CHAPTER 3

INDUSTRIAL POLICY: MANAGING TRADE-OFFS TO PROMOTE GROWTH AND RESILIENCE

ONLINE ANNEXES

This Online Annex to Chapter 3 of the October 2025 World Economic Outlook lays out the data sources, sample coverage, variable definitions and methodologies used in the main chapter. The Online Annex follows the structure of the Chapter. The Chapter draws on a variety of datasets which are described in detail in what follows. Further the chapter harnesses three distinct macroeconomic models that focus on different aspects of IP. The Learning by doing (LBD) model is a dynamic partial equilibrium model that focuses on sector level outcomes for one sector. GMMET is a new Keynesian dynamic general equilibrium model with energy sector detail used to assess how productivity changes from LBD are transmitted across the economy. The Quantitative Trade model (QTM) is a static trade model with sectoral economies of scale, that allows for the study of IPs and spillovers across sectors in a framework with rich input-output linkages. These are detailed further below, including how the LBD model and GMMET are combined for scenario analysis.

Online Annex 3.1. Data Sources, Sample Coverage, and Variable Definitions

The analysis in the Chapter draws from multiple datasets. Details on each dataset, the sample coverage and variable definitions are provided below.

U.S. Energy Information Administration (U.S. EIA)

Country-year level data on total energy consumption and production from the U.S. EIA are used to define energy dependence in Figure 3.1 panel 2. A country is classified as a net energy importer if its total energy consumption exceeds its total production, and as a net energy exporter if the opposite holds. U.S. EIA data are also used to produce Figure 3.4 panel 2 on the sources of electricity production. Specifically, the data is used to calculate the share of fossil fuel in electricity production. The analysis includes 34 AEs and 27 EMDEs.

International Energy Agency (IEA)

This study uses the International Energy Agency World Energy Balances dataset. To produce Figure 3.4 panel 1 in the main text, it uses information on total Energy demand (= Production + Imports - Exports - International marine bunkers - International aviation bunkers +/- Stock changes); fossil fuel imports and exports, with fossil fuels including "Coal, peat and oil shale", "Crude, NGL and feedstocks", "Natural gas", and "Oil products". This study also uses the IEA Energy End-uses and Efficiency Indicators dataset to produce Figure 3.4 panel 2 in the main text on the share of electricity in total energy consumption.

Eurostat

European Union's energy import dependency data from Eurostat is used to produce Figure 3.4 panel 1 in the main text. The indicator defines as the share of total energy needs of a country met by imports from other countries. It is calculated as net imports divided by the gross available energy.

New Industrial Policy Observatory (NIPO) Database

The NIPO dataset for the period 2009-2022 contains information on the stated motive of trade-related industrial policy measures included in the Global Trade Alert (see Evenett and others 2024, forthcoming). This dataset is used to produce Figure 3.3 panel 1 in the main text. Each intervention is classified based on official statements or direct quotes from senior officials, as collected and reviewed by the GTA team, subject to data availability. An intervention can be associated with more than one stated motive. The motives are categorized as follows:

- *Strategic competitiveness*: the action seeks to promote domestic competitiveness or innovation in a strategic product or sector.
- *Climate mitigation*: the action is motivated by climate change mitigation or the transition to the low-carbon economy.
- *GVC resilience*: the government stated motive of the action taken refers to raising the stability or security of local supplies of non-food products, either currently or in the future.
- *National security*: the government stated motive of the action taken refers to the current or future military security of the implementing country or specifically quotes "national security".
- *Geopolitical concerns*: the government stated motive of the action taken refers to countering the risk from a country or a class of countries.

Global Trade Alert (GTA) Dataset

The Global Trade Alert (GTA) dataset, spanning the period from 2008 to 2024, is a comprehensive resource for monitoring trade-distorting policy measures and their global implications. The dataset is structured as a panel, where each observation represents a unique country-policy intervention-product-year combination (for the regression analysis, the dataset is further collapsed at the country-product-year level). Products are classified based on HS 2012 codes or CPC codes. It includes policies active between their announcement and removal dates, categorized by type and evaluation (e.g., "Green," "Red/Amber").

The version of the dataset used in this chapter excludes policies implemented at the "subnational" government level, keeping in the sample policies implemented by national and supranational authorities, as well as policies implemented by International Financial Institutions (IFIs) and National Financial Institutions (NFIs).

In the analysis, policy dummies have been created based on the following policy instruments (labelled "intervention_type" in GTA) grouping:

- Subsidized financing measures: "Trade finance", "State loan", "Loan guarantee", "Financial assistance in foreign market", "Capital injection and equity stakes (including bailouts)", "Interest payment subsidy", "Trade payment measures".

- Direct support measures: "Financial grant", "Production subsidy", "Tax or social insurance relief", "State aid, unspecified", "Tax-based export incentive", "Price stabilization", "Export subsidy", "Other export incentive", "In-kind grant", "Import incentive", "State aid, nes".
- Other measures: "Anti-dumping", "Controls on commercial transaction and investment instruments", "Controls on credit operations", "Export ban", "Export licensing requirement", "Export quota", "Export tariff quota", "Export tax", "Export-related non-tariff measure, nes", "FDI: Entry and ownership rule", "FDI: Financial incentive", "FDI: Treatment and operations, nes", "Import ban", "Import licensing requirement", "Import quota", "Import tariff", "Import tariff quota", "Import-related non-tariff measure, nes", "Internal taxation of imports", "Labour market access", "Local content incentive", "Local content requirement", "Local labour requirement", "Local operations requirement", "Local supply requirement for exports", "Local value added incentive", "Localisation, nes", "Public procurement access", "Public procurement localisation", "Public procurement preference margin", "Public procurement, nes", "Repatriation & surrender requirements", "Instrument unclear".

In the chapter, we only consider policy interventions that have been identified as "industrial policies" by Juhász and others (2022, 2025). Moreover, each policy instrument described above is separately classified based on whether it is evaluated by GTA as liberalizing (i.e., green evaluation) or protectionist (i.e., red/amber evaluation).

Orbis

Sector-level data is constructed by aggregating firm-level data from the Bureau van Dijk (BvD) Orbis global database. Orbis is the largest cross-country firm-level database, reporting data on private and public firms from most industries. It collects data from various sources (in particular, publicly available national company registries) and harmonizes the data into an internationally comparable format. The dataset used in the analysis follows the cleaning steps described in Kalemli-Özcan and others (2015) and Gopinath and others (2017). The variables used in the analysis are labor compensation, age, total assets, operating revenue (gross output), tangible and intangible fixed assets, material costs, liabilities, earnings before interest and taxes, and cash flow. All variables are converted into constant 2010 US dollars. Sectoral TFP and allocative efficiency are calculated following Hsieh and Klenow (2009) and IMF (2024).

GTAP Database

The empirical analysis of how IPs in the energy sector affect downstream industries uses country-specific IO matrices calculated with the Global Trade Analysis Project (GTAP) database. The GTAP data provides a consistent and detailed representation of global economic interactions by integrating national IO tables, trade flows, and other economic data into a unified framework. We assign each NACE Rev. 2 4-digit industry code to one or more of the 65 GTAP sectors. We classify the following GTAP sectors as energy: Coal: mining and agglomeration of hard coal, lignite and peat; Oil: extraction of crude petroleum, service activities incidental to oil and gas extraction excluding surveying (part); Gas: extraction of natural gas, service activities incidental to oil and gas extraction excluding surveying (part); Petroleum & Coke: manufacture of coke and refined petroleum products; Electricity: steam and air conditioning supply; and Gas: manufacture, distribution. The main variable used from GTAP tracks "domestic purchases by firms at basic prices" between all GTAP sectors. These are then normalized and used as the IO coefficients in each country to construct upstream IP exposure measures, as in Baquie and others (2025).

OECD Inter-Country Input-Output Tables

The quantitative trade model draws on the OECD inter-country input-output tables, which capture granular input-output tables for over 70 countries. Key datapoints for the model calibration are bilateral sector-level trade flows within and between countries, gross sectoral output and value-added. The raw data captures 45 narrowly defined industries. The data is aggregated to the level of 45 individual countries, the EU, and the rest of the world that subsumes all remaining countries and to the level of 20 industries.

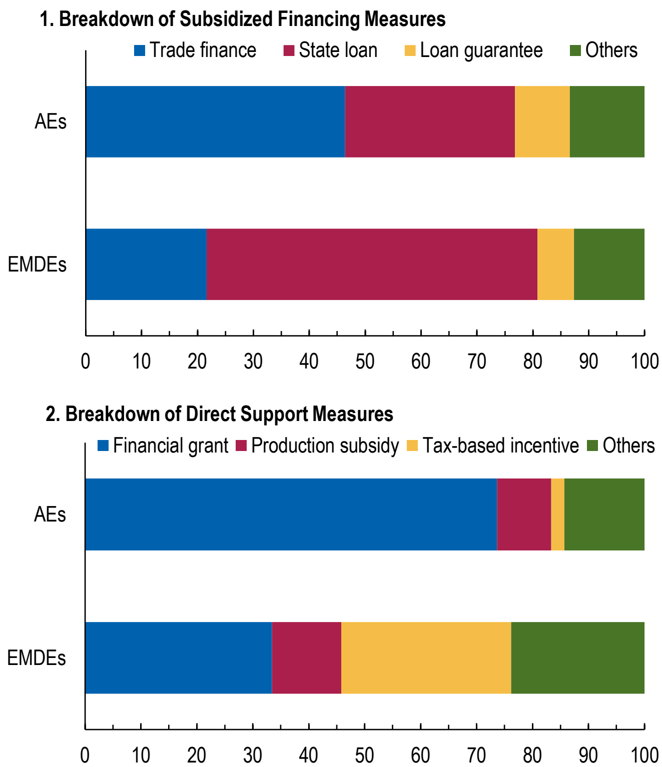
Online Annex 3.2. Additional Stylized Facts

This section displays additional stylized facts.

Online Annex Figure 3.2.1 expands on Figure 3.2 panel 1 by detailing the types of "subsidized financing" and "direct support" interventions. Panel 1 shows that advanced economies supported firms with both trade finance and state loans, while emerging and developing economies mainly used state loans. Looking at the breakdown of direct support measures in panel 2, advanced economies offered financial grants, whereas emerging and developing economies relied more on tax incentives due to limited fiscal space.

Online Annex Figure 3.2.1. Breakdown of Policy Types within Subsidized Financing and Direct Support Measures

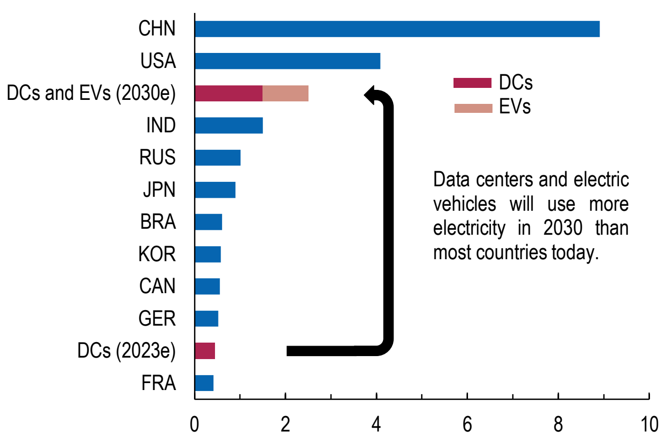
(Percent of total measures)



Sources: Global Trade Alert; Juhász and others 2022; Juhász and others 2025; and IMF staff calculations.
Note: AEs = advanced economies; EMDEs = emerging market and developing economies.

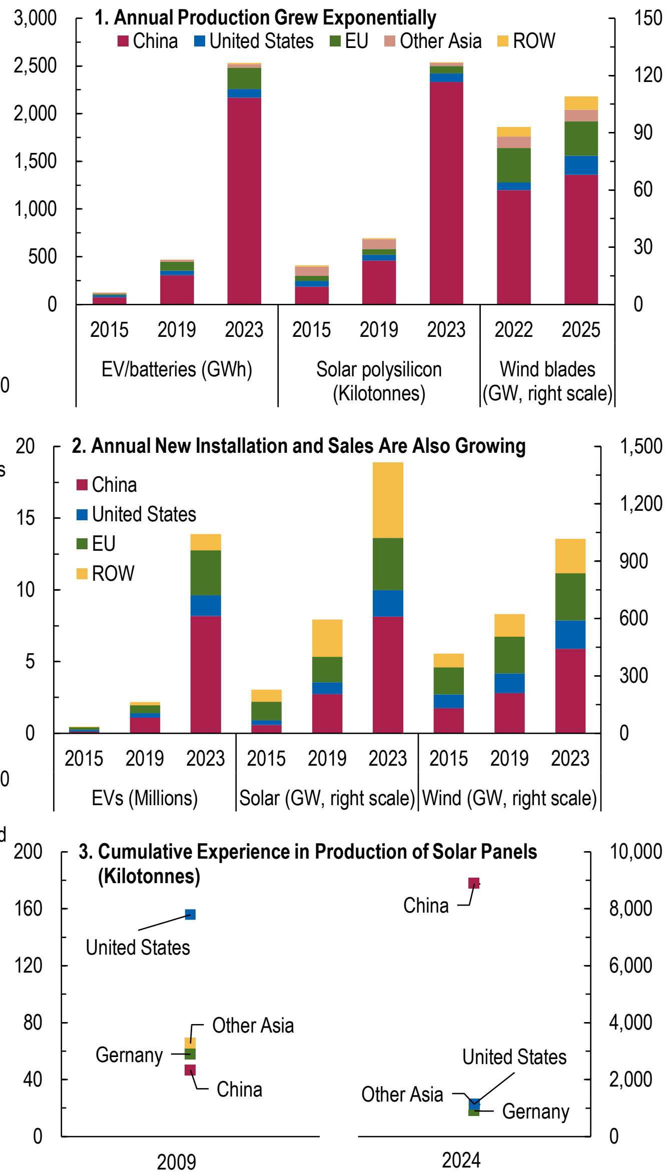
Online Annex Figure 3.2.2. Electricity Demand: Total by Country (2023) and New Needs (2030-estimates)

(Thousands of terawatt-hours)



Sources: Eurostat; International Energy Agency (IEA); Organization of the Petroleum Exporting Countries (OPEC); U.S. Energy Information Administration; and IMF staff calculations.
Note: In this figure, estimates for data centers (DCs) and electric vehicles (EVs) are for the world and come from OPEC and the IEA, respectively. Data labels in the figure use International Organization for Standardization (ISO) country codes.

Online Annex Figure 3.2.3. Production and Adoption Volumes of Clean Technologies



Sources: Bloomberg New Energy Finance; International Renewable Energy Agency; and IMF staff calculations.
Note: In Panel 1, for solar polysilicon, EU only contains Germany. For EV/batteries, the blue bars represent North America. In panel 2, for solar and wind, EU includes EU countries and United Kingdom. Panel 3 shows the cumulative solar production 2004–2009; and 2004–2024. EVs = electric vehicles; EU = European Union; ROW = rest of the world.

Online Annex 3.3. Stylized Learning-by-doing Model: Theoretical Justification and Economic Channels of Industrial Policy

The stylized learning-by-doing (LBD) model incorporates the structure and mechanisms from the infant industry protection literature (e.g., Harrison and Rodriguez-Clare 2009, Melitz 2005, Redding 1999).

3.3.1. Description of the Model

The partial equilibrium model features two countries and two goods – a high-tech good in the infant industry[1] and an outside good. Consumers have quasilinear preferences with a CES aggregator over varieties of the high-tech good[2]:

$$u^i(x_{i.1}, x_{i,2}, V) = V + a^{\frac{1}{\sigma}} \frac{\sigma}{\sigma - 1} C_i^{\frac{\sigma-1}{\sigma}}$$

$$C_i = (\alpha_1^{\frac{1}{\varepsilon}} (x_{i,1})^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_2^{\frac{1}{\varepsilon}} (x_{i,2})^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{\varepsilon-1}}$$

Consumers in country i have preferences over the outside good V and over clean tech varieties $x_{i,j}$ produced in country j. Income is given exogenously. ε is the elasticity of substitution between clean tech varieties $x_{i,j}$ and σ is the elasticity of demand.

Production costs are pre-determined at the beginning of period t before consumption decisions are made. Production of the high-tech good exhibits country-level learning-by-doing based on accumulated experience in domestic high-tech production where knowledge is given by the sum of past high-tech production quantities. Domestic production costs in period t are given by:

$$c_{i,t}(Q_{i,t}^{hist}) = k_i {Q_{i,t}^{hist}}^{-\beta} \quad \text{where} \quad Q_{i,t}^{hist} = \textstyle\sum_{s=0}^{t-1} Q_{i.s} \quad \text{for given} \quad Q_{i,0}^{hist} \qquad (1)$$

Initial experience $Q_{i,0}^{hist}$ is given. Production costs decline with knowledge accumulation over time as captured by the learning rate β. A higher β implies faster cost declines as production experience grows. Experience is assumed to be given by the sum of past production in the high-tech sector: $Q_{i,t}^{hist} = \sum_{s=0}^{t} Q_{i.s}$. Each period, total production must satisfy $Q_{i.t} = \sum_z x_{z,i,t}$ Producers operate under perfect competition so consumer prices equal production costs plus (if present) trade protections and subsidies.

The model features two trade-policy instruments at the country level. First, either country may impose an ad-valorem import tariff, τ_i. Second, countries may impose domestic production subsidies, θ_j. Those subsidies are assumed to be non-discriminatory and uniform regardless of

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[1] For the stylized model, industries are at the infant industry stage in a country if they have low or no historical accumulated production, have low current production volumes, and can currently only produce at a higher cost relative to the global frontier. Details are given in Online Annex Table 3.3.1.

[2] For simplicity and because consumers do not make dynamic decisions, time subscripts are omitted here.

whether domestic production is sold domestically or abroad, that is there are no export taxes. Revenues are rebated to households. Hence, the price of the high-tech good $x_{i.j,t}$ consumed in country i and produced in country j is given by:

$$p_{i,j,t} = c_{j,t}\,(1 + \tau_i)(1 - \theta_j) \tag{2}$$

The household budget constraint is given by:

$$I_t + T_t = V_t + p_t' X_t \tag{3}$$

Where T_t indicates a lump sum fiscal transfer (which may be negative) consisting of tariff revenues and subsidy expenses.

In equilibrium, consumers in both the home and foreign countries maximize their utility subject to their budget constraint as given by equation (3) and taking prices as given as determined by equation (2).

3.3.2. Calibration

Throughout, we consider simulations where the home country is a technological laggard, and the foreign country is the technological leader which starts from lower initial costs. Online Annex Table 3.3.1. summarizes the key parameters. While illustrative, the calibration aims to broadly mimic the situation of countries that lag behind the global frontier in an infant industry as documented in the main chapter.

Online Annex Table 3.3.1. Model Calibration

	Home	Foreign
	(1)	(2)
Initial Cost	1.0	0.7
Initial Experience	2.0	10.0
Baseline Learning Rate (Percent)	19.0	19.0
Trade Elasticity	5.0	5.0
Demand Elasticity	2.0	2.0

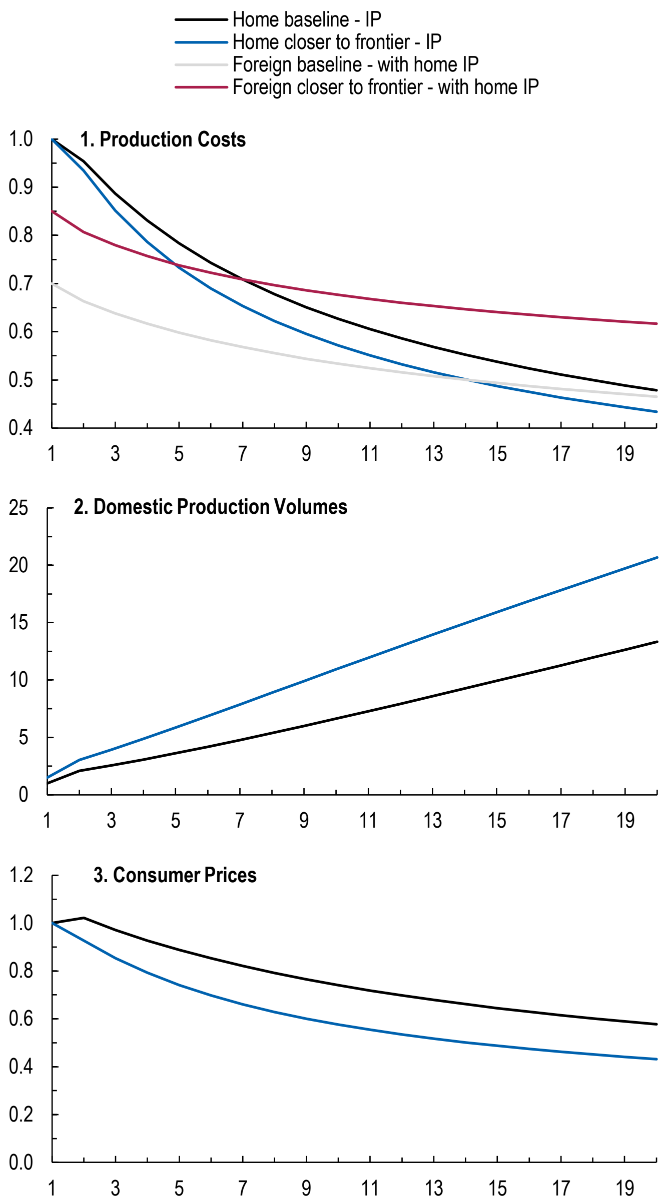
Source: IMF staff compilation.

Elasticities are calibrated to standard values in the literature. Learning rates mimic historic learning rates as documented in the chapter. Cost gaps and initial experience gaps are set to broadly reflect current cost gaps.

3.3.3. Learning-by-doing under different starting conditions

Online Annex Figure 3.3.1. Starting Closer to the Frontier

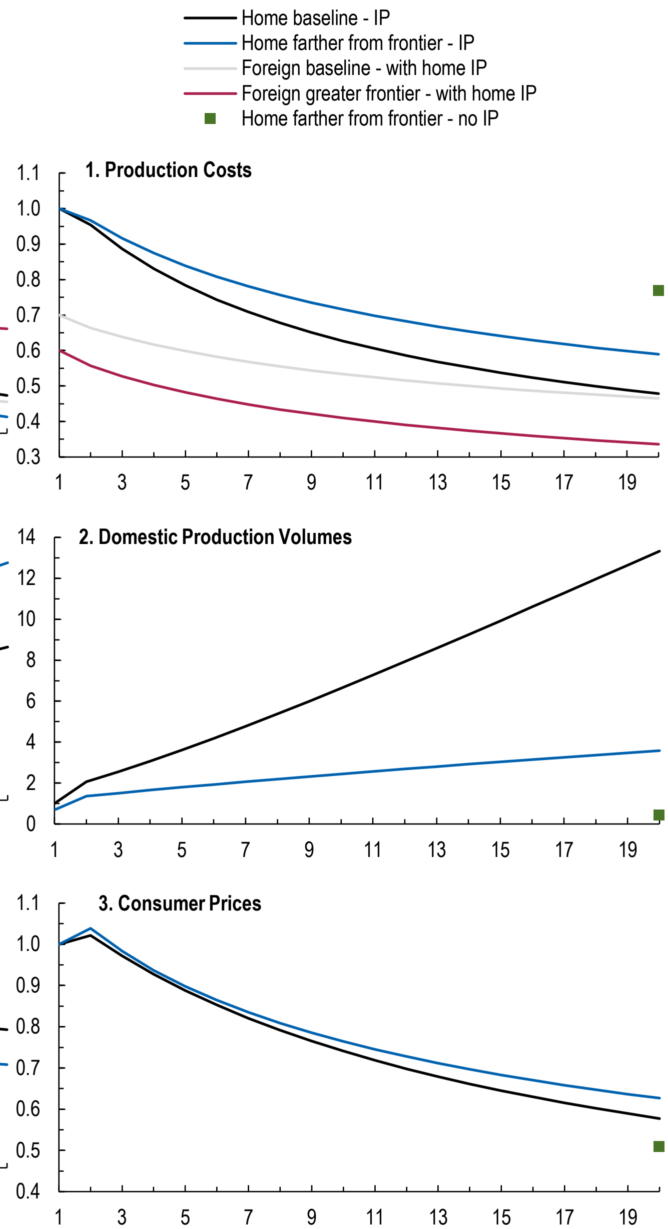
(Home baseline in period 1 = 1; time on x-axis)



Source: IMF staff calculations.
Note: For all panels, t = 1 features no industrial policy (IP) and IP is introduced at t = 2. The figure compares home economy outcomes under IP (12 percent production subsidy and 10 percent tariff) when the foreign country has 15 percent lower costs to a baseline simulation where the foreign country has 30 percent lower costs. The outcomes considered are production costs (panel 1), domestic production (panel 2), and consumer prices (panel 3).

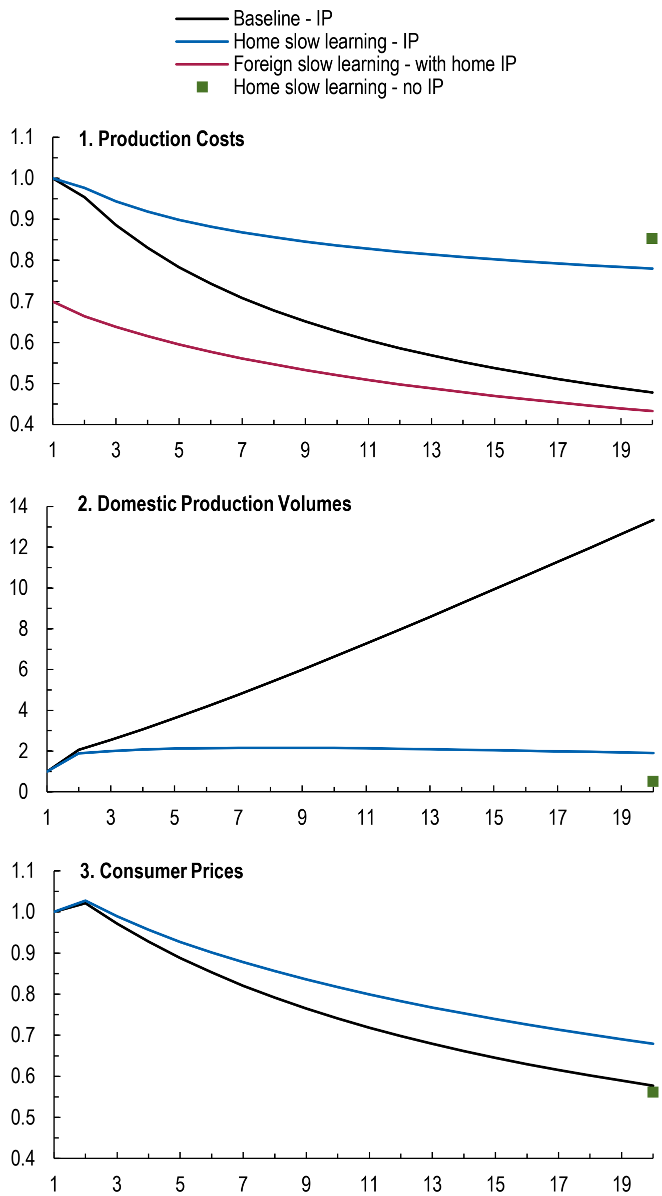
Online Annex Figure 3.3.2. Starting Farther from the Frontier

(Home baseline in period 1 = 1; time on x-axis)



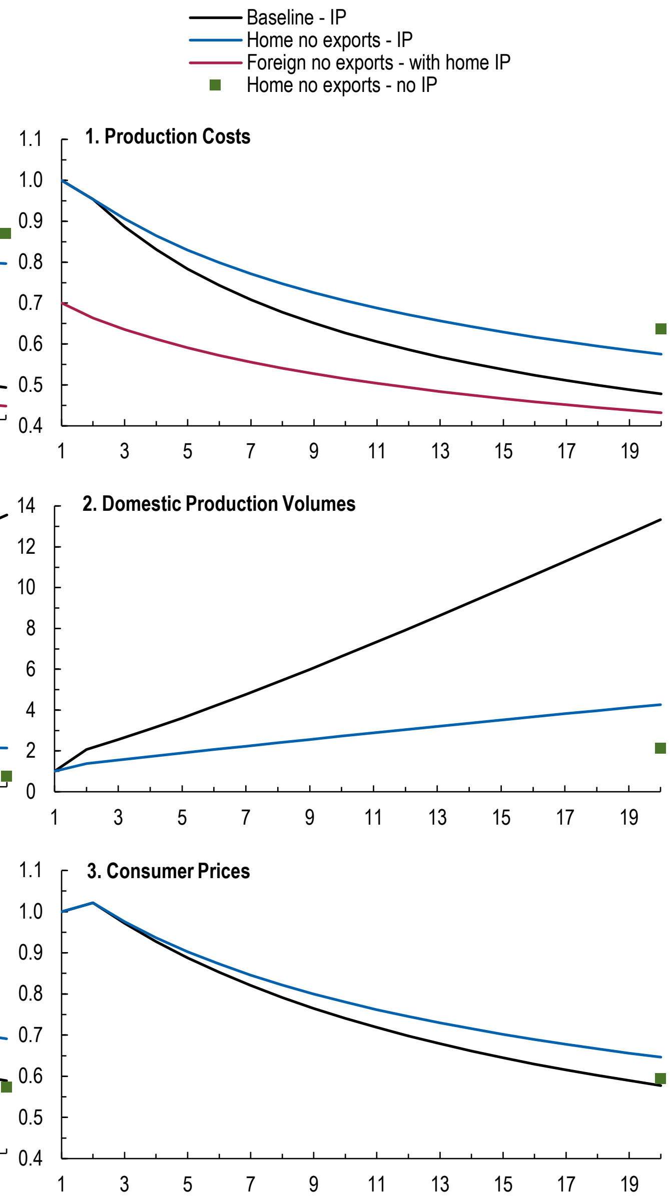
Source: IMF staff calculations.
Note: For all panels, t = 1 features no industrial policy (IP) and IP is introduced at t = 2. The figure compares home economy outcomes under IP (12 percent production subsidy and 10 percent tariff) when foreign country has a 40 percent cost advantage to outcomes under baseline where the foreign country has a 30 percent cost advantage for production costs (panel 1), domestic production (panel 2), and consumer prices (panel 3). Squares indicate home country outcomes in period 20 in scenario with a greater foreign cost advantage in the absence of IP, that is, with 0 percent subsidy and 0 percent tariff.

Online Annex Figure 3.3.3. Lower Domestic Learning Rate
(Home baseline in period 1 = 1; time on x-axis)



Source: IMF staff calculations.
Note: For all panels, t = 1 features no industrial policy (IP) and IP is introduced at t = 2. The figure compares home economy outcomes under IP (12 percent production subsidy and 10 percent tariff) when the home country has a 9.5 percent learning rate to baseline where the home country has a 19 percent learning rate. Outcomes considered are production costs (panel 1), domestic production (panel 2), and consumer prices (panel 3). Squares indicate home country outcomes in period 20 in the slow domestic learning rate scenario in the absence of IP, that is, with 0 percent subsidy and 0 percent tariff.

Online Annex Figure 3.3.4. No Access to Export Market
(Home baseline in period 1 = 1; time on x-axis)



Source: IMF staff calculations.
Note: For all panels, t = 1 features no industrial policy (IP) and IP is introduced at t = 2. The figure compares home economy outcomes under IP (12 percent production subsidy and 10 percent tariff) when the home country has no access to export markets to a baseline simulation where the home country has access to export markets. Outcomes considered are production costs (panel 1), domestic production (panel 2), and consumer prices (panel 3). Squares indicate outcomes in period 20 in the scenario with no exports by the home country in the absence of IP, that is, with 0 percent subsidy and 0 percent tariff.

The dynamic paths of production costs, production volumes, and consumer prices critically depend on the starting conditions of an economy.

For example, if a country gets closer to the frontier from the start by attracting FDIs from the technology leader or benefits from knowledge spillovers from the frontier, the home country could not only catch up to the global frontier but leapfrog the incumbent technological leader. Online Annex Figure 3.3.1. reports results from a simulation where the foreign country starts with a 15% cost advantage, rather than 30% as assumed in the baseline. After implementing IP, the home country now leapfrogs the foreign technological leader within a few years as production volumes ramp up faster than in the baseline case with a 30% cost gap.

On the other hand, the effects of IP are more muted when starting from less favorable starting conditions. The next figures show detailed results and dynamics for the alternative scenarios shown in Figure 3.6 in the main chapter. While industrial policies can lead to the ramp up of domestic production and dynamic cost declines through learning-by-doing, the conditions for IP to enable sizable cost declines and catching up with the global frontier are narrow. As shown in Online Annex Figures 3.3.2. – 3.3.4. IP far away from the frontier or in sectors with low learning rates, and IP that is conducted in small markets, is unlikely to boost domestic production.

Online Annex Figure 3.3.2. shows results under the assumption that the home country starts farther away from the frontier. With a larger cost gap, domestic learning-by-doing dynamics are more muted. Rather than ramping up domestic production, the home country relies more heavily on imports and domestic production only increases slowly while consumer prices for the high tech good also decline more slowly.

Online Annex Figure 3.3.3. shows results from a simulation that assumes that the domestic learning rate is only half as large as the foreign learning rate. This captures a situation where domestic policymakers mistarget IP to a sector that has a relatively low domestic learning rate. The lower domestic learning rate effectively attenuates the effectiveness of domestic IP.

Finally, market size is a critical determinant for the speed of learning-by-doing. A larger effective market (both domestically and through exports) facilitates expanding production and thus learning-by-doing. Online Annex Figure 3.3.4. reports results from a simulation that assumes that the home country does not have access to exports.[3] This shrinks the effective market size considerably as domestic producers lose access to the foreign market. As a result, domestic production quantities grow only slowly in the presence of IP. Domestic costs decline gradually but with very limited catch-up to the global frontier. Even after 20 years, domestic costs remain significantly higher than production costs at the global frontier.

Online Annex 3.4. Industrial Policy, the Power Sector, and Energy Security

This section provides further details on the models; data sources and simulations used to assess industrial policy in the energy sector and discusses additional results from the scenarios. This includes additional details on the extended infant industry model which is calibrated using clean technology data across four regions. This model is used to produce production cost estimates under alternative industrial policy regimes. This section also provides a description of the GMMET model

[3] Technically, this is simulated through a prohibitively high import tariff by the foreign country.

which integrates the above cost estimates to simulate technology adoption and macroeconomic outcomes.

3.4.1. Quantitative 4-country Learning-by-Doing Model

The stylized LBD model presented in Online Annex 3.3. is extended to align with the country blocks in GMMET. The model features China, the EU, the US, and the rest of the world and is simulated twice – first for renewable energy and second for electric vehicles.[4]

The production structure remains unchanged to Annex 3.3 except that there are four countries. Consumers likewise have preferences over the outside good and 4 varieties of renewable energy or electric vehicles:

$$u^i\left(x_{i.1}, x_{i,2}, x_{i,3}, x_{i,4}, V\right) = V + a^{\frac{1}{\sigma}} \frac{\sigma}{\sigma - 1} C_1^{\frac{\sigma-1}{\sigma}}$$

$$C_1 = \left(\alpha_1^{\frac{1}{\varepsilon}} \left(x_{i,1}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_2^{\frac{1}{\varepsilon}} \left(x_{i,2}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_3^{\frac{1}{\varepsilon}} \left(x_{i,3}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_4^{\frac{1}{\varepsilon}} \left(x_{i,4}\right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

To bring the model to the data, we calibrate parameters as follows:

Online Annex Table 3.4.1. Renewable Energy Parameters

	Renewables				
	China	European Union	Rest of the World	United States	Sources
	(1)	(2)	(3)	(4)	(5)
Initial Cost (USD/kW)	238	503	503	480	IEA; IRENA 2023
Domestic Market Size (2023)	293	65	73	31	IRENA 2023
Learning Rate (Percent)	21	21	21	21	IRENA 2023

Sources: International Energy Agency (IEA); International Renewable Energy Agency (IRENA) 2023; and IMF staff compilation.

Demand and trade elasticities are calibrated as before following standard values in the literature.

Online Annex Table 3.4.2. Electric Vehicle Parameters

	Electric Vehicles				
	China	European Union	Rest of the World	United States	Source
	(1)	(2)	(3)	(4)	(5)
Initial Cost (USD/kWh)	94.0	139.0	139.0	123.0	BNEF 2024
Domestic Market Size (Million vehicles, 2023)	9.9	2.9	2.1	1.8	BNEF 2024
Learning Rate (Percent)	18.0	18.0	18.0	18.0	Barwick and others 2024; BNEF 2024

Sources: Barwick and others 2024; Bloomberg New Energy Finance (BNEF) 2024; and IMF staff compilation.

[4] GMMET has 5 regions with both the Oil exporters and Rest of world blocs in GMMET aligning with the Rest of world bloc in the LBD model.

3.4.2. Description of the GMMET Model

GMMET is a large-scale, dynamic, non-linear, micro-founded, multicounty model whose purpose is to analyze the short- and medium-term macroeconomic impacts of energy policies.[5] Compared to the standard version of GMMET featured in past publications (see, for example, Carton et al 2023 or Oct 2022 WEO) the version used here includes a detailed representation of trade in renewable energy capital goods and electric vehicles. Trade in each good is modeled using an Armington trade elasticity of 5, consistent with the LBD model described above. The electricity sector and transport sector calibration was updated to reflect the growing importance of renewable generation and electric vehicles. The broader calibration is as in Carton et al (2023), where further detail can be found.

3.4.4. Model integration and scenario details

GMMET does not include endogenous Learning by doing (LBD). Therefore, changes in production costs of clean tech goods due to LBD are taken from the infant industry model, described in section 3.4.1. These are implemented as exogenous productivity changes. GMMET does not feature dedicated sectors for producing clean tech goods, instead clean tech goods are a

Online Annex Table 3.4.3. Bilateral Import Tariff Rates
(Percent)

	Importing Regions \ Exporting Regions	Electric Vehicles				Renewables			
		China	EU	ROW	US	China	EU	ROW	US
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline	China	—	15.0	15.0	15.0	—	1.6	1.6	1.6
	EU	30.7	—	10.0	10.0	16.7	—	16.7	16.7
	ROW	16.0	16.0	—	16.0	3.9	3.9	—	3.9
	US	50.0	2.3	2.3	—	39.6	38.3	38.3	—
No IP	China	—	0.0	0.0	0.0	—	0.0	0.0	0.0
	EU	0.0	—	0.0	0.0	0.0	—	0.0	0.0
	ROW	0.0	0.0	—	0.0	0.0	0.0	—	0.0
	US	0.0	0.0	0.0	—	0.0	0.0	0.0	—
Reshoring	China	—	15.0	15.0	15.0	—	1.6	1.6	1.6
	EU	30.7	—	10.0	10.0	16.7	—	16.7	16.7
	ROW	16.0	16.0	—	16.0	3.9	3.9	—	3.9
	US	50.0	2.3	2.3	—	39.6	38.3	38.3	—

Sources: International Trade Centre (ITC), Market Access Map; and IMF staff calculations.
Note: Tariffs are based on product-level tariffs from the ITC Market Access Map for latest year available (2022 for most countries and 2021 in some instances). Data retrieved on December 19th, 2024. These tariffs are supplemented with country-specific information that capture deviations and updates relative to 2022 Market Access Map tariff rates. Based on end products listed in Rosenow and Mealy (2024), renewables are identified as HS6 codes 854140 (solar) and HS6 codes 841290, 850300, and 730820 (wind). EVs and EV batteries are identified as HS6 codes 850710, 850619, 850780, 870390, 870290. Aggregations across products and across countries are computed as simple averages. EU = European Union; ROW = rest of the world; US = United States; IP = industrial policy.

[5] Further details can be found in Carton and others (2023).

product of the final goods sector. As such, the productivity is applied to the transformation of final goods.[6]

Online Annex Tables 3.4.3 and 3.4.4 show the import tariff rates and subsidies used in each of the 3 scenarios modeled: the baseline scenario, the No Industrial policy (no-IP) scenario, and the Reshoring scenario. These policy changes are assumed to be implemented in 2025.

Online Annex Table 3.4.4. Subsidy Rates

(Percent)

	Producing Region							
	Electric Vehicles				Renewables			
	China	European Union	Rest of the World	United States	China	European Union	Rest of the World	United States
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline	1.2	0.3	0.0	1.5	1.2	0.3	0.0	1.5
No IP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Reshoring	1.2	15.0	0.0	15.0	1.2	30.0	0.0	30.0

Sources: Global Trade Alert; New Industrial Policy Observatory; and IMF staff calculations.

Note: Baseline subsidy rates are computed from NIPO and GTA following the methodology in Rotunno and others (forthcoming). Subsidy rates for EVs and renewables are set equal to the NIPO-GTA implied subsidy rate on "electrical equipment" sector. IP = industrial policy.

The scenarios assumed that all other policy settings in place in 2024 remain unchanged. For example, all other fiscal policies are kept constant to 2024 levels throughout the simulation period. In addition, announced or planned policies designed to limit future GHG emissions over the simulation period are not modeled. For example, legislated future increase in the stringency of policies under the EU's Fit for 55 package are not modeled. These policies would interact with cheaper clean-tech prices and drive additional or cheaper uptake. The expected revenues from EU carbon pricing policies provide potential financing of IP (Carton et al forthcoming). In the scenarios here the government's budget is balanced in each period through lump sum transfers.

3.4.5. Industrial Policy Scenarios: Main Channels and additional results

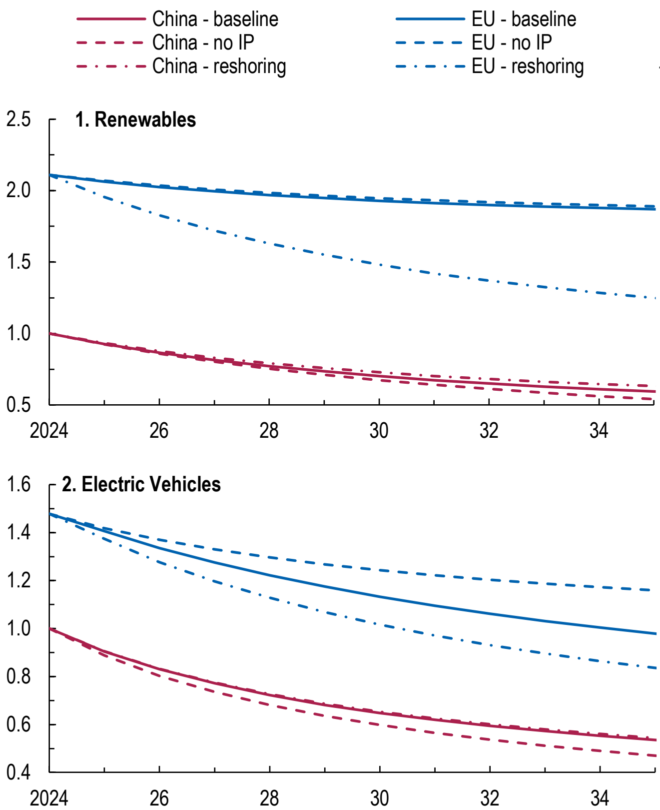
The underlying changes in production costs, along with policy changes drive purchaser prices of clean tech. Figure 3.4.1 shows the production costs for China and the EU for each technology under the 3 scenarios (US production costs, while not shown, largely followed EU costs). As noted above, the speed of learning for each region depends on cumulative domestic production quantities and the learning-by-doing rate. Production quantities depend on competitiveness which results from both underlying production costs and the direct effects of policy, being tariff and subsidies. Hence there is a circular relationship between production volumes, production costs, and prices faced by users.

Figure 3.4.2 shows the share of clean tech that the EU purchases from each region for all scenarios, and technologies, in 2035, compared with 2024 data. The introduction of larger subsidies under the reshoring scenario leads to significant shifts to domestic production. These production

[6] This implementation of productivity changes is equivalent to changing the productivity of a clean tech sector that directly combines capital, labor and intermediates. However, the production of clean tech goods in GMMET can adjust rapidly as final goods can be redirected from other uses to clean tech goods. Specifically, there is not a capital stock specific to clean tech good production that takes time to build up so that output can be increased.

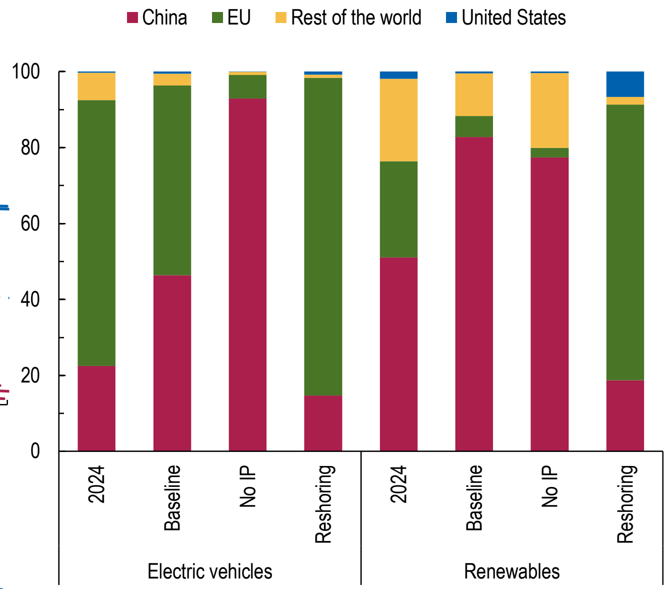
shifts occur initially due to the subsidies but over time due to lower domestic production costs from learning-by-doing.

Online Annex Figure 3.4.1. Production Cost over Time by Scenario, Region and Technology
(Normalized, Chinese 2024 costs = 1)



Sources: Quantitative four-country learning-by-doing model; and IMF staff calculations.
Note: Under the baseline scenario, the EU continues to impose status quo industrial policies (IPs). Under the no-IP scenario, all IPs are removed starting in 2025. Under the reshoring scenario, 15 percent electric vehicle and 30 percent renewable production subsidy are introduced starting in 2025. EU = European Union.

Online Annex Figure 3.4.2. EU Clean Tech Sourcing by Scenario in 2035
(Percent)



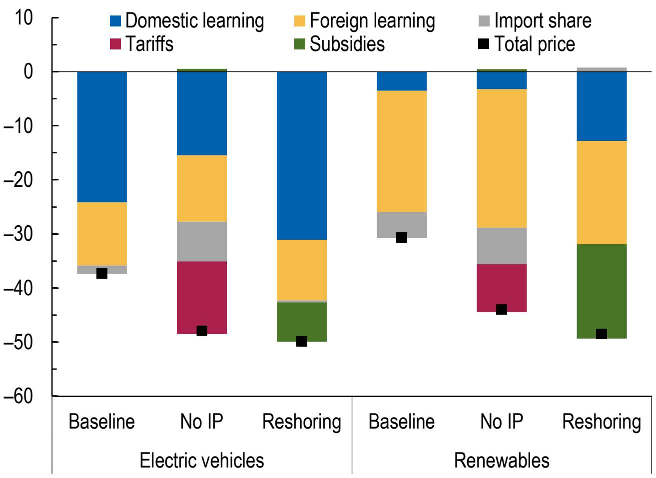
Sources: Bloomberg New Energy Finance (BNEF) 2024; International Renewable Energy Agency (IRENA) 2023; Quantitative four-country learning-by-doing model; and IMF staff estimates.
Note: The 2024 shares are derived from quantity data provided by BNEF for electric vehicles and IRENA for renewable energy, with renewable energy market shares assumed to remain consistent with those implied by IRENA's 2023 data. Under the baseline scenario, the EU continues to impose status quo industrial policies (IPs). Under the no-IP scenario, all IPs are removed starting in 2025. Under the reshoring scenario, 15 percent electric vehicle and 30 percent renewable production subsidies are introduced starting in 2025. EU = European Union.

Under the no IP scenario, tariffs and subsidies are removed and users switch to cheaper Chinese products (imports increase), and there is less domestic learning-by-doing. For renewables particularly, the smaller production share in Europe, related to the large initial price difference, limits learning-by-doing if there is not a subsidy. Even with the reshoring subsidy, EU production costs do not reach current Chinese costs before 2035. For EVs, with the reshoring subsidy EU production costs are around 7 years behind Chinese costs.

Online Annex Figure 3.4.3 reproduces Figure 3.7 in the main text for both EVs and renewables, it shows the change in purchaser clean tech prices in the EU in 2035, relative to 2024 prices, and under each scenario. The price changes are broken into impacts from production costs, the impacts of tariffs and subsidies, and the price change from changing imported share. Prices fall in all scenarios, primarily driven by learning-by-doing. User prices are lowest in the Reshoring scenario for both technologies, driven by the subsidies and more domestic learning-by-doing.

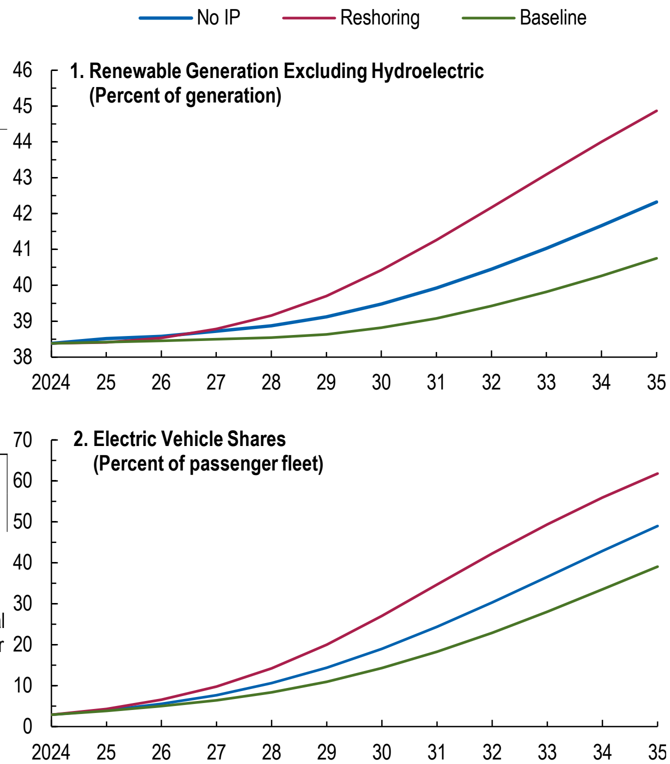
Online Annex Figure 3.4.3. EU Clean Tech Price Declines to 2035 Decomposition

(Percent change between 2024 and 2035)



Sources: Quantitative four-country learning-by-doing model; and IMF staff calculations.
Note: Under the baseline scenario, the EU continues to impose status quo industrial policies (IPs). Under the no-IP scenario, all IPs are removed starting in 2025. Under the reshoring scenario, 15 percent electric vehicle and 30 percent renewable production subsidies are introduced starting in 2025. EU = European Union.

Online Annex Figure 3.4.4. EU Clean Tech Adoption



Sources: Global Macroeconomic Model for the Energy Transition; and IMF staff calculations.
Note: Under the baseline scenario, the EU continues to impose status quo industrial policies (IPs). Under the no-IP scenario, all IPs are removed starting in 2025. Under the reshoring scenario, 15 percent electric vehicle and 30 percent renewable production subsidies are introduced starting in 2025. EU = European Union.

Online Annex Figure 3.4.4 shows clean tech adoption in the EU under each scenario, with falling EV and renewable prices driving uptake. As noted above, clean tech prices are lowest in the Reshoring scenario and hence uptake is the strongest in that case.[7] Generally, EVs see a sharper uptake than renewable generation for a variety of factors. Firstly, generators are a longer-lived asset and more planning and permitting is involved in renewable deployment. Renewables are part of a system where intermittency and transition needs must be accounted for.[8] Further the uptake of EVs is more sensitive to technology prices and less impacted by fuel prices than generation.

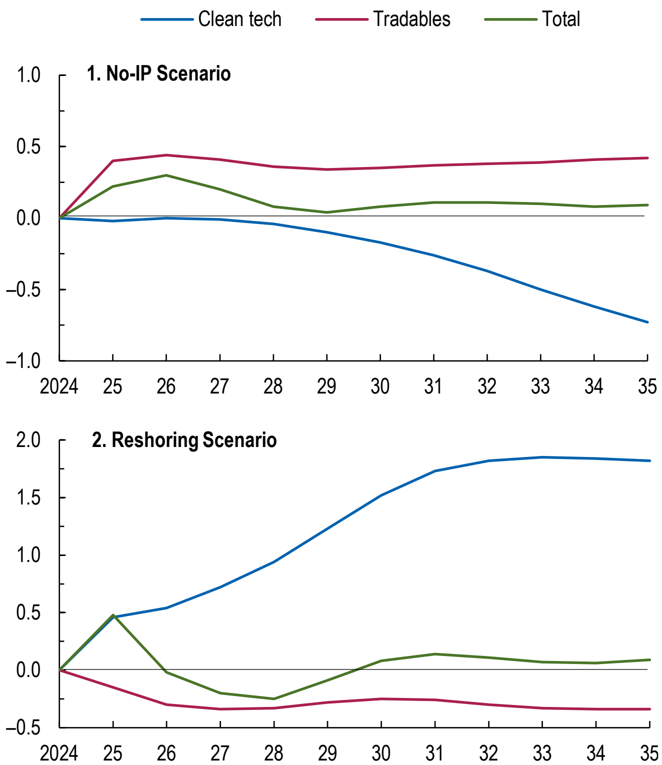
Figure 3.4.5 shows the changes in the components of the labor market as deviations from the baseline in each scenario for the EU. Increased domestic production of clean tech under the Reshoring scenario raises labor associated with that production but lowers labor in the overall tradables sector due to lower exports, from the appreciated exchange rate. This narrative flips under the No IP scenario where labor associated with clean tech production declines in the EU but

[7] The price changes shown in Figure 3.4.3 are from the Quantitative 4-country LBD model, the productivity changes that come out of that model are exogenously inputted to GMMET. However, GMMET has additional second round effects, such as exchange rate movements. The exchange rate appreciates in the reshoring scenario making these trade exposed clean tech goods even cheaper, while it depreciates in the No IP scenario making clean tech good somewhat more expensive domestically. This drives some of the additional uptake under the Reshoring scenario.

[8] The model accounts for EV's required charging infrastructure.

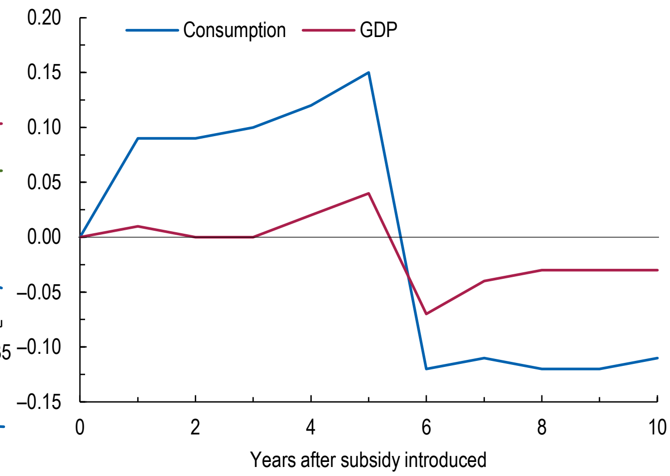
tradables employment rises, from the lower exchange rate. Aggregate labor market outcomes reflect both aggregate demand for labor and household decisions.

Online Annex Figure 3.4.5. EU Labor Market Impacts
(Deviation from baseline, percent of labor market)



Sources: Global Macroeconomic Model for the Energy Transition; and IMF staff calculations.
Note: Under the baseline scenario, the EU continues to impose status quo industrial policies (IPs). Under the no-IP scenario, all IPs are removed starting in 2025. Under the reshoring scenario, 15 percent electric vehicle and 30 percent renewable production subsidies are introduced starting in 2025. EU = European Union.

Online Annex Figure 3.4.6. Impact of Fiscal Expansion Associated with Industrial Policy
(Change in variable as a percentage of GDP)



Sources: Global Macroeconomic Model for the Energy Transition; and IMF staff calculations.
Note: This figure shows the impact of a fiscal expansion equivalent to cost of reshoring subsidy for the first five years, repaid over the following five years.

While aggregate labor is broadly flat, aggregate output is driven by sectoral productivity changes. By 2035, GDP under Reshoring is 1.8% higher relative to the baseline scenario, this is both from the sectoral productivity increase from additional learning-by-doing, the shift in activity to this higher productivity sector and additional investment across the economy from cheaper renewables and electricity. This result is particularly sensitive to the degree of learning. In the No IP scenario GDP is 1.5% lower in 2035 relative to the baseline, again driven by learning. This contrasts with Wingender et al. (2024) who find that tariffs on Chinese electric vehicles only raise the GDP cost of the electric vehicle transition, including for those countries heavily reliant on auto production.

3.4.6. Short term potential stimulatory effects of Industrial Policies

Industrial policies, particularly those involving additional government expenditure such as subsidies can raise economic activity through the associated fiscal expansion. To highlight this, we compare (1) a reshoring scenario in which IP subsidies are financed through an increase in debt-to-GDP ratio in the first five years, which then need to be paid back in the following five years; which is contrasted with (2) a reshoring scenario where IP subsidies are financed through lump-sum taxes, as in standard simulations. By comparing these two scenarios, we can isolate the GDP and consumption effects of a fiscal expansion, followed by a fiscal contraction. In the fiscal expansion scenario Debt to GDP is 1.2 ppt higher after the first five years due to the fiscal expansion.

The fiscal expansion leads to a temporary increase in activity. Figure 3.4.6 shows the increase in consumtpion and GDP assoociated with the fiscal expansion followed by the pay-back phase, relative to the case where the subsidy is funded by lump sum taxes throughout. Consumption increases driven in part by hand to mouth households whose transfers are no longer reduced, as in the standard scenarios. GDP is also boosted initially, but remains only marginally higher, offset by increased imports and decreased exports and investment in sectors that are not targeted by IP. After the expansionary period, GDP ends up lower, largely driven by the fiscal contraction required to repay the debt.

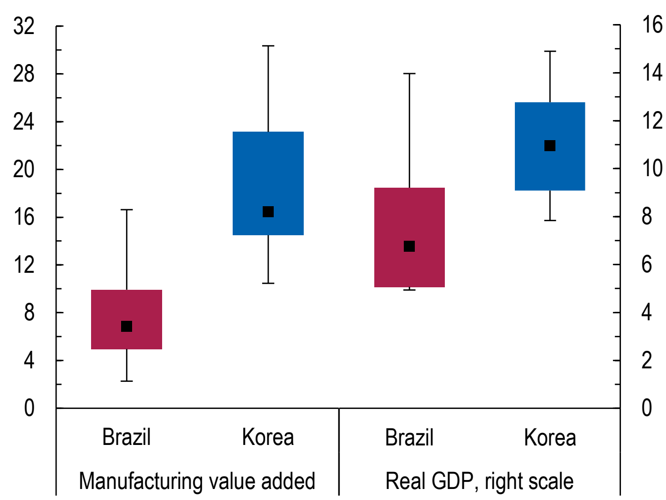
Online Annex 3.5. Historical Case Studies

The case studies of *Brazil* and *Korea* focus on the 1970s. The two countries' cases are well-documented in the literature. Between 1973 and 1979, *Korea*, under President Park Chung Hee, pursued export-oriented industrial policies targeting six strategic sectors: steel, nonferrous metals, transportation, machinery, electronics, and petrochemicals. These industries were considered essential for *Korea*'s military and industrial modernization, as well as its long-term development; particularly in the wake of political crises triggered by North Korea's growing militarization and aggressive actions, and by the threat of the United States troop withdrawal from the Korean Peninsula. Large business conglomerates, or *chaebol*, served as the main vehicles for implementing this agenda.

Brazil adopted an import-substitution industrialization strategy, broadly from the 1930s to the 1980s. Its industrial policy during the 1970s was guided by two successive national development plans. The first (1972–74) emphasized infrastructure development and the expansion of state-owned enterprises. Following the 1973 oil crisis, the second plan (1975–79) shifted focus to four strategic sectors: manufacturing, energy, transportation, and communications. A key objective became reducing dependence on oil imports by investing in domestic oil production and alternative energy sources, including ethanol and nuclear power.

Korea's experience is often considered a more successful case of industrial policy than *Brazil*'s (see, for example, Ocampo and Porcile 2020). This is also reflected in Online Annex Figure 3.5.1, which shows that *Korea* experienced higher growth rates of manufacturing valued-added and real GDP during the period 1973-79 compared to *Brazil*. Contrasting these two cases offers broad yet valuable insight into the

Online Annex Figure 3.5.1. Manufacturing Value Added and Real GDP
(Annual growth rate)



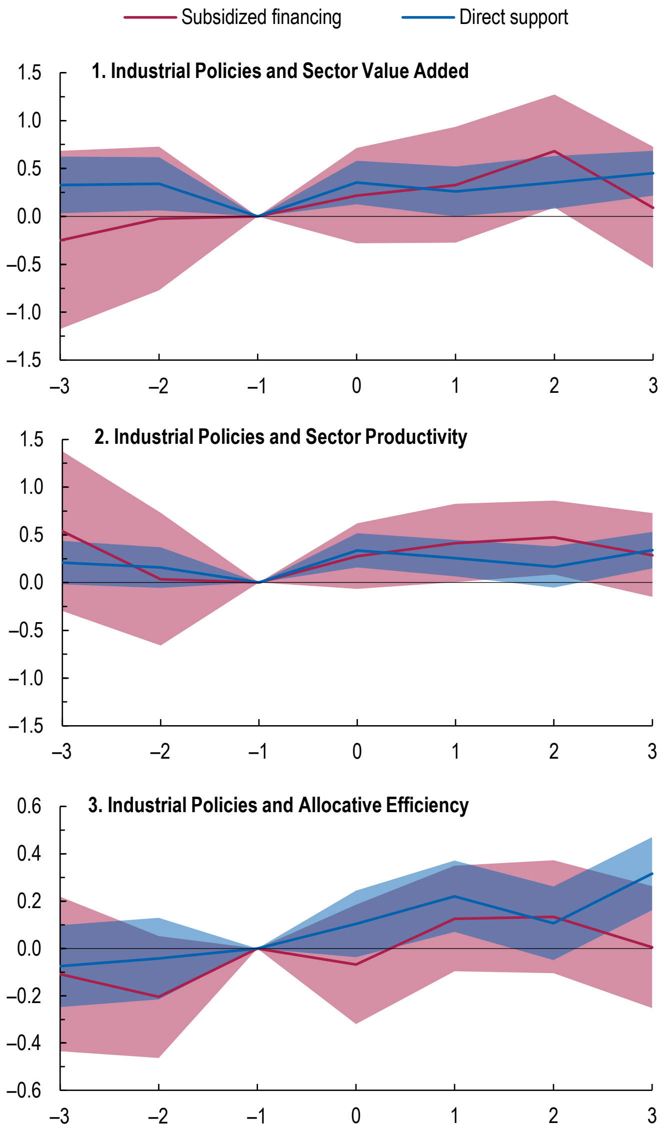
Sources: World Bank, *World Development Indicators*; and IMF staff calculations.
Note: The figure shows the annual growth rate of real manufacturing value added and real GDP for Brazil and Korea during the periods 1973–79. Manufacturing includes industries classified under ISIC divisions 15–37. The boxes denote the interquartile range, the squares denote the median, and the whiskers denote the range of maximum and minimum values.

importance of policy design, implementation, and complementary measures for contemporary industrial policy strategies.

Online Annex 3.6. Additional Empirical Findings

Online Annex Figure 3.6.1. Industrial Policies and Targeted Sectors Economic Performance

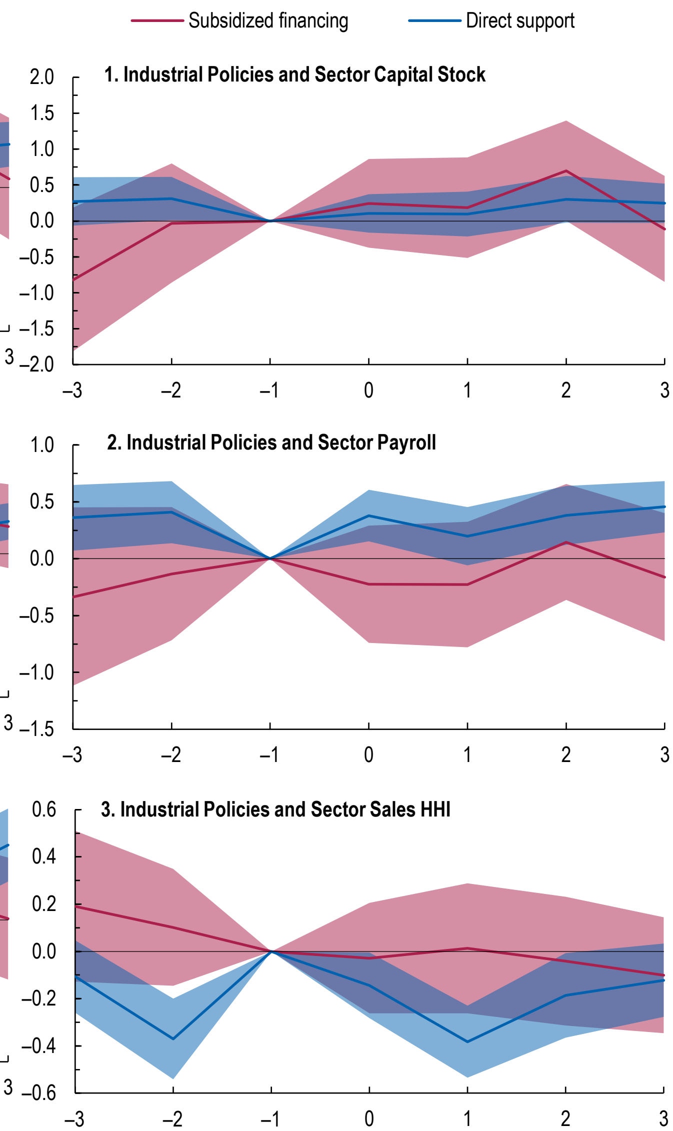
(Percent; horizon on x-axis)



Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.
Note: The figure estimates the impact of industrial policies (IPs) using the local projection method. The dependent variables are the log difference in sectoral value added, TFP, or allocative efficiency over the specified horizon. The key independent variables are the change in the number of subsidized financing and direct support IPs targeting that sector. All specifications control for one lag of dependent and independent variables and include country-sector, country-year, and sector-year fixed effects. Shaded areas represent 90 percent confidence intervals. TFP = total factor productivity.

Online Annex Figure 3.6.2. Industrial Policies and Targeted Sectors Economic Performance: Additional Outcomes of Interest

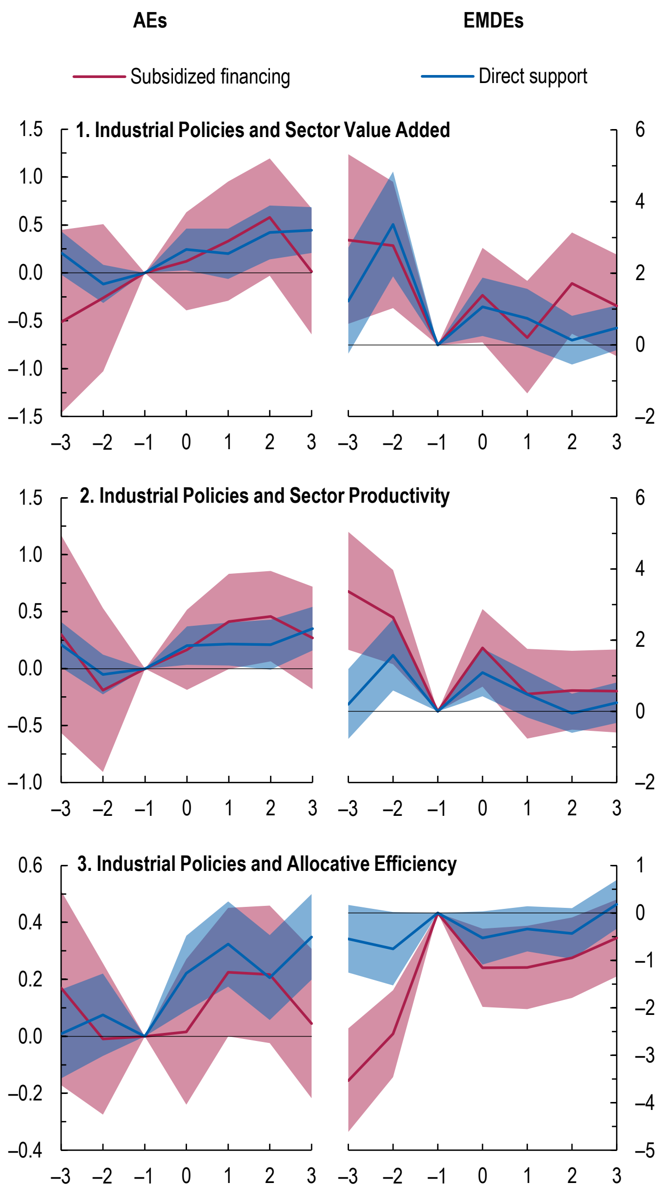
(Percent; horizon on x-axis)



Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.
Note: The figure estimates the impact of industrial policies (IPs) using the local projection method. The dependent variables are the log difference in sectoral capital stock, wage bill, or sales Herfindahl-Hirschman Index (HHI) over the specified horizon. The key independent variables are the change in the number of subsidized financing and direct support IPs targeting that sector. All specifications control for one lag of dependent and independent variables and include country-sector, country-year, and sector-year fixed effects. Shaded areas represent 90 percent confidence intervals.

Online Annex Figure 3.6.3. Industrial Policies and Targeted Sectors Economic Performance: AEs versus EMDEs

(Percent; horizon on x-axis)

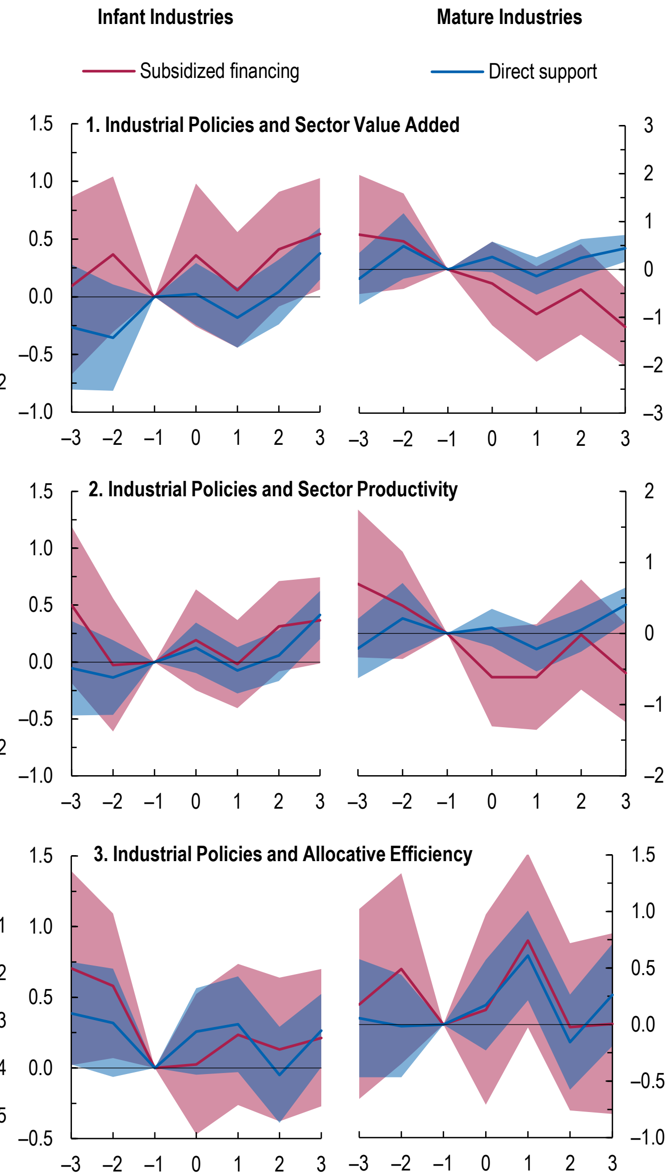


Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.

Note: The figure estimates the impact of industrial policies (IPs) using the local projection method. The dependent variables are the log difference in sectoral value added, TFP, and allocative efficiency over the specified horizon. The key independent variables are the change in the number of subsidized financing and direct support IPs targeting that sector interacted with a dummy indicating whether each country is an AE or an EMDE. All specifications control for one lag of dependent and independent variables and include country-sector, country-year, and sector-year fixed effects. Shaded areas represent 90 percent confidence intervals. AEs = advanced economies; EMDEs = emerging market and developing economies; TFP = total factor productivity.

Online Annex Figure 3.6.4. Industrial Policies and Targeted Sectors Economic Performance: Infant versus Mature Industries

(Percent; horizon on x-axis)



Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.

Note: The figure estimates the impact of industrial policies (IPs) using the local projection method. The dependent variables are the log difference in sectoral value added, TFP, and allocative efficiency. The key independent variables are the change in the number of subsidized financing and direct support IPs targeting that sector interacted with a dummy indicating whether each industry is infant or mature. In each country, infant industries are industries with above-average share of young and leveraged firms, and above-average distance to the world productivity frontier. All specifications control for one lag of dependent and independent variables and include country-sector, country-year, and sector-year fixed effects. Shaded areas are 90 percent confidence intervals. TFP = total factor productivity.

This section presents the regression specification for the empirical analysis of industrial policies and sector performance. It then presents the complete local projection results, with supporting pre-trend estimates and additional outcomes. It also presents a table with the number of observations per country; a table summarizing the key point estimates across different specifications and discusses the robustness checks to the main findings.

The local projection analysis follows Baquie and others (2025):

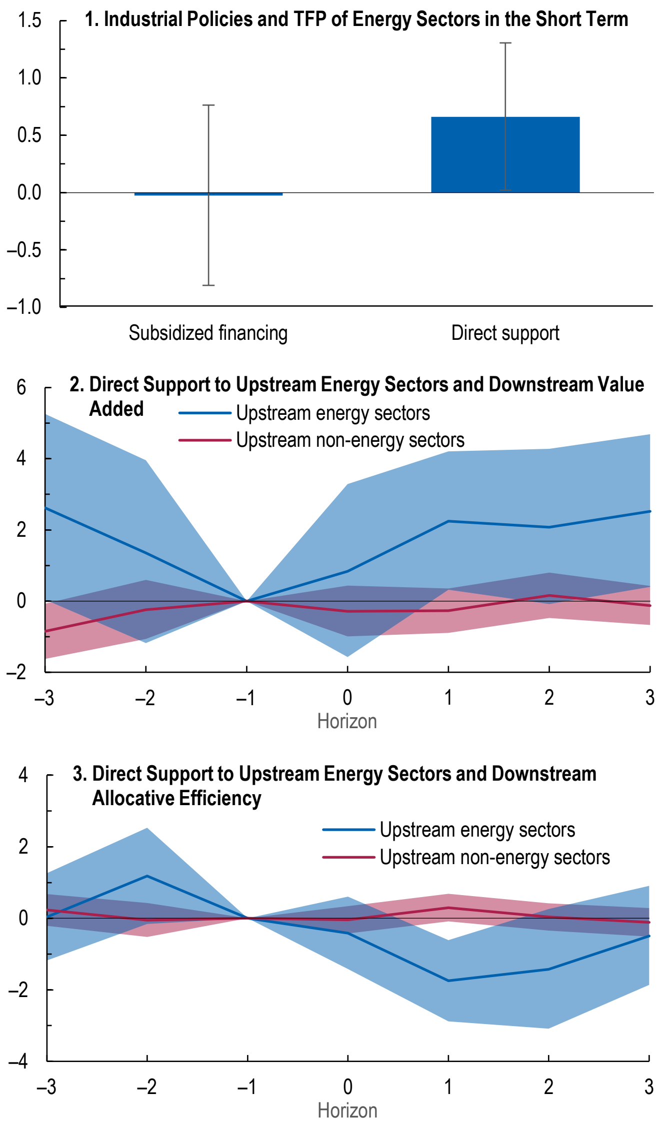
$$\ln y_{c,s,t+h} - \ln y_{c,s,t-1} = \delta^h_{c,s} + \delta^h_{c,t} + \delta^h_{s,t} + \sum_{instr\ k} \beta^h_{1,k}\left(\Delta IP^k_{c,s,t}\right) + \beta^h_2\left(\Delta Upstr_{c,s,t}\right)$$
$$+ \sum_{j=1}^{p} \gamma^h_j \ln y_{c,s,\ t-j} + \sum_{j=1}^{p} \sum_{instr\ k} \lambda^h_{t-j} \quad IP^k_{c,s,t-j} + \sum_{j=1}^{p} \lambda^h_{t-j} Upstr_{c,s,t-j}$$
$$+ \zeta^h X_{c,s,t} + \epsilon^h_{c,s,t}$$

Where *c* denotes country; *s* denotes sector/industry; *t* denotes year; *h* denotes the horizon of interest; *y* represents the main outcome of analysis, constructed from Orbis data; δ's represent country-sector, country-year and sector-year fixed effects; $\Delta IP^k_{cs,t}$ is the first variable of interest and represents the change in the stock of IPs of a given instrument *k* in a given country and industry between *t* and *t-1*, constructed from the Global Trade Alert database and the text-mining identification algorithm from Juhász and others (2022, 2025); $\Delta Upstr_{cs,t}$ is the second variable of interest and represents the change in the stock of IPs in the average sector *upstream* of a given sector-in a given country between years *t* and *t-1*, generated from same data sources; and $X_{cs,t}$ represents additional controls, like the stock of non-IP GTA policies. Standard errors are clustered by country and sector.

The local projection plots report the *percentage change* in the outcome variable *h* years after the introduction of an additional policy: $100 \times \left(\exp\left(\beta^h_{1,k}\right) - 1\right)$. The main outcomes of interest in the chapter are sector value added, productivity and allocative efficiency, calculated following Hsieh and Klenow (2009) (Online Annex Figure 3.6.1). Online Annex Figure 3.6.2 also reports results for capital stock, wage bill and sales HHI to support the analysis in the main text.

The analysis of differential impacts of IPs is made by interacting with the changes in IPs with group indicators specific to countries and industries. For example, the impact of IPs on AEs/EMDEs is estimated by replacing $\Delta IP^k_{cs,t}$ with $\Delta IP^k_{cs,t} \cdot I\{c \in AEs\}$ and $\Delta IP^k_{cs,t} \cdot I\{c \in EMDEs\}$ in the local projection above while allowing for two separate regression coefficients (Online Annex Figure 3.6.3). A similar approach holds for the analysis of infant and mature industries (Online Annex Figure 3.6.4). For the purposes of this exercise, infant (mature) industries are identified, in each country, as industries with above-average (below-average) share of young and

Online Annex Figure 3.6.5. Industrial Policies in the Energy Sector and Cross-Sectoral Spillovers
(Percent)



Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.
Note: The figure estimates the impact of IPs using the local projection method. The dependent variables are the log difference in TFP, value added, and allocative efficiency over the specified horizon. 0 = the short-term horizon corresponding to when industrial policies are introduced. In panel 1, the key independent variables are the change in the number of subsidized financing and direct support IPs targeting energy sectors. Whiskers represent 90 percent confidence intervals. In panel 2 and panel 3, the key independent variables are the change in the number of direct support IPs in upstream energy (yellow) and non-energy (gray) sectors. All specifications control for one lag of dependent and independent variables, for IPs implemented in downstream sectors, and include country-sector, country-year, and sector-year fixed effects. Shaded areas represent 90 percent confidence intervals. TFP = total factor productivity.

leveraged firms and above-average (below-average) distance to the world productivity frontier.[9] To tease out the impact of upstream energy IPs from non-energy IPs, the chapter breaks down the upstream exposure measure into two additive components: $\Delta Upstr_{cs,t} = \Delta Upstr_{cs,t}^{Energy} + \Delta Upstr_{cs,t}^{Non-energy}$ and allow for these two components to have separate coefficients in the local projection above (see Figure 3.11 panel 2 for the results on exposure to an industrial policy shock in an upstream energy sector).

Table 3.6.1 reports all the countries included in the regression specifications and their respective number of observations (industry-years). Table 3.6.2 summarizes the key medium-term estimates for the relation between industrial policies and sector performance across different specifications, alongside the average yearly growth rate of different outcome variables.

Lastly, the main empirical findings are robust to alternative specifications, like controlling for 2 lags of the dependent variable to mitigate concerns about bias with autocorrelation that arises in small samples, and to alternative industrial policy definitions, including the use of the historical NIPO (Evenett and others forthcoming).

[9] In advanced economies, infant industries are in tech- and knowledge-intensive services, such as the retail sale of telecommunications equipment in specialized stores, rental and leasing of office machinery and equipment (including computers), and advertising agencies. In emerging markets, infant industries lie more in manufacturing and logistics, including the manufacture of ceramic tiles and flags, freight transport by road, and the manufacture of builders' ware of plastic. Some industries appear as infant industries in both groups; these include plumbing and air-conditioning installation, rental and leasing of cars and light motor vehicles, and restaurants and mobile food services.

Online Annex Table 3.6.1. Number of Observations for Each Country in the Regression Sample

ISO3 Country Code (1)	Region (2)	Industry-Year Observation (3)	ISO3 Country Code (4)	Region (5)	Industry-Year Observation (6)
AUS	AEs	2349	ARE	EMDEs	55
AUT	AEs	3176	ARG	EMDEs	85
BEL	AEs	4509	BGR	EMDEs	4028
CAN	AEs	914	BRA	EMDEs	83
CHE	AEs	958	CHL	EMDEs	72
CYP	AEs	46	CHN	EMDEs	192
CZE	AEs	5501	EGY	EMDEs	227
DEU	AEs	5236	GHA	EMDEs	4
DNK	AEs	3570	HUN	EMDEs	4736
ESP	AEs	4752	IDN	EMDEs	917
EST	AEs	3773	IND	EMDEs	3131
FIN	AEs	4440	IRN	EMDEs	406
FRA	AEs	4840	KEN	EMDEs	9
GBR	AEs	4784	MAR	EMDEs	2852
GRC	AEs	46	MYS	EMDEs	1930
IRL	AEs	2597	NGA	EMDEs	108
ISL	AEs	2397	PER	EMDEs	7
ISR	AEs	336	PHL	EMDEs	323
ITA	AEs	6233	POL	EMDEs	4682
JPN	AEs	3653	ROU	EMDEs	4731
KOR	AEs	3471	RUS	EMDEs	4
LUX	AEs	1838	SAU	EMDEs	241
LVA	AEs	2133	SRB	EMDEs	4600
NLD	AEs	2356	THA	EMDEs	2676
NOR	AEs	4167	TUR	EMDEs	490
NZL	AEs	2137	VNM	EMDEs	494
PRT	AEs	4652	ZAF	EMDEs	407
SVK	AEs	4333		Share EMDEs	27.519
SVN	AEs	4148			
SWE	AEs	4225			
USA	AEs	1174			

Source: IMF staff compilation.
Note: This table reports the number of observations (industry-years) for each country and the share of observations for EMDEs in the regression sample. AEs = advanced economies; EMDEs = emerging market and developing economies.

Online Annex Table 3.6.2. Industrial Policies and Medium-Term Sectoral Performance: Summary of Findings

		Value Added	TFP	Allocative Efficiency
		(1)	(2)	(3)
Direct Support	All	0.45*	0.34*	0.32*
	AEs	0.45*	0.35*	0.35*
	EMDEs	0.48	0.24	0.18
	Infant	0.37*	0.41*	0.27*
	Mature	0.44*	0.40*	0.26
Subsidized Financing	All	0.09	0.29	0.01
	AEs	0.01	0.27	0.04
	EMDEs	1.09	0.56	-0.53
	Infant	0.54*	0.37	0.21
	Mature	-1.20*	-0.56	0.01
Upstream Direct Support to Energy		2.52*	0.56	-0.49
Average of Outcome Variable		6.58	4.01	-1.31

Sources: Global Trade Alert; Juhász and others 2022, 2025; Orbis; and IMF staff calculations.
Note: This table reports the local projection coefficients three years after the shock across different specifications, alongside the average of the yearly growth rate of the main outcome variables. AEs = advanced economies; EMDEs = emerging market and developing economies; TFP = total factor productivity. * p<0.1.

Online Annex 3.7. Quantitative Trade Model

The quantitative trade model builds on the recent literature (e.g. Bartelme and others 2024, Lashkaripour and Lugovskyy 2023) and follows closely the related paper by Ju and others (2024).

3.7.1 Model

The model extends the canonical multi-country multi-sector framework of Caliendo and Parro (2015) to allow for sectoral external economies of scale. The model features 20 granular sectors (19 goods sectors and one aggregate services sector) with sectoral external economies of scale and input-output linkages.

Relative to the canonical Caliendo and Parro (2015) model, the production technology is extended to allow for sectoral external economies of scale. As in Ju and others (2024) the production technology can be summarized by a unit cost function where the unit cost variety ω of intermediate j in country i is given by:

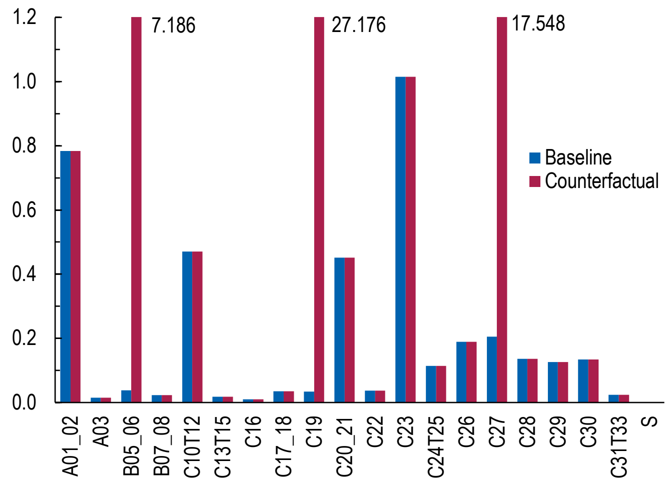
$$c_i^j(\omega) = \frac{1}{z_i^j(\omega)} c_i^j \qquad where$$

$$c_i^j = \frac{1}{(L_i^j)^{\psi_j}} \omega_i^{\beta_i^j} [\Pi_{s=1}^J (P_i^s)^{\gamma_i^{sj}}]^{1-\beta_i^j}$$

Where P_i^s is the price index of good s in country i and L_i^j is labor allocated to a given sector in each country. ψ_j is the sectoral scale elasticity parameter and $z_i^j(\omega)$ is a Hicks-neutral productivity that is drawn independently from a Fréchet distribution.

The model captures the aggregate trade and efficiency effects of changes in industrial policies resulting from the reallocation of resources across sectors and countries. The impacts should be interpreted as long-run effects derived from the comparison of steady-state equilibria induced by different industrial policies. Given the model assumptions, however, the simulated effects may represent a lower bound of the actual impacts, which may encompass static distortionary effects due to the entry of less productive firms (which can be represented in a Melitz-style model, as in Caliendo and others 2023), as well as dynamic factors such as changes to capital accumulation.

Online Annex Figure 3.7.1. Subsidy Rates in the European Union and the United States: Baseline versus Energy Industrial Policy Counterfactual
(Percent of sectoral output)



Sources: Global Trade Alert (GTA); New Industrial Policy Observatory (NIPO); Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.
Note: Figure reports average subsidies by sector under the baseline and in the energy industrial policy counterfactual. Baseline subsidies are computed from NIPO and GTA following the methodology in Rotunno and others (forthcoming). The vertical axis is cut off at 1.2 percent. Counterfactual subsidies assume that subsidies in the energy sector (B05–06, C19, C27) are increased to "optimal level", where the optimal level is proportional to sectoral increasing returns to scale and optimal subsidies are computed using the methodology from Ju and others (2024). The codes on the *x*-axis represent different economic activities, as defined in the Development of the OECD Inter-Country Input-Output Database 2023, table A D.2.

3.7.2 Solution Method

The exact model solution to the quantitative trade model depends on a set of parameters such as iceberg trade costs that are difficult to calibrate. Following Ju and others (2024), the model is therefore solved using the "exact-hat" algebra introduced by Dekle and others (2008), which computes changes in equilibrium outcomes with respect to changes in industrial policies.

3.7.3 IP Counterfactuals

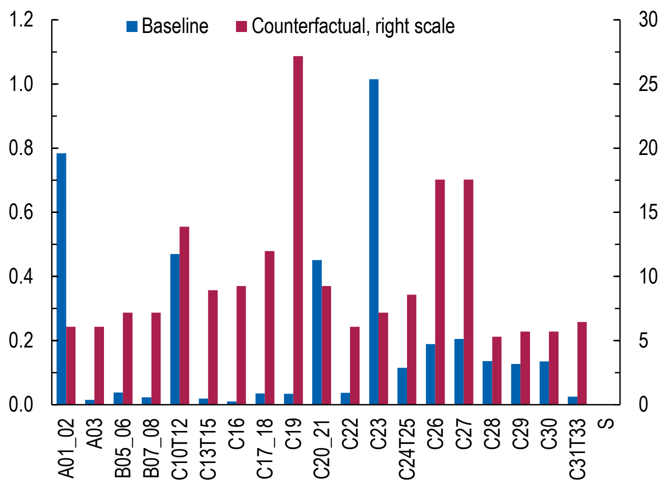
The policy counterfactuals assume that the Advanced Economies in the model – consisting of Australia, Canada, the EU, Iceland, Israel, Japan, Korea, Norway, New Zealand, Switzerland, the US, and the United Kingdom, impose subsidies in a set of sectors.

In the first two policy counterfactuals, subsidy rates are set to the welfare-optimal level. Following Bartelme and others (2025), Ju and others (2024), and Lashkaripour and Lugovskyy (2023), we solve for optimal subsidies by conjecturing that optimal subsidies are proportional to sectoral economies of scale. Let ψ_j denote the sectoral scale elasticity of sector j and s_i^j the optimal subsidy rate on sector j in country i. We then solve for subsidies conjecturing that the following linear relationship characterizes optimal subsidies:

$$s_i^j = \alpha_i + \beta_i \, x \, \frac{\psi_j}{1+\psi_j} \qquad \forall \, j$$

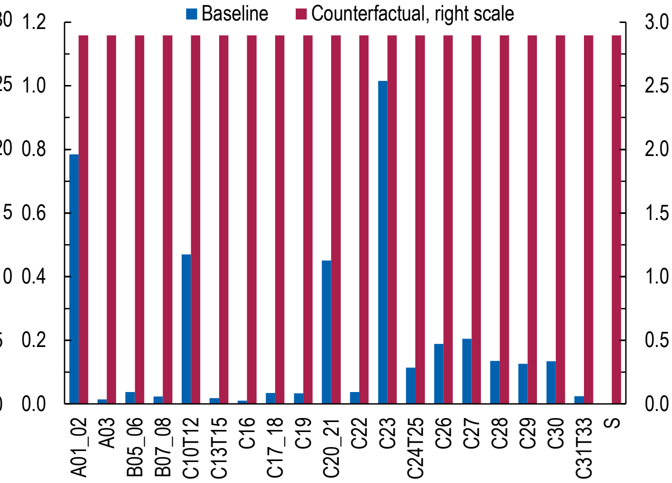
Effectively, this simplifies the problem of solving for 20 parameters per country to a problem of solving for two parameters per country. We then iteratively solve for the parameters α_i and β_i that maximize domestic welfare. The resulting structure of optimal subsidy rates is increasing in the scale elasticity $\psi_j, i.e. \widehat{\beta_\iota} > 0$. This is consistent with the notion that the externality arising from external increasing returns to scale at the sector level is increasing in the size of the scale elasticity. The average subsidy rates for AEs across industries are plotted in Online Annex Figures 3.7.1. – 3.7.3.

Online Annex Figure 3.7.2. Subsidy Rates in the European Union and the United States: Baseline versus Optimal Industrial Policy across Sectors Counterfactual
(Percent of sectoral output)



Sources: Global Trade Alert (GTA); New Industrial Policy Observatory (NIPO); Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.
Note: Figure reports average subsidies by sector under the baseline and in the targeted industrial policy counterfactual. Baseline subsidies are computed from NIPO and GTA following the methodology in Rotunno and others (forthcoming). Counterfactual subsidies assume that subsidies in all goods-producing sectors are raised to "optimal level", where the optimal level is proportional to sectoral increasing returns to scale and optimal subsidies are computed using the methodology from Ju and others (2024). The codes on the *x*-axis represent different economic activities, as defined in the Development of the OECD Inter-Country Input-Output Database 2023, table A D.2.

Online Annex Figure 3.7.3. Subsidy Rates in the European Union and the United States: Baseline versus Uniform Subsidies Counterfactual
(Percent of sectoral output)



Sources: Global Trade Alert (GTA); New Industrial Policy Observatory (NIPO); Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.
Note: Figure reports average subsidies by sector under the baseline and in the uniform industrial policy (IP) counterfactual. Baseline subsidies are computed from NIPO and GTA following the methodology in Rotunno and others (forthcoming). Counterfactual uniform subsidies are set uniformly across all goods producing sectors and the services sector such that the overall fiscal envelope remains the same as in the targeted IP scenario. The codes on the x-axis represent different economic activities, as defined in the Development of the OECD Inter-Country Input-Output Database 2023, table A D.2.

The third policy counterfactual assumes that the block of AEs sets subsidies uniformly across all sectors, regardless of whether they have external economies of scale or not. The fiscal envelope is set as to approximately equal the fiscal envelope in the previous scenario with optimal subsidies in all goods producing sectors.

3.7.4 Data and Calibration

The model baseline relative to which outcomes for the three scenarios will be compared to is calibrated to a pre-2025 steady state. Data on within-country and cross-country input-output linkages comes from the OECD's inter-country input-output tables, which captures granular flows of intermediate goods across sectors as well as the breakdown of sectoral output between use as intermediate goods and final demand. The model features 46 individual countries (12 AEs with the EU counted as one country block and 34 EMDEs) while all remaining countries are subsumed as the rest of the world.

Tariffs are calibrated to pre-2025 tariff data from ITC MacMap and TRAINS. Subsidies are calibrated based on estimates of country-sector-level subsidy rates from NIPO based on the estimation strategy from Rotunno and others (2025).

3.7.5 Results

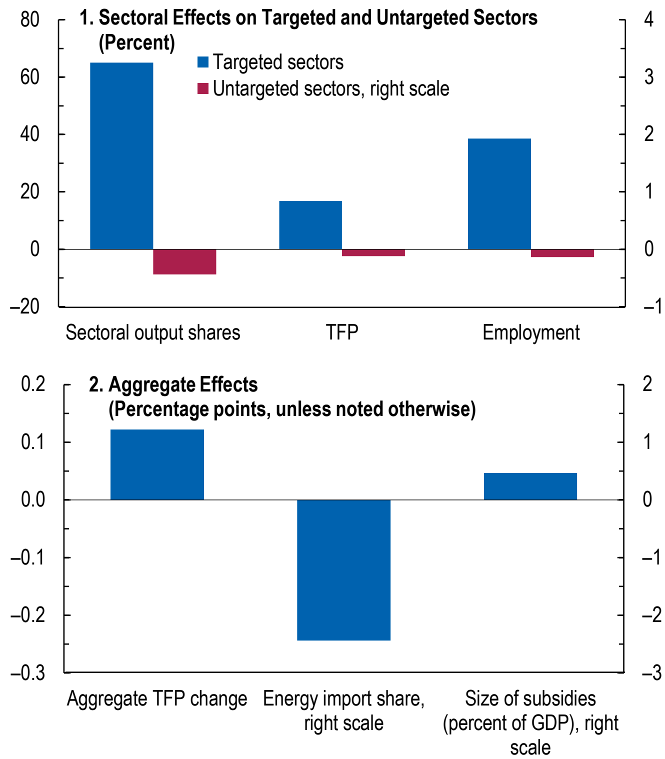
The estimation is conducted at the level of 46 disaggregated economies with the EU aggregated to one country block. All other countries are aggregated to the ROW as a 47th country block. After estimating the model, results are reported in the main text for the 12 AEs in the data – those countries that impose subsidies – and for all other countries jointly, as they are assumed not to impose subsidies

In addition to the main energy IP scenario in Figures 3.12., Online Annex Figure 3.7.4. reports results from a scenario with IP only in the clean tech sector, where the clean tech sector is identified as the "electrical equipment" sector. This counterfactual imposes the same "electrical equipment" sector as in the energy IP scenario but leaves subsidies unchanged relative to the baseline for all other sectors.

Sectoral output in the clean tech sector rises by 65 percent while TFP and employment also grow sizably. Although IP is only imposed in one small sector of the economy, aggregate TFP slightly increases due to the large boost to the clean tech sector.

While the model features labor as the only factor of production, the employment effects should be interpreted as changes in factor demand, since data on sectoral value added (including payments to factors other than labor) are used in the calibration

Online Annex Figure 3.7.4. Sectoral and Aggregate Effects of Industrial Policy in the Clean Tech Sector



Sources: Global Trade Alert; Market Access Map; Organisation for Economic Co-operation and Development, Inter-Country Input-Output tables and Trade in Value-Added indicators; and IMF staff calculations.
Note: Figure shows changes in clean tech industrial policy (IP) scenario relative to the status quo baseline from estimates of quantitative trade model. Clean tech IP scenario simulates introduction of optimal subsidies in the clean tech sector. IPs are introduced for the AEs in the sample (Australia, Canada, European Union, Iceland, Israel, Japan, Korea, New Zealand, Norway, Switzerland, United Kingdom, United States) and results are reported as weighted average effect across all AEs, unless noted otherwise. Weights are shares in total output by AEs. The targeted sector is "electrical equipment". IPs in all other sectors (untargeted sectors) remain unchanged. Panel 1 reports percentage change in sectoral output, TFP, and employment calculated as the weighted sum across targeted and untargeted sectors. Panel 2 reports percentage changes in aggregate TFP. Subsidy costs are reported as change relative to the status quo baseline. AEs = advanced economies; TFP = total factor productivity.

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