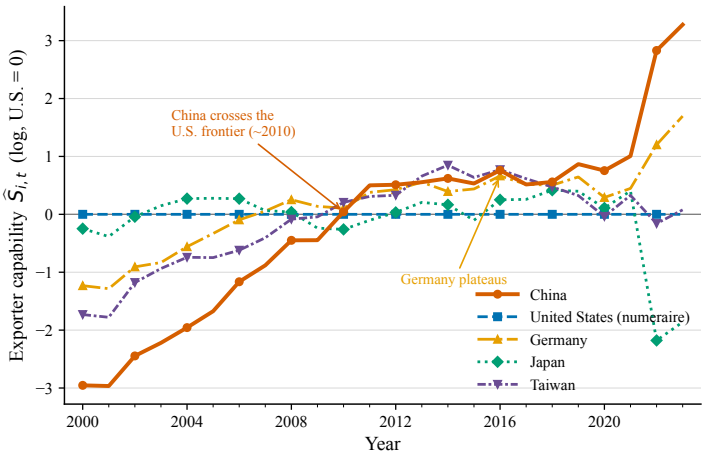


Figure B.2: Solar exporter capability $\hat{S}^S_{n,t}$, 2000–2023, normalized to the United States within each year. China's gravity capability rises sharply and overtakes the U.S. numeraire around 2010 while Germany plateaus—the reallocation of competitiveness that identifies the local learning elasticity $\lambda^S_L \nu^S_{\text{tot}}$.

Table B.3: Learning Decomposition: Total Elasticity and Local Share

	ν^k_{tot}	$\lambda^k_L \nu^k_{\text{tot}}$	λ^k_L	LR^k_{tot}	Identifying moment
Solar	1.91	0.30	0.16	21.8%	price curve / gravity
	(0.18)	(0.07)	(0.04)		
Wind	1.00†	≈ 0.6	$\gtrsim 0.5$	14.6%	calibrated / gravity (directional)

Note: ν^k_{tot} is the total learning elasticity in the Fréchet location parameter, from a polysilicon/steel-controlled world experience curve (Moment 1). $\lambda^k_L \nu^k_{\text{tot}}$ is the own-country elasticity from the structural-gravity exporter capability (Moment 2), and λ^k_L is the implied local share. $LR^k_{\text{tot}} = 1 - 2^{-\nu^k_{\text{tot}}/\theta^k}$ with $\theta^S = 5.38$, $\theta^W = 4.38$. Standard errors in parentheses (Newey–West for ν^S_{tot}; cluster-robust/delta-method otherwise). †Wind ν^W_{tot} is calibrated rather than estimated (the turbine-price series is short and trend-collinear), bracketed empirically by $[0.5, 1.2]$; the wind local share is a directional inequality, identified off China on a small manufacturer-country panel. The quantitative benchmark adopts $\nu^S_{\text{tot}} = 2.00$, the integer rounding of the estimated 1.91; via $LR^k_{\text{tot}} = 1 - 2^{-\nu^k_{\text{tot}}/\theta^k}$ the adopted 2.00 implies $LR^S = 22.7\%$ and the estimated 1.91 implies $LR^S = 21.8\%$ (the value tabulated above). It further adopts the estimated $\lambda^S_L = 0.16$, and a conservative $\lambda^W_L = 0.50$ (the floor of the directional wind estimate).

Wind. I build country wind-manufacturing output by mapping turbine-maker market shares (LBNL/GWEC, 2006–2024, capturing China's rise from under 8% to over half of global production) to manufacturer-headquarters countries and scaling by global installations—distinct from deployment, since the largest makers (e.g. Vestas) install little domestically. On this panel the own-country elasticity is large (≈ 0.6), implying $\lambda^W_L \gtrsim 0.5$, several times the solar share. I read this as a *directional* result rather than a point estimate—ν^W_{tot} is calibrated, and the elasticity is identified off China on a small manufacturer-country panel—but the cross-technology pattern is robust: the local share rises as equipment becomes less tradable and more geographically mobile. Light, modular, highly traded solar modules learn predominantly globally; heavy, regionally assembled wind turbines retain a larger locally appropriable share (Figures B.4 and B.5).

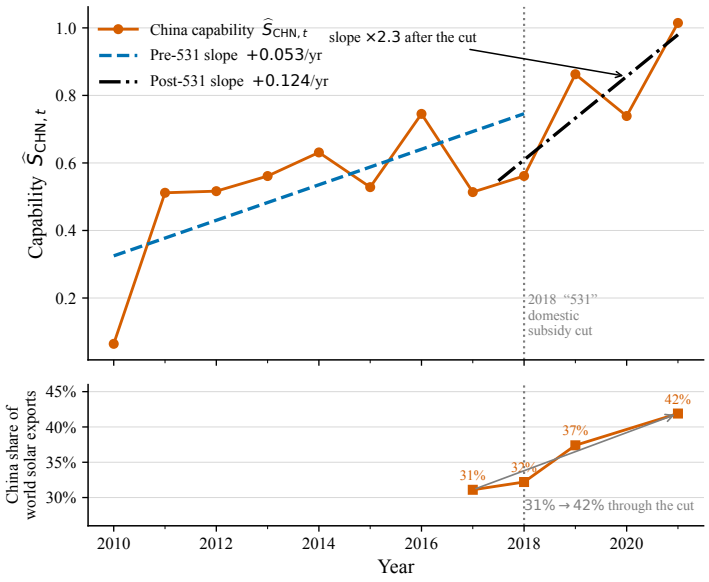


Figure B.3: The 2018 "531" episode. China's solar exporter capability and world export share through the abrupt withdrawal of China's domestic deployment subsidy in May 2018. Capability accelerates rather than falls, indicating an irreversible learning stock rather than subsidized scale.

From estimates to calibration. The price–experience mapping is $LR^k = 1 - 2^{-\nu^k_{\text{tot}}/\theta^k}$, with trade elasticities $\theta^S = 5.38$ and $\theta^W = 4.38$ from Fontagné et al. (2022). The estimated total elasticities validate the external benchmarks $(\nu^S_{\text{tot}}, \nu^W_{\text{tot}}) = (2.00, 1.00)$, implying $LR^S \approx 22\%$ and $LR^W \approx 15\%$ per doubling: the polysilicon-controlled solar estimate (1.91) is statistically indistinguishable from 2.00 and sits in the central empirical range—Nemet (2006) reports approximately 20%, Lafond et al. (2018) 20–25% across PV cost components, the Fraunhofer ISE *Photovoltaics Report 2025* (Fraunhofer Institute for Solar Energy Systems, 2025) 23–26%, and National Renewable Energy Laboratory (2025) 23% over 1976–2024 module shipments. For wind I retain the calibration because the turbine-price series is too short and trend-collinear to pin the slope (steel-controlled and IRENA installed-cost variants bracket it by $[0.5, 1.2]$); $LR^W \approx 15\%$ sits in the central range of Wiser et al. (2024), Rubin et al. (2015), Bolinger et al. (2022), and Covert and Sweeney (2024). The earlier Arkolakis and Walsh (2023) calibration $\nu^S_{\text{tot}} = 3.23$ ($LR^S \approx 34\%$), from global IRENA cost data, is a high-learning benchmark.[4]

The structural-gravity moment puts the *local share* at $\lambda^S_L \approx 0.16$ and, directionally, $\lambda^W_L \gtrsim 0.5$: solar learning is overwhelmingly global, while wind learning is substantially more local—consistent with the codified–tacit knowledge distinction (Polanyi, 1966; Cohen and Levinthal, 1990), in which a global frontier of codified process improvements diffuses across borders (Bahar et al., 2014; Ver-

[4] See also Baker et al. (2013), Bolinger et al. (2022) (US: 24% solar, 15% wind), Kavlak et al. (2018), and Covert and Sweeney (2024) (wind: 14–29%).

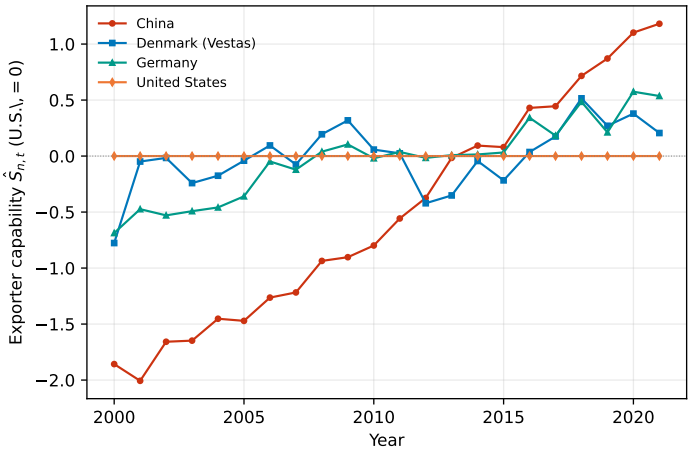


Figure B.4: Wind exporter capability $\hat{S}^W_{n,t}$. Denmark (Vestas) and Germany lead early; China's manufacturing-linked capability rises over the sample. Wind capability is identified from a thinner trade matrix than solar and is read as suggestive rather than definitive.

dolini and Galeotti, 2011; Costantini et al., 2017) while an origin-specific tacit component (production know-how, organizational capital, supplier networks) stays stickier for the heavier, less-traded wind technology (Bollinger and Gillingham, 2012; Covert and Sweeney, 2024). The quantitative benchmark adopts the estimated $\lambda^S_L = 0.16$ (so $(1-\lambda^S_L)\nu^S_{\text{tot}} = 1.68$ operates through the global frontier and 0.32 is local-tacit) and a conservative $\lambda^W_L = 0.50$ for wind, the floor of the directional estimate; the no-learning, fully global, and pure-local limits remain robustness exercises, and the higher wind point estimate (≈ 0.6) is explored as a sensitivity. I treat the pure-local limit as an extreme boundary case used to bound the mechanism rather than as a standard policy counterfactual. Initialization of the cumulative experience stock $Q^k_{n,0}$ for producers with negligible 2022 production uses a small positive floor ($\epsilon = 10^{-3}$ of the global stock), renormalized to preserve the global total, representing latent absorptive capacity rather than economic experience.

B.4.1 Data Construction for the LBD Estimation

This section details the construction of $c^j_{n,t}$, $\pi^j_{nn,t}$, and $P^j_{n,t}$ used to invert (B.1). 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 $w_{n,t}$ 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

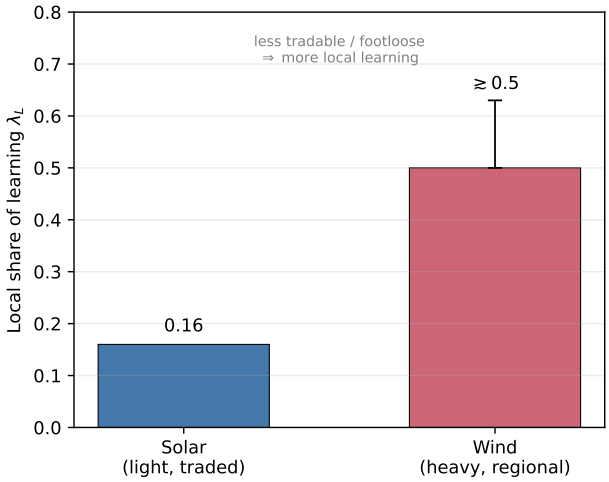


Figure B.5: Local share of learning by technology. The own-country share λ_L is small for solar (light, modular, highly traded equipment; learning predominantly global) and substantially larger for wind (heavy, regionally assembled, integration-intensive); the whisker marks the wind point estimate (≈ 0.6). The local share rises as the equipment becomes less tradable.

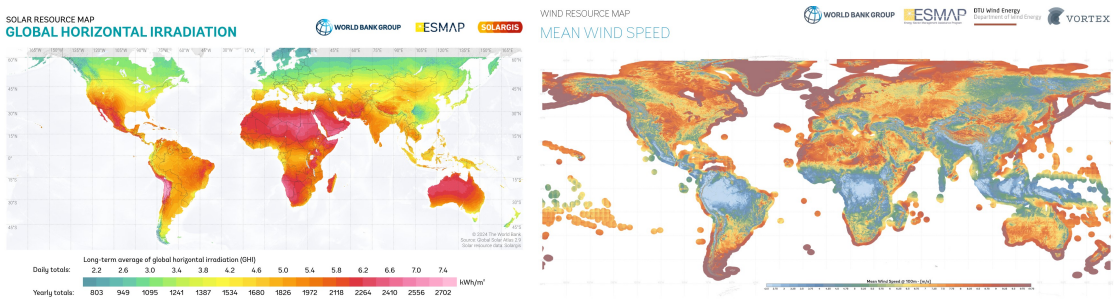
Agency Photovoltaic Power Systems Programme (PVPS). PVPS provides historic price and quantity of solar energy equipment in major countries. I construct the domestic expenditure share sequence $\pi^S_{nn,t}$ by combining export data from Comtrade and output and price data from PVPS. That is, I compute 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 Comtrade 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.

Figure B.6: Renewable Potentials

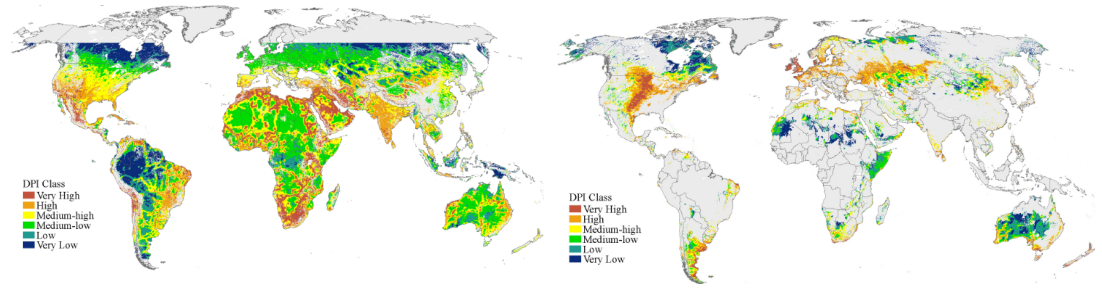
(a) Solar Potential

(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) display 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).

B.5 Renewable Potential

B.5.1 Geospatial Data for Renewable Potential

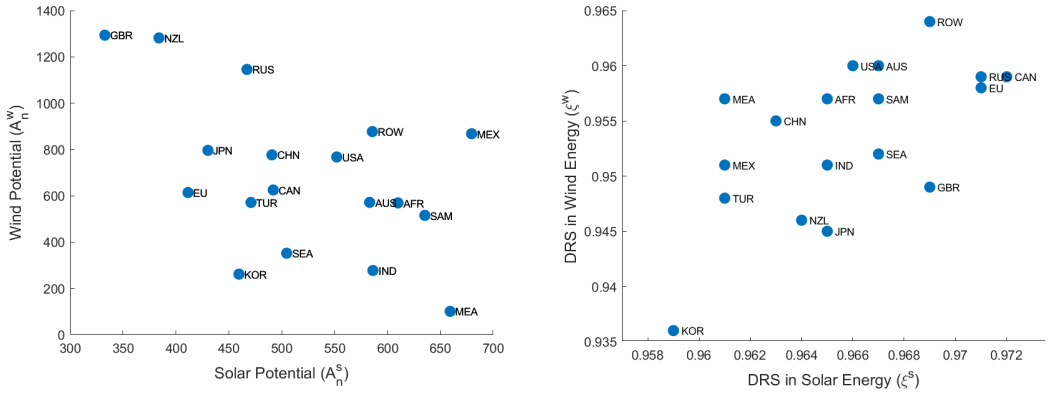
I measure raw renewable potential from the Global Solar and Wind Atlas, and siting feasibility from the Development Potential Index (DPI) of Oakleaf et al. (2019), a 1 km-resolution index that combines sector-specific land constraints with proximity to infrastructure (roads, the grid, and demand centers). Figure B.6 maps both: across the entire globe (Panels (a) and (b)) and across feasibility-adjusted potential (Panels (c) and (d)). Two patterns emerge. First, within-country heterogeneity rises once feasibility is accounted for; second, feasible siting area is limited, especially for wind. I incorporate both measures directly into the model and calibrate the corresponding parameters.

B.5.2 Alternative Method to Calibrate DRS

As an alternative to the DPI-based calibration, I recover diminishing returns by combining solar and wind farm location data with time-invariant resource-potential maps. Using each plant's commissioning year and coordinates, I compute, for each country and year, the average resource potential of installed sites, and regress it on cumulative installed capacity, $\log(A^j_{n,t}) = \xi^{j,\text{ALT}} \log(K^j_{n,t}) + \text{FE}^j_n +$

Figure B.7: Renewable Potentials and DRS in Renewable Energy Production

(a) Renewable Potentials (A_n^s) (b) Decreasing Returns to Scale (ξ_n^s)



Note: Panel (a) displays country-level solar and wind potentials measured by global horizontal irradiation. Panel (b) depicts the measured decreasing returns to scale parameter in solar and wind energy productions.

Table B.4: Additional Evidence of DRS

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

Standard errors in parentheses

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

$\varepsilon^j_{n,t}$, for $j \in \Omega_{RE}$, with country fixed effects FE^j_n. A negative $\xi^{j,\text{ALT}}$ indicates that, as installations rise, developers move to lower-potential sites. Table B.4 reports the estimates: average site potential declines with additional installations for both technologies, and the decline is steeper for wind than for solar. In magnitude these patterns are broadly similar to the main DPI-based measure, with DPI implying a slightly faster diminishing return for solar and a somewhat slower one for wind.

B.6 Measuring Initial Capital Stocks

I measure initial capital stocks for each asset type (fossil fuel, solar, wind, and non-energy) as follows:

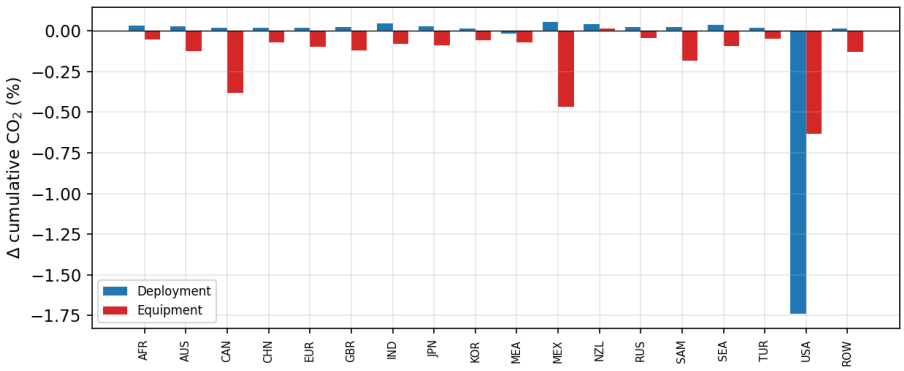
1. **Aggregate capital.** I construct each country's total capital stock using the Penn World Table, which reports capital stocks normalized to the U.S. level. I scale each country's value by the

U.S. level to obtain absolute amounts.[5]

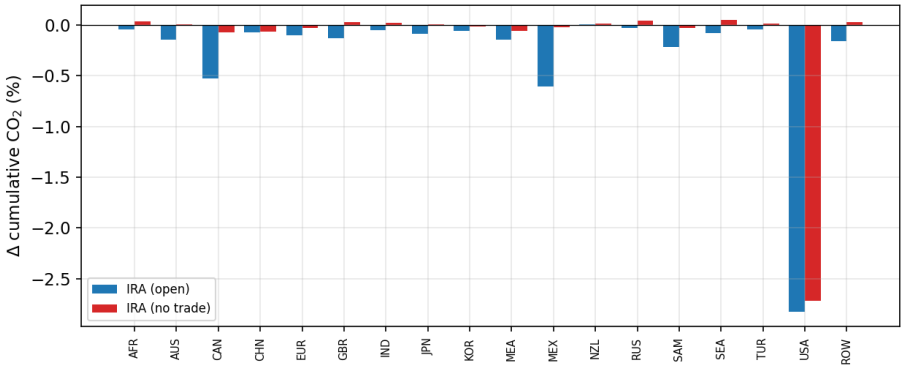
2. **Fossil fuel capital.** I take nominal capital by industry from the WIOD Socio-Economic Accounts. For countries not covered by WIOD but included in my analysis, I impute fossil fuel capital using the average ratio of fossil fuel capital to fossil fuel output from the WIOD dataset.
3. **Solar and wind capital.** I convert installed capacity (kW) into dollar values. As of 2021, the global capital value of wind farms (USD 2.22 trillion) is taken from industry estimates.[6] I first recover gross capital stock using a cumulative depreciation rate, and then allocate this

Figure C.2: Geographic Incidence of CO_2 Reductions (Who Abates)

(a) Under Energy / Equipment Subsidies



(b) Under IRA with and without Equipment Trade



Notes: Each panel reports the percent change relative to the baseline in cumulative CO_2 emissions through 2100, by country. Panel (a) shows the individual instruments—deployment subsidy (blue bars) and equipment subsidy (red bars); Panel (b) shows the combined IRA under the baseline model (blue bars) and under an alternative model without equipment trade (red bars). Negative values indicate emission reductions; positive values indicate emission increases (carbon leakage).

demand surge is met largely by domestic supply, expanding eligible output; conversely, the equipment subsidy lowers unit costs and expands domestic manufacturing, which in turn supports more renewable deployment. These interactions raise total spending relative to running either instrument in isolation.

C.3 Who Reduces Carbon Emissions?

The subsidies' distinct mechanisms generate different spillovers for global carbon emissions, summarized in panel (a) in Figure C.2. The deployment subsidy concentrates abatement in the U.S. with some carbon leakage to other countries (blue bars); the equipment subsidy (red bars) spreads abatement more broadly by lowering world equipment prices. Blue bars in Panel (b) plot the outcome under the combined IRA; the IRA combines these channels to diffuse decarbonization across

Table C.1: Selected Welfare Decomposition (to 2100, %)

Region	Policy	Real Income	Carbon Benefit	Welfare
United States	Deployment subsidy	-0.036	0.030	-0.007
	Equipment subsidy	-0.027	0.013	-0.014
	IRA	-0.110	0.050	-0.060
China	Deployment subsidy	0.014	0.028	0.042
	Equipment subsidy	-0.004	0.011	0.008
	IRA	0.003	0.046	0.049
EU	Deployment subsidy	0.004	0.031	0.035
	Equipment subsidy	0.003	0.013	0.017
	IRA	0.005	0.052	0.056
Global aggregate	Deployment subsidy	0.001	0.029	0.030
	Equipment subsidy	-0.010	0.012	0.003
	IRA	-0.019	0.049	0.030

Notes: Values are percentage changes relative to the no-policy baseline. Global aggregate entries are working-age-population weighted and include the U.S. "Carbon Benefit" is the welfare contribution from reduced emissions; "Real Income" is the non-carbon component; "Welfare" is their sum.

countries. The aggregate magnitudes (-0.195%, -0.165%, and -0.443%) are reported in Table 5 and discussed in §5; the contribution here is geographic—a substantial share of the IRA's abatement occurs outside the U.S.

C.4 Welfare Decomposition

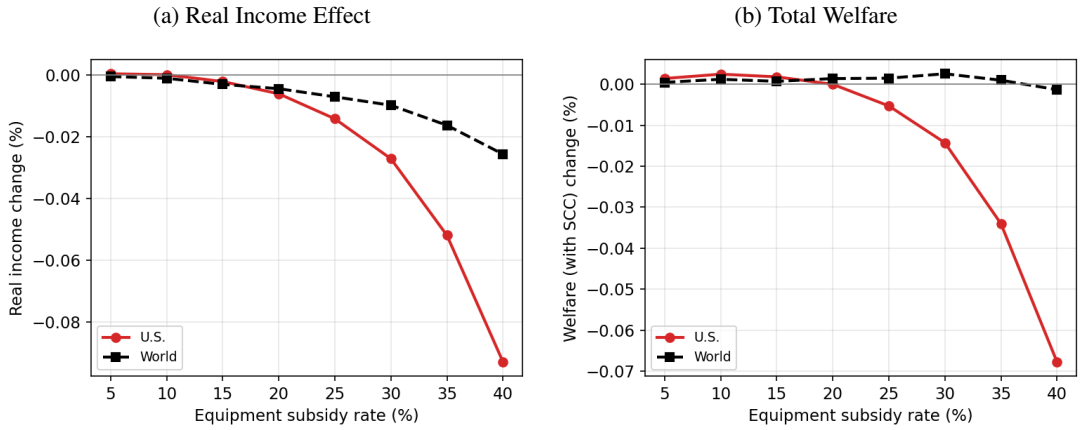
Table C.1 reports the welfare decomposition—real income (non-carbon), carbon benefit, and their sum—for selected countries and the global aggregate, cumulated through 2100. The cell values trace the assignment logic developed in §5–§6: the carbon component is uniformly positive, while the real-income component carries the cross-country incidence, and at the world level the discounted carbon gains are large enough to make the full IRA welfare-positive despite its negative world real-income effect.

C.5 Optimal Subsidy

In this section, I examine how varying deployment- and equipment-subsidy rates over the policy grid alters U.S. and global welfare—decomposed into real-income and carbon components—with Figure C.3 Panel (a) reporting real-income effects and Panel (b) adding the carbon benefit. Fiscal costs vary across grid points and are reported for the main policy comparisons.

Real-income effects. Panel (a) in Figure C.3 traces real-income responses as the grid moves from

Figure C.3: Welfare by Subsidy Ratio



Note: This figure plots percent changes in welfare under different combinations of energy and equipment subsidies, holding the policy duration to 10 years. The horizontal axis varies the *ad valorem* equipment subsidy rate, while different lines correspond to varying deployment subsidy rates (0%, 5%, and 10%). Solid lines report U.S. welfare and dotted lines report global welfare. Panel (a) plots the real-income component; Panel (b) adds the SCC-valued carbon component. All changes are cumulative through 2100 relative to the no-policy baseline.

deployment toward equipment support. The U.S. real-income effect under equipment support is inverted-U shaped—modest support raises real income through lower unit costs and stronger learning, then bends down as diminishing returns and fiscal incidence mount—whereas the global effect is monotonically negative in the equipment rate, the beggar-thy-neighbor pattern documented elsewhere. Higher deployment subsidies lower U.S. real income, consistent with the import pass-through channel above.

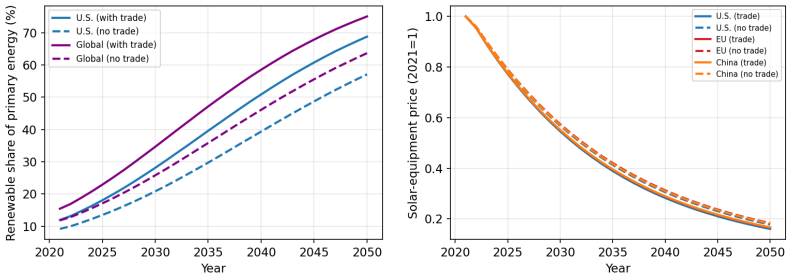
Adding carbon benefits. Panel (b) adds the carbon component. A more equipment-tilted mix compresses world equipment prices and diffuses abatement abroad, so the global CO_2 reduction grows with the equipment share; but the equipment subsidy's negative world real-income effect roughly offsets this carbon benefit, leaving global welfare small across the grid. For the U.S., welfare is hump-shaped, peaking at only about $+0.002\%$ near a 10% rate—so no point on the grid delivers the U.S. a meaningful national gain.

C.6 Comparative Statics

The main text emphasizes equipment trade as the channel through which deployment demand becomes production revenue abroad and manufacturing support diffuses lower equipment prices internationally. The transition-path diagnostics below isolate this mechanism by comparing calibrated equipment trade with a no-trade counterfactual for renewable-energy equipment.

Figure C.4: Role of Renewable-Energy Equipment Trade

(a) Share of Renewable Energy (b) Price of solar equipment



Note: Panel (a) shows the share of renewable energy in total primary energy use from 2021 to 2050 in the U.S. (blue) and globally (purple). Panel (b) shows the solar-equipment price index over the same period in the U.S. (blue), the EU (red), and China (yellow). Solid lines denote the baseline with calibrated trade costs; dashed lines denote the no-trade counterfactual for renewable-energy equipment.

C.6.1 Role of Renewable-Energy Equipment Trade on the Transition

To assess the role of renewable-energy equipment trade in the transition, I compare the baseline scenario with calibrated trade costs to a scenario with no trade. In the no trade scenario, I eliminate trade in renewable-energy equipment by setting the trade cost to infinity, i.e., $\kappa^j_{in,t} = \infty$ for $j \in S, W$ and $i \neq n$.

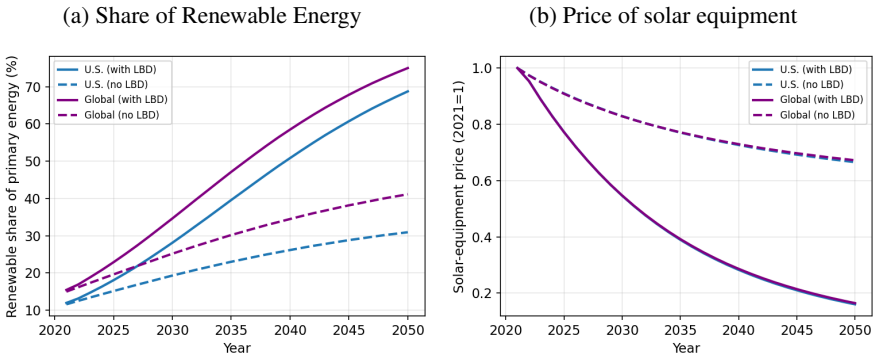
Panel (a) of figure C.4 compares the share of renewable energy in the U.S. and globally under the baseline and the no-trade scenario. In the baseline scenario, represented by the solid line, the share of renewable energy in primary energy use reaches 49% in the U.S. and 53% globally. In contrast, Without trade, the share of renewable energy in primary energy use only reaches 38% in the U.S. 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. In the no trade scenario, the price spikes in the U.S. and EU, while the increase in China is relatively small, as China has been the main exporter under the baseline. Overall, higher equipment prices in the no equipment trade scenario discourages investment in renewable energy in each country, slowing the energy transition.

C.6.2 Role of Learning-by-doing on the Transition

A central component of the model is learning-by-doing in renewable-equipment production. To assess its impact, I shut down learning-by-doing by setting $\nu^S_{\text{tot}} = \nu^W_{\text{tot}} = 0$ and re-simulate the transition path. Panel (a) of Figure C.5 compares the renewable-energy share in the U.S. and global from 2021 to 2050 with and without learning-by-doing. With learning-by-doing enabled, the renewable share in primary energy reaches about 69% in the U.S. (and 75% globally) by 2050; without

Figure C.5: Role of Learning-by-doing



Note: Panel (a) plots the share of renewable energy in total primary energy use from 2021–2050 for the U.S. (blue) and the world (purple). Panel (b) shows the price index for solar equipment over the same period in the U.S. (blue), the European Union (red), and China (yellow). Solid lines denote the baseline with learning-by-doing; dashed lines shut down learning-by-doing.

learning-by-doing, it reaches only about 31% in the U.S. (and 41% globally).

Panel (b) displays the evolution of solar equipment prices in the U.S., the European Union, and China. In the absence of learning-by-doing, equipment-price indexes fall much more slowly because there is no endogenous productivity growth. The muted cost declines depress investment relative to the baseline, producing a markedly slower transition in each country.

C.7 Additional Results on IRA under Trade Policy

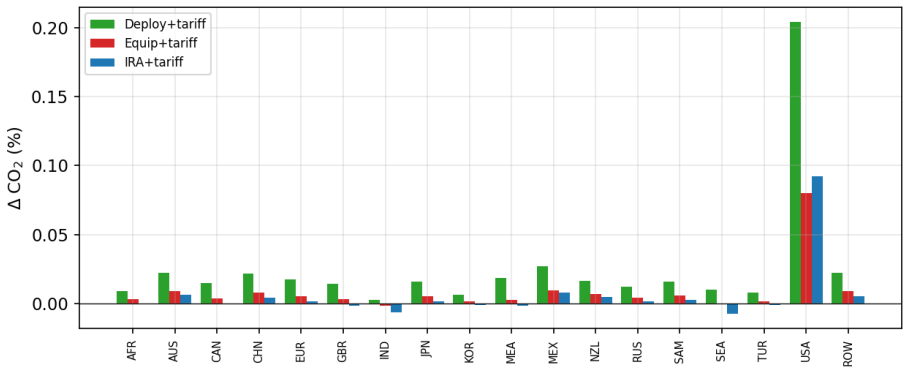
Section 6 reports the aggregate effects of layering a U.S. solar-equipment tariff onto each subsidy scenario; in the calibration the tariff's price distortion is largely offset by the IRA subsidies, leaving the full IRA+tariff mix close to IRA alone (global CO_2 falls by about 0.43% vs. 0.44%, global welfare $+0.019\%$, U.S. welfare -0.091%; Table C.2). Figure C.6 adds the cross-country incidence relative to the no-tariff counterpart: countries directly targeted by the tariff (e.g., India, China, Southeast Asia) bear the largest welfare losses through reduced exports and slower learning-by-doing abroad, while some third countries (e.g., Korea, Mexico) gain modestly by diverting exports toward the U.S. market.

C.8 Additional Results on U.S.-China-EU Policy Competition

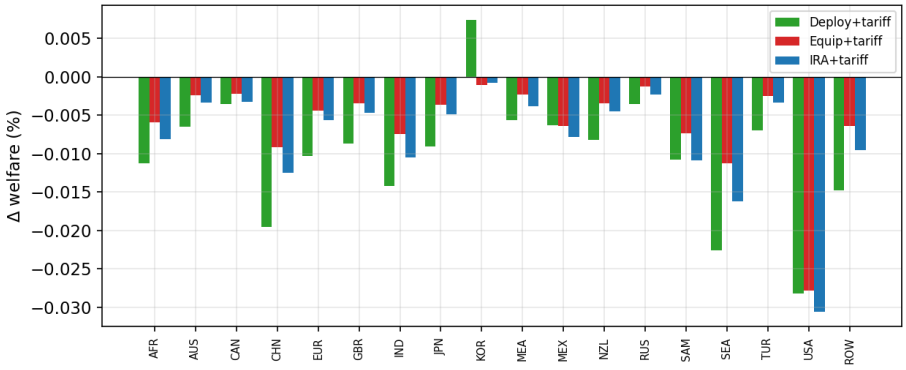
Section 6 reports the aggregate effects when the U.S., China, and the EU each implement IRA-like policies (Table C.2, panel (c)): relative to the U.S.-only mirror policies, multilateral deployment subsidies cut global CO_2 by 1.05% (global welfare $+0.08\%$, U.S. welfare $+0.08\%$), multilateral equipment subsidies by 1.82% (global welfare $+0.07\%$, U.S. welfare $+0.24\%$, while China still loses real income, -0.057%, the same incidence it bears acting alone), and the full multilateral IRA by 3.86% (vs. 0.44% under U.S.-only IRA; global welfare $+0.25\%$, U.S. welfare $+0.41\%$).

Figure C.6: Welfare and Carbon Effects of IRA with a Solar Tariff Across Countries

(a) Cumulative CO_2 effect (%)



(b) Welfare effect (%)



Notes: Panel (a) plots the effect of adding a U.S. solar-equipment tariff to each subsidy scenario on cumulative CO_2 emissions by 2100, *relative to the same scenario without the tariff*. Panel (b) plots the corresponding welfare effects for residents in each country. Bars are differences relative to the no-tariff counterpart (not absolute levels).

Figure C.7 adds the country-by-country incidence the aggregates omit: under the full multilateral IRA, U.S. emissions decline less than in the U.S.-only case because multilateral subsidies depress global fossil-fuel prices and induce some domestic leakage (panel (a)), and distributional patterns track trade positions—fossil-fuel exporters (Middle East, Russia, and South America) lose as global demand falls, while net importers (e.g., Japan, Korea) gain from improved terms of trade and faster adoption (panel (b)).

C.9 Robustness Check

The impact of the IRA hinges principally on four sets of parameters: (i) the elasticity of substitution between renewable energy and fossil fuels, ψ, which determines how readily cheaper renewables displace fossil generation; (ii) the locality of equipment learning, governed by the local tacit shares

Table C.2: Extension Outcome Comparisons

	Global CO_2 (%)	U.S. Welfare (%)	Global Welfare (%)	World Real GDP (%)
(a) Baseline specification				
IRA	-0.443	-0.060	0.030	-0.028
(b) IRA + Solar Tariff				
Tariff	0.041	-0.034	-0.013	-0.011
Deployment Subs. + Tariff	-0.156	-0.035	0.015	-0.016
Equipment Subs. + Tariff	-0.151	-0.042	-0.006	-0.016
IRA + Tariff	-0.430	-0.091	0.019	-0.038
(c) U.S.–China–EU Policy				
Deployment Subs.	-1.054	0.078	0.077	-0.028
Equipment Subs.	-1.824	0.244	0.069	0.029
IRA	-3.860	0.407	0.249	0.006

Notes: Global Welfare is population-weighted (incl. SCC); *World Real GDP* is the GDP-weighted real-income aggregate (efficiency, excl. carbon).

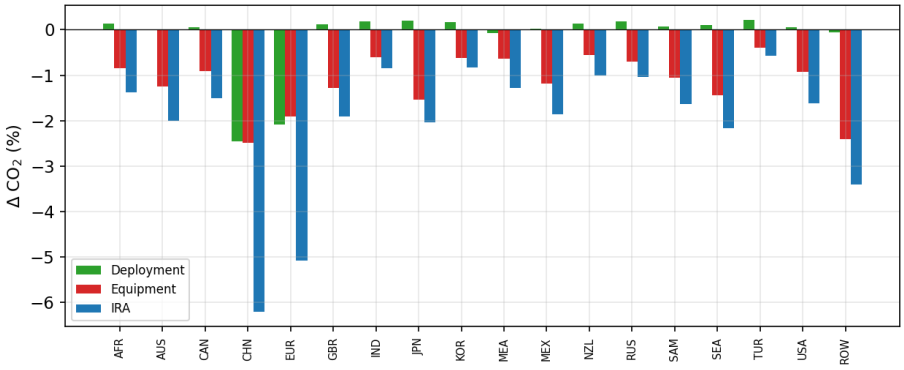
λ_L^S and λ_L^W, which dictate how far the gains from learning-by-doing spill across borders; (iii) the equipment trade elasticities θ^S and θ^W, which shape how production reallocates in response to subsidies; and (iv) the damage parameter, SCC_t, which prices the carbon externality. I examine how variation in each of these parameters shapes the IRA's outcomes.

Higher elasticity of substitution between renewables and fossil fuels. Re-running the experiments with $\psi = 5$ against the baseline $\psi = 3.08$ (Panel (b) of Table C.3), every instrument cuts more carbon once renewables and fossil fuels are more substitutable. Acting directly on renewable use, deployment support delivers the deepest abatement (-1.358%, against -0.977% for the equipment subsidy) and the larger global-welfare gain ($+0.088\%$ versus $+0.044\%$). The two-lens reading is instructive: these welfare gains rise mainly through the larger shared carbon benefit, while in real income (carbon-excluded) the U.S. return stays negligible—a deployment and equipment gain of $+0.009\%$ and $+0.005\%$, and an IRA loss of -0.034%. Higher substitutability thus deepens abatement and lifts the carbon-inclusive welfare numbers without overturning the instruments' real-income ordering.

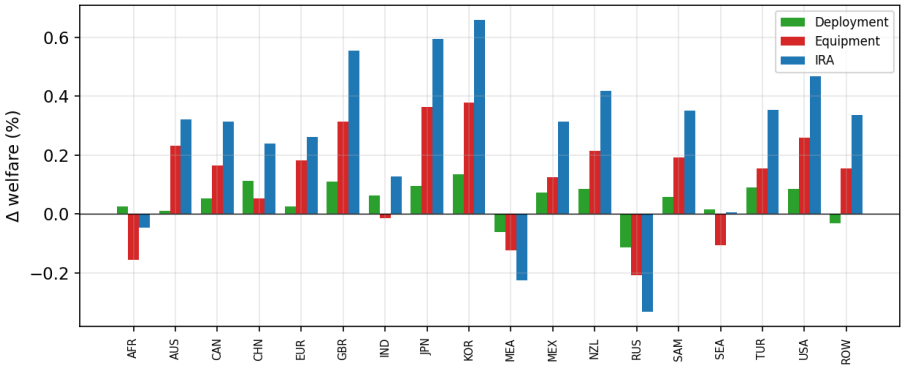
No global spillover. Switching off the global learning spillover ($\nu_G^S = \nu_G^W = 0$) makes each country's equipment productivity depend only on its own cumulative output—the estimated local component—which isolates the role of cross-border diffusion. Panel (c) reports the U.S. instruments, and their sign is unchanged: deployment, equipment, and the IRA each leave U.S. welfare slightly negative (-0.006%, -0.020%, and -0.066%), because the local component of learning is itself too small for the U.S. to build a durable advantage. A national return would require local learning far stronger than the data imply, as the strong-local benchmark of Section 5.2 shows; removing the spillover alone does not deliver it. Because the U.S. is a minor equipment producer, switching diffusion off barely moves the U.S. return and does little for the rest of the world—its effect on

Figure C.7: Welfare and Carbon Effects of U.S.–China–EU Policies Across Countries

(a) Cumulative CO_2 effect (%)



(b) Welfare effect (%)



Notes: Panels plot the change in cumulative CO_2 by 2100 (panel (a)) and welfare (panel (b)) across countries when the U.S., China, and the EU implement IRA-like policies. Each bar is measured *relative to the corresponding U.S.-only (mirror) policy:* U.S.–China–EU IRA vs. U.S.-only IRA; U.S.–China–EU deployment subsidy vs. U.S.-only deployment subsidy; U.S.–China–EU equipment subsidy vs. U.S.-only equipment subsidy. Bars are differences relative to the mirror policy (not absolute levels).

global welfare is essentially nil (0.000% for the equipment subsidy)—so the location of support, not the reach of learning alone, governs the global return.

Frictionless spillovers of learning-by-doing. Panel (d) examines frictionless cross-country LBD spillovers following Arkolakis and Walsh (2023). I modify the LBD law of motion in Equation (19) so that productivity gains accumulate from global rather than local production:

$$A^k_{n,t} = \nu^k_n \Big(\sum_{n}^{N} \sum_{i=1}^{t-1} (\mu)^i y^k_{n,t-i} \Big)^{\nu^k_G}, \quad \text{for } k \in \Omega_{REE}.$$

Global LBD elasticities are set to 35% for solar and 20% for wind ($\nu^S_G = 1.67$ and $\nu^W_G = 0.52$), matching Arkolakis and Walsh (2023). Under frictionless global LBD, the productivity gains from cumulative production diffuse internationally, and at this pole the U.S. return to equipment support is

negative: a 30% U.S. equipment subsidy lowers global CO_2 by 0.077% and changes global welfare by -0.005%, while reducing U.S. welfare by 0.041%. At the opposite, strong-local pole the same subsidy would instead raise U.S. welfare by 0.108%; the estimated baseline ($\lambda_L^S = 0.16$) sits near the global end, with a U.S. welfare effect of -0.014%. Any U.S. equipment-subsidy return is thus tied to local production-linked learning, which the estimates place low: when learning is largely shared, the policy effectively subsidizes foreign productivity and secures no persistent U.S. market-share advantage. The remaining global-LBD rows in Table C.3 are reported as robustness diagnostics.

Low equipment trade elasticities. Setting $\theta^S = \theta^W = 2$ (in line with Boehm et al. (2023)) shifts the rankings toward the carbon channel and strengthens the role of the deployment subsidy.[8] The deployment subsidy delivers a larger CO_2 decline (-0.80%) and raises both global and U.S. welfare (about $+0.09\%$ each). The equipment subsidy still reduces CO_2 (-0.62%) but leaves U.S. welfare essentially unchanged ($\approx 0.00\%$) and global welfare slightly negative (-0.01%), consistent with muted international pass-through and limited displacement of incumbents. The IRA blends these forces: CO_2 falls by -1.51%, and global welfare rises more than U.S. welfare (0.07% and 0.04%). Intuitively, lower cross-origin substitutability dampens world price declines and market-share reallocation, weakening the industrial (terms-of-trade/learning) channel while leaving the carbon channel relatively stronger.

Extending policy periods. In the baseline IRA the policy is not strong enough to generate a lasting increase in the U.S. equipment-market share, so a natural adjustment is to extend the subsidy's duration. Panel (f) lengthens the window from ten years (2022–2031) to twenty (2022–2041). The longer horizon magnifies the CO_2 reduction, raises global welfare, and increases the U.S. share of the global equipment market, yet it leaves the qualitative ranking of instruments unchanged. Extension nonetheless deepens the U.S. welfare loss, from -0.060% to -0.249% for the IRA, as the additional fiscal cost of the longer window outweighs the incremental gains. The larger short-run effects remain transitory: once the subsidies expire, the U.S. equipment-market share returns to its initial level.

Heterogeneous damage function. Allowing country-specific marginal damages (Panel (g), following Ricke et al. (2018)) leaves the aggregates close to the baseline: global welfare for the IRA ticks up by about 0.05 percentage points, from 0.030% to 0.08%, while U.S. welfare is marginally smaller, at $\approx 0.03\%$. The distribution, however, shifts. Because the social cost of carbon is now apportioned according to where damages fall, countries with high marginal climate damages—notably India and China—capture a larger share of the carbon-benefit component than under the homogeneous-damage case, even though the global aggregate moves little. The reallocation operates entirely through the carbon channel: abatement is valued more highly by the countries that would otherwise bear the heaviest damages, so the same emissions reduction registers as a larger welfare gain for them. The assignment logic is unaffected, since the terms-of-trade and learning channels do not depend on the

[8] I re-estimate κ_{ni}^j and ν_{tot}^j to re-match baseline bilateral equipment trade shares and cost trajectories, since $\{\kappa_{ni}^j, \nu_{\text{tot}}^j\}$ are identified in the gravity–LBD system given θ^j.

geographic incidence of damages.

Table C.3: Robustness Check

	Global CO_2 (%)	U.S. Welfare (%)	Global Welfare (%)
(a) Baseline Specification			
IRA	-0.443	-0.060	0.030
Deployment Subs.	-0.195	-0.007	0.030
Equipment Subs.	-0.165	-0.014	0.003
(b) Elasticity of Substitution (ψ = 5)			
IRA	-2.614	0.146	0.215
Deployment Subs.	-1.358	0.085	0.088
Equipment Subs.	-0.977	0.056	0.044
(c) No Global Spillover ($\nu_G^S = \nu_G^W = 0$)			
IRA	-0.327	-0.066	0.043
Deployment Subs.	-0.161	-0.006	0.042
Equipment Subs.	-0.110	-0.020	0.000
(d) Frictionless Learning-by-doing ($\nu_G^S = 1.67$, $\nu_G^W = 0.52$)			
IRA	-0.27	-0.10	0.03
Deployment Subs.	-0.17	-0.01	0.04
Equipment Subs.	-0.077	-0.041	-0.005
(e) Equipment Trade Elasticity ($\theta^S = 2$, $\theta^W = 2$)			
IRA	-1.51	0.04	0.07
Deployment Subs.	-0.80	0.09	0.09
Equipment Subs.	-0.62	0.00	-0.01
(f) Extending Policy Periods (2022-2041)			
IRA	-1.583	-0.249	0.133
Deployment Subs.	-0.688	-0.069	0.087
Equipment Subs.	-0.654	-0.049	0.037
(g) Country-level Social Cost of Carbon ($SCC_{n,t}$; Ricke et al. (2018))			
IRA	-0.63	0.03	0.08
Deployment Subs.	-0.16	-0.05	0.05
Equipment Subs.	-0.27	0.08	0.01

Notes: Each panel varies one feature relative to the baseline in panel (a); all other parameters are held at their benchmark values.

Appendix D Algorithm

This section describes the algorithm used to solve the model.

To compute the transition path and steady state, I set T sufficiently large to ensure convergence to the steady state. In practice, $T = 200$ suffices.

1. Take the calibrated parameters of Section 4 as given (equipment productivities $A^j_{n,t}$ start from initial values and evolve *endogenously* through learning-by-doing).
2. Guess the investment-rate sequence $\{\varphi^k_{n,t}\}_{n,t}$ for each capital good $k \in \Omega_K$, which pins down investment from the current stock via

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

3. **Static trade block.** For each $t = 1, \ldots, T$, given the capital stocks, solve the static general-equilibrium allocation using the algorithm of Alvarez and Lucas (2007): guess factor and energy prices (with world GDP as the numeraire), then iterate to a fixed point on the price equations (10)–(7), trade shares (12), and total expenditures (13)–(14) until the labor- and capital-market-clearing conditions (15)–(16) hold. Advance the stocks across periods with the accumulation equation (20) and (D.1).
4. **Euler/excess-demand update.** Plug the resulting stock paths $\{K^k_{n,t}\}$ into the intertemporal Euler equation to obtain the excess demand $Z^k_{n,t}$ for each n, k, t, then update the investment-rate guess with step size $\zeta > 0$:

$$\varphi^{k,\text{NEW}}_{n,t} \;=\; \varphi^k_{n,t} + \zeta\, Z^k_{n,t}\Big(\{\varphi^k_{n,t}\}_{t=1}^{T}\Big) \quad \forall\, n, k, t.$$

5. Iterate Steps 3–4 until $\{\varphi^k_{n,t}\}$ converges to a fixed point ($Z^k_{n,t} \to 0$).