The Power of Industrial Policy: The Global Impact of Chinese Subsidies on Solar Innovation and Emissions Reduction

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Abstract

Solar panel production costs have experienced a dramatic decline in the last two decades. This trend is concomitant with the remarkable rise of China as a global solar producer, in part sparked by industrial policies. We study the impact of the introduction of subsidies for the solar manufacturing sector in China on innovation, emissions reduction, and output at the global level. We use firm-level patent data to show that the increase in Chinese competition in the solar PV manufacturing sector driven by the policy had a negative impact on innovation in the rest of the world. Building on this observation, we develop an open economy growth model with endogenous innovation in solar energy technologies to evaluate the overall effect of Chinese industrial policies on solar panel costs through their effects on domestic and foreign innovation, combined with their effects on production.

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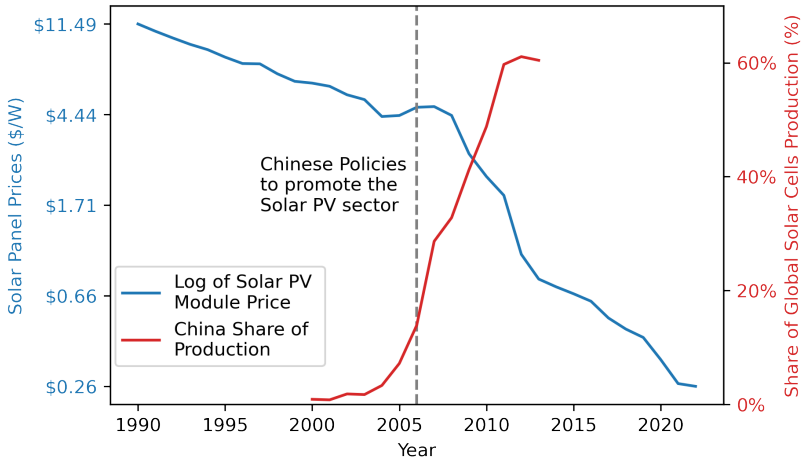
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1 Introduction

The global decline in the cost of solar photovoltaic (PV) technology has been one of the most significant developments in the energy sector over the past two decades. From 2000 to 2020, the cost of solar PV modules dropped by more than 95%, making solar energy increasingly competitive with traditional energy sources (figure 1). Solar panel costs have been declining since the 1990s, but this trend has accelerated from 2007 onward. As it is clear from figure 1, this remarkable decline is concomitant with the outstanding rise of China as a dominant player in global solar manufacturing. China's industrial policies, supporting the solar sector through demand, production, and innovation subsidies (Banares-Sanchez et al., 2023), have been an important driver of the growing Chinese market share. While the resulting drop in solar prices has been widely seen as a positive step toward a greener future, it has sparked protectionist responses from countries such as the United States and Europe, concerned about the impact of Chinese policies on local green industries (Bollinger et al., 2024). Particularly concerning is the marked decline in innovation in solar technologies outside of China over the last decade (figure 2a), which suggests that China's rise in solar manufacturing may be undermining long-term cost reductions through global innovation in solar technologies. Given these dynamics, it is worth asking: Is China's industrial policy truly the gift to global clean energy development that it initially appears to be? This paper offers the first quantitative analysis of this critical question.

Figure 1. Price Decline in the Solar PV Sector and the Role of China



Notes: The blue line shows the solar panel prices in $/W, and the red line displays the Chinese share of global solar cells production. The data sources are, respectively, the International Renewable Energy Agency (2023) and the Earth Policy Institute (2014).

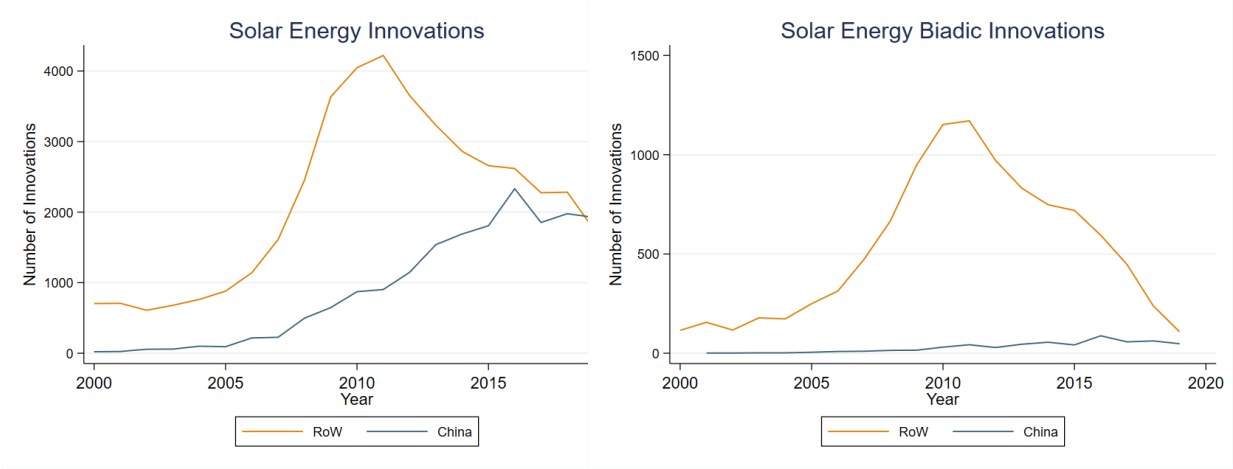
Our contribution is two-fold. First, we empirically document that the increase in Chinese competition harmed innovation in solar technologies in the rest of the world. Second, we develop a trade model with endogenous solar innovation that rationalizes this phenomenon.

We calibrate the model to the Chinese and US economies in order to quantitatively assess the trade-off between the short-run reduction in emissions - resulting from lower solar prices driven by the Chinese subsidies - and the potential longer-term increase in emissions due to a slowdown in solar innovation globally. Furthermore, we observe similar trends in costs, industrial policies, market shares, and innovation in other crucial green technologies, such as electric vehicles (EVs) and wind power. Therefore, our paper provides valuable economic insights and a suitable framework to evaluate the costs and benefits of Chinese industrial policies for the global transition to clean technologies and global emissions reduction.

The Chinese government started subsidizing production and innovation in the solar PV sector in 2006 (Banares-Sanchez et al., 2023). Post-policy implementation, China's market share in the solar PV sector surged dramatically: from virtually null in 2005 to 60% by 2013 (Earth Policy Institute, 2015). In 2022, China accounts for 95% of global solar cells exports[1] and 73% of global solar cell manufacturing capacity[2]. As China displaced the rest of the world (RoW) in production, it also did so in innovation: Figure 2a shows that solar PV patents peaked in the RoW in 2011 while Chinese patents have continuously increased and represent a majority of solar PV patents by 2019. Perhaps more concerning, Figure 2b shows that for biadic patents, the rise of China is close to nonexistent so that the global amount of biadic patents sharply declined. Biadic patents are those that are applied for in at least two different countries and generally considered to be higher-quality patents in the literature. These figures raise the question of whether the new Chinese innovations can make up for the lost innovation in the RoW.

[1]Source: UN Comtrade data.
[2]Source: Solar panel sector reports from Paula Mints.

Figure 2. Innovation in Solar Photovoltaic Energy Technologies



(a) All Patents

(b) Biadic Patents

Notes: The figures are computed using PATSTAT data. Figure (a) reports the number of solar innovations in China and in the rest of the world (RoW), per year. Each patent is assigned to a country based on the nationality of its innovators. Patents with innovators from multiple countries are assigned to each country with a corresponding weight. Patents whose innovators' nationality is not reported are assigned to the country where their claim has been submitted. The sample contains 173755 observations, over the years 2000-2019. Figure (b) reports the number of biadic solar innovations in China and in the rest of the world, per year. Claims of biadic patents have been submitted to at least two national authorities. The sample contains 22755 observations, over the years 2000-2019

Our empirical analysis establishes that the increase in Chinese competition in the solar PV industry had a negative impact on solar innovation of firms in the rest of the world. We use patent data on the universe of solar patenting firms from Orbis IP and PATSTAT. We build a firm-level measure of the exposure to Chinese competition before the introduction of the Chinese policies. Our measure captures whether countries that constitute an important market for a given firm, are also important export markets for Chinese firms. More specifically, our measure is a shift-share in the spirit of Aghion et al. (2016): we compute each country's share in Chinese exports (proxied by patent data), and take a firm-level weighted average using firm's market share in each country (again proxied by patent data). We find that an increase in the exposure of a firm to Chinese competition has a statistically significant negative impact on a firm patenting activity from 2014 onward. An increase in the Chinese exposure measure by 1 standard deviation decreases the expected patent count in 2014 by 24%, relative to the expected patent count in 2008. The magnitude of the effect is increasing over time. In 2017 and 2018, a 1 standard deviation increase in Chinese competition exposure decreases patenting activity by 38 and 40%, respectively, relative to patenting activity in 2008. The results are consistent with a negative impact of the policy-driven increase in Chinese competition on the innovation of firms in the rest of the world. However, the timing of our effects suggests

that there are other factors behind the decline in global solar innovation from 2011 onward.

Building on these observations, we develop an open economy growth model with endogenous innovation in solar energy technologies, to evaluate the overall effect of Chinese industrial policies on solar panel costs through their counteracting effects on production and domestic and foreign innovation. The economy is composed of two regions: China and the rest of the world (RoW). The two regions trade in intermediate inputs for solar energy production and for final good production. We use the model to analyze the different channels through which the policies affect the economy. Consistent with our empirical observations, the policies reduce the cost of production of solar PV, increase solar production and innovation in China, and decrease innovation in the rest of the world. Analytically, the overall effect on emissions and global welfare is ambiguous. Therefore, we calibrate our model to match pre-subsidy (2006) key empirical moments for the US and China. In particular, we target aggregate variables such as total employment and GDP, and energy-specific variables such as R&D, labor, levelized costs and output in solar and non-solar energy. We calibrate subsidies by using the China Stock Market & Accounting Research Database (CSMAR), which provides information on the balance sheet of publicly listed firms quoted on the Chinese stock market. In the future, we intend to use our framework to evaluate the impact of industrial policies in the rest of the world, such as the Inflation Reduction Act, and of trade policies both in China and in the rest of the world.

The calibration is still work-in-progress, therefore this draft does not include the final quantitative results of the calibrated model. We instead illustrate the key mechanisms at play by simulating our model under reasonable parameters. We simulate the model first with exogenous innovation, and then with endogenous innovation. The simulations show that considering the endogenous innovation response is crucial to evaluating the impact of subsidies. On one hand, endogenous innovation can amplify the benefits of subsidies in terms of emissions reduction. Subsidies increase the size of the solar PV market by decreasing the relative price of solar energy intermediate inputs, which incentivizes more innovation in solar energy technologies via a market size effect. Solar innovation further decreases the price of solar intermediate inputs, therefore pushing for further adoption of solar energy and reducing emissions. On the other hand, if the policies shift innovation away from the most innovative regions towards the least innovative regions, policies can have long-term negative effects on technological levels, and therefore on aggregate output. The simulations highlight the presence of a trade-off between global emissions reduction and output, which can be affected in opposite ways by the introduction of the Chinese solar PV subsidies. We are currently working on the model calibration, which will allow us to quantitatively estimate the overall impact of the Chinese solar PV subsidies on global emissions reduction and welfare.

This project contributes to several strands of the literature. First, it relates to the literature studying the impact of increased competition on innovation. Aghion et al. (2005)

finds theoretically and empirically the existence of an inverted U-shaped relationship between competition and innovation. When the level of competition is low, an increase in competition is expected to have a positive impact on innovation. When the level of competition is high, a further increase in competition is expected to have a negative impact on innovation. The solar PV sector is very competitive: it has a high degree of trade openness, sells homogeneous products, and the entry rate was high in the last decades. Through the lenses of the inverted U-shaped relationship, we would expect an increase in competition to be detrimental to innovation in the solar PV sector. Other papers study the impact of increased Chinese competition on innovation using firm-level data (Autor et al., 2020; Bloom et al., 2016; Campbell & Mau, 2021) and find mixed results. Our paper contributes to the literature by shedding more light on the empirical relationship between competition and innovation. We study this question in the context of clean energy technologies, and in particular the solar PV sector, in which innovation is of particular relevance for the energy transition.

Secondly, the paper directly relates to the literature studying the impact of firm-level subsidies by the Chinese government. The existing literature has mostly focused on studying the impact of these subsidies on Chinese firms and the Chinese economy. Banares-Sanchez et al. (2023) study the impact of Chinese subsidies to the solar PV sector on local outcomes. The authors find solar energy demand subsidies have no impact at the local level, while production and innovation subsidies both have a strong positive impact on innovation and production of firms in the region where the policies are implemented, as well as on the number of firms. Boeing (2016) find that subsidies to listed firms crowd out private R&D investment. This paper contributes to the literature by studying the impact of Chinese subsidies on innovation in the rest of the world, and by evaluating the overall impact of the Chinese policies in the solar PV sector on the clean energy transition and global welfare.

Finally, this project falls within the literature that examines the impact of industrial and trade policies on key green technologies. Many governments have introduced duties and tariffs to protect domestic firms in these industries from the increased Chinese competition driven by the Chinese government's public support. Bollinger et al. (2024) and Houde and Wang (2023) find that the US tariffs on Chinese solar PV products increased modestly US solar PV production, reduced substantially solar PV adoption, and had a negative impact on the environment and on consumer surplus. Allcott et al. (2024) evaluates the short-run effects of the EV tax credits and domestic requirements of the US Inflation Reduction Act. They find that domestic firms and the environment benefit from the policies, at the expense of foreign producers. Our paper complements this literature by investigating the impact of increased Chinese competition on domestic and foreign innovation, which is crucial to evaluating the long-term impact of Chinese policies and tariffs implemented abroad.

The rest of the paper is organized as follows. The coming section describes the empirical strategy and the key findings on the impact of increased Chinese competition on solar

innovation outside of China. Section 3 presents the open economy growth model with endogenous innovation in solar energy technologies. Sections 4, 5, and 6 describe, respectively, the decentralized model equilibrium, the asymptotic behavior, and analytical results on the key mechanisms through which a subsidy affects the economy. Section 7 discusses the results of the model simulations on the impact of the Chinese subsidies on solar innovation, emissions, and output. Finally, Section 8 concludes and lays out the next steps of the project.

2 The Increase in Chinese Competition and Solar Innovation in the Rest of the World

The Chinese government has implemented several policies to promote the development of the solar PV sector. The first policies were introduced in 2006 and consisted of subsidies to the production and innovation of firms in the solar PV sector (Banares-Sanchez et al., 2023). The production subsidies decreased investment costs or labor costs for producing firms. These policies decreased production costs for Chinese firms, allowing them to charge lower prices. The policies decreased the price of Chinese solar panels relative to solar panels manufactured in other countries, therefore making Chinese firms more competitive. This increase in Chinese competitiveness is reflected in the share of global solar cells produced in China, which started at approximately 5% in 2005 and reached 60% by 2012. The increase in Chinese competitiveness is expected to harm the profitability of firms manufacturing solar panels in the rest of the world and, in turn, their incentives to innovate. In this section, we investigate the impact of increased Chinese competition in the solar PV manufacturing sector on solar innovation in the rest of the world.

Empirical Strategy. The major solar PV producers are exporters, and firms generally sell their products both domestically and to multiple foreign markets. Firms differ in their market exposure, that is, in the share of sales they realize in a given country, because of, e.g., trade barriers, heterogeneous customer tastes, or government policies to promote domestic producers. Given the differences in market exposure, firms are not equally affected by increased Chinese competition. The firms selling to markets where China has a higher market share will be more affected by an increase in Chinese competition, than the firms selling to markets where China has a low market share. In our empirical strategy, we study whether, as Chinese policies are introduced and Chinese competitiveness increases, the innovation of firms more exposed to Chinese competition decreases relative to the innovation of firms less exposed to Chinese competition.

Due to data limitations, we do not observe market shares at the firm level. We use patents shares as a proxy for market shares. We assess the significance of the various markets in which a firm operates by analyzing its history of patent filings, employing a methodology inspired by Aghion et al. (2016). A patent provides its owner the exclusive rights to commercially use an innovation within a particular country for a defined time. Inventors are required to

file a patent in every country where they want to protect their invention. The process of patenting is expensive; it necessitates the hiring of legal experts, possibly translators, and the payment of filing fees. Consequently, firms only pursue patent protection in countries where they perceive substantial market potential for their technology. Indeed, empirical evidence suggests that inventors do not patent widely and indiscriminately, with the average invention being patented in only two countries (Dechezleprêtre et al., 2011). Coelli et al. (2022) use firm-level exports and patents data, respectively, from the EFIGE survey and PATSTAT to verify whether patent shares in the period 1998-2008 are a good proxy for expected future market shares.[3]

Using patent data, we build a measure of exposure to Chinese competition for every firm. We compute this measure using patent data from the period before the introduction of the policies to ensure that this measure is not affected by the policies[4]. For every patent of a given firm, we keep track of two locations: the country of the firm owning the patent and the country of the application authority where the owner/firm has applied for patent protection.

First, we build a measure of the importance of export market (country) n for firm i:[5]

$$\omega_n^i = \frac{\#Patents_{n,i,2000-2007} * GDP_n^{0.35}}{\sum_m \#Patents_{m,i,2000-2007} * GDP_m^{0.35}}. \tag{1}$$

The measure is given by the number of patents that firm i has applied for in country n, divided by the total number of patents firm i has applied for in any country. Similarly, we build the measure of the importance of the export market (country) n for China as a whole.

$$\omega_n^{China} = \frac{\#Patents_{n,China,2000-2007} * GDP_n^{0.35}}{\sum_m \#Patents_{m,China,2000-2007} * GDP_m^{0.35}} \tag{2}$$

In order to build a measure of the exposure of firm i to Chinese competition, we sum the importance of market n for firm i across all countries n in which firm i is patenting, multiplied by the importance of market n for China.

$$\textbf{Chinese_exposure}_\textbf{i} = \sum_n \omega_n^i \cdot \omega_n^{China}$$

The Chinese exposure measure is higher for firms that have high market shares in countries

[3]Using a representative panel of 15,000 manufacturing firms from 7 European countries, they find that regressing patent weights from the period 1998-2008 on sales weights in 2008 gives a coefficient of 0.89 with a standard error of 0.008. These results confirm that patent shares are a good proxy of expected future market shares.

[4]If firms more exposed to Chinese competition are more negatively impacted by the policies, they will tend to mainly decrease patenting in the markets where they face high Chinese competition. Therefore, if we measure the market shares using post-policies years, the exposure measure will be biased downward for those initially exposed firms.

[5]As Hemous et al. (forthcoming) in a similar exercise, we adjust for country-size through the term $GDP_n^{0.35}$. The coefficient 0.35 reflects the elasticity of firms' exports with respect to market size from Eaton et al. (2011).

that are important export markets for China, where we use patent shares as a proxy to measure the importance of different markets. We are interested in studying the impact of Chinese competition on the innovation of foreign firms. Given that foreign firms have applied for protection in China for only a small share of their patents (6%), we drop n=China from these measures. This means that we can focus on studying the importance of different foreign markets for China, and how this correlates with foreign firms' market exposures.
In the main specification, we study the impact of being exposed to Chinese competition on firms' patents by using a Poisson regression to account for the fact that patents are a count variable.

$$E(Solar_Patents_{it}) = exp(\beta_0 + \beta_{1,t}\delta_t Chinese_exposure_i + \delta_i + \delta_t). \quad (3)$$

The independent variable $Solar_patents_{it}$ is the number of patents in solar photovoltaic energy technologies of RoW firm i in year t. The Chinese exposure measure is interacted with a time dummy δ_t, to study how the impact of being exposed to Chinese competition on firms' patenting activity changes over time with the rise of China as a solar PV producer. δ_i denotes a firm fixed effect and δ_t is a year fixed effect that captures trends affecting all solar innovators equally.

Data. We focus the analysis on the universe of firms patenting in solar photovoltaic energy technologies. We select all firms that have at least one patent in the $Y02E10/5$ CPC class (solar photovoltaic energy). To identify firms, we use Orbis Intellectual Property, which matches global patent data to the companies in Orbis. We use PATSTAT to obtain additional information on patents. Technically, our measure $Solar_Patents_{it}$ corresponds to the number of patent families in solar PV by firm i with a first application in year t – patent families group together patent applications corresponding to the same invention.[6] As our measure of Chinese exposure is built using patent data in the years 2000-2007, our dataset is restricted to firms with at least one patent in the $Y02E10/5$ CPC class between 2000 and 2007.

Table 1 provides summary statistics on the dependent variable, which is the count of solar PV patents firm i has applied for in year t. On average a firm applies for 1.41 patents per year. The maximum number of patents any of the firm applies for in a given year is 307. The 75th percentile is zero, meaning that many firms don't fill out any applications every year. Table 2 provides summary statistics on the firms' country weights, ω_n^i. On average, the weight for the largest country n for a firm i is 0.86. This means that, on average, 86% of the patent applications of a firm are filled in the country in which this firm applies the most. On average, the weights for the second and third largest countries are respectively 0.26 and 0.17. The median of the weight is 1, meaning many firms apply for patent protection in only

[6] We use the INPADOC family defined by the European Patent Office (EPO) in PATSTAT. A family groups together all patent documents (for instance from different patent offices) that are linked directly or indirectly by a priority claim.

one country. Finally, figure 3 shows the importance of different markets (countries) for China measured by patent shares, that is ω_n^{China}. The three countries where Chinese firms apply for the largest number of patents (outside of China) are, in order of importance, Japan, the US, and Germany. There is substantial variation in this measure, which suggests that not all foreign markets are equally important for China. Foreign firms that are selling (and filling out patent claims) in countries where ω_n^{China} is high (i.e., Japan, the US, and Germany) will be more affected by an increase in Chinese competition, than the firms selling in Austria and Spain, or in countries where the Chinese market share is null, not displayed in the figure. We leverage these variations to carry out our empirical analysis.

Table 1: Summary Statistics of Patents Counts

Mean	Std	75%	Max
1.41	7.02	0	307

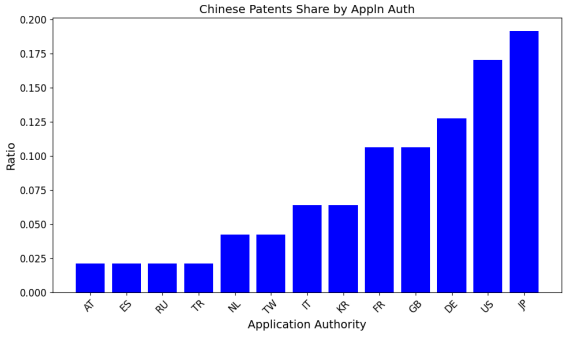
Notes: This table reports the annual mean, standard deviation, 75^{th} percentile and maximum number of solar patents applied for by the firms in our sample. Solar patents are defined with the Y02E10/5 CPC code.

Table 2: Summary statistics of firms' country weights

	Largest country	Second largest	Third largest
Mean	0.86	0.26	0.17
Std	0.27	0.16	0.09
Median	1.00	0.24	0.17

Notes: This table reports statistics on the the firms' country weights, ω_n^i, as defined in equation (1). The weights measure the number of patents that a firm has applied for in a specific country, divided by the total number of patents that this firm has applied for in any country. The table reports the average weight of the firms' three largest markets, that is the three countries in which the firm has applied for the most patents.

Figure 3. Chinese patent shares by country

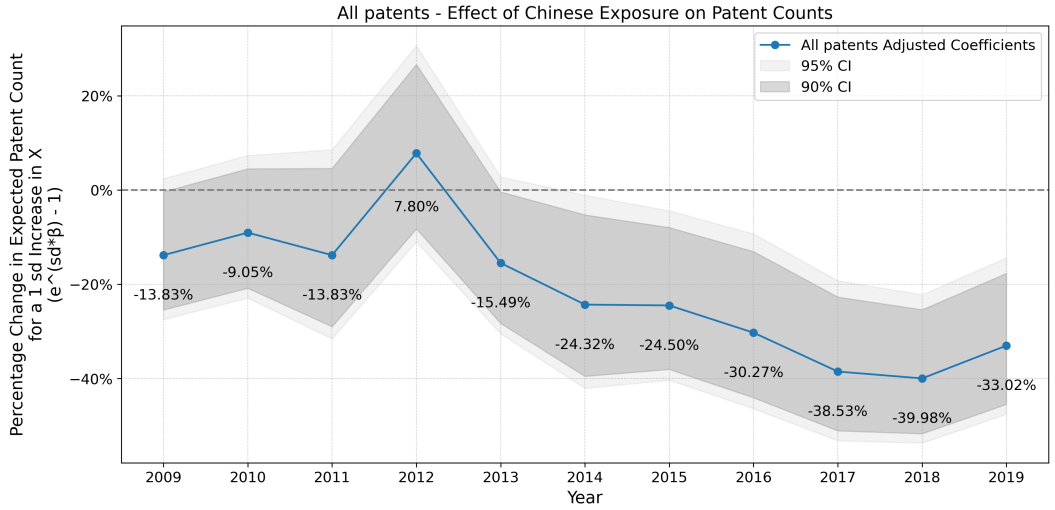


Notes: This figure reports the importance of a country for China, that is, ω_n^{China} as defined in equation (2), for the most important countries (excluding China). This importance is measured as the number of Chinese patents applied for in a country, divided by the total number of Chinese patents.

Results. Table 3 in Appendix A.1 shows the main results of the empirical analysis. The table reports the coefficients β_{1t} on the interaction terms between the Chinese exposure measure and the time dummies. We find a statistically significant negative impact of being exposed to Chinese competition on solar patents from 2013 onwards (2014 at the 5% significance level). Figure 4 reports the transformed coefficients (β_{1t}^T)[7] which are easier to interpret. An increase in the Chinese exposure measure by 1 standard deviation decreases the expected patent count in 2014 by 24%, relative to the expected patent count in 2008. The magnitude of the effect is increasing over time, with the largest effects found in the most recent years. In 2017 and 2018, a 1 standard deviation increase in Chinese competition exposure decreased foreign firms' patenting activity by 38 and 40%, respectively, relative to its patenting activity in 2008.

One might rightly wonder why the negative effect of Chinese competition is only significant in 2013 onward, when the first policies that increased Chinese competitiveness were introduced in 2006. First, Chinese subsidy policies were initially introduced in 2006, but the number of implemented policies has steadily increased up to 2017 (Banares-Sanchez et al., 2023) and developing an industry almost from scratch takes some time. Second, Chinese competition should affect firms' R&D which in turn affects patent applications with a delay (previous studies, such as Aghion et al. (2016) point toward a delay of 2-3 years). Therefore, the results are consistent with a negative impact of the policy-driven increase in Chinese competition on the long-term innovation of firms in the rest of the world. However, they also point out that the rise of China on its own is unlikely to be the sole driver of the decline in solar patenting in the RoW highlighted by Figure 2a

Figure 4



Notes: Number of firms: 617. The regressions include firm and year fixed effects. SEs clustered at the firm level. 1 sd of x is 0.1547

[7] All coefficient of the Poisson regression are transformed using $\beta_{1t}^T = exp(0.01 * \beta_{1t}) - 1$.

3 An Open Economy Growth Model with Trade and Innovation in Solar Energy Technologies

Our empirical analysis, jointly with our stylized facts on solar panel costs, have highlighted that several counteracting forces have affected the development of the global solar PV industry following the introduction of the Chinese industrial policies. To assess their overall effect on emissions and welfare, we need a comprehensive framework that rationalizes these mechanisms and can be quantified. We therefore build an open economy growth model with endogenous innovation in solar energy technologies, which we describe in this section. Two countries trade in intermediate inputs for solar energy production and final good production. The first subsection describes the household preferences and the climate cycle. The following subsections describe, in turn, output and energy production, innovation in solar technologies, and finally, the economy resource constraints.

3.1 Preferences, Final Good Production, and the Climate Cycle

The economy is composed of two regions indexed by n: China and the rest of the world ($n = \{c, r\}$). The structure of preferences, emissions, production and innovation is symmetric across regions. Time is discrete, and each region is populated by an immobile representative household of fixed size P_n. The representative household is composed of workers who can work in production or innovation. Its utility is given by

$$U_0 = \sum_{t=0} \beta^t \frac{C_{nt}^{1-\vartheta}}{1-\vartheta}. \tag{4}$$

β is the rate of time preference. C_{nt} is consumption in region n. ϑ is the inverse elasticity of intertemporal substitution.

The final good in region n is produced using intermediate inputs and energy, which are combined with an elasticity of substitution $\psi < 1$:

$$Y_{nt} = ((1-\alpha)(Y_{rnt}^p + Y_{cnt}^p)^{\frac{\psi-1}{\psi}} + \alpha(\beta_e E_{nt})^{\frac{\psi-1}{\psi}})^{\frac{\psi}{\psi-1}}. \tag{5}$$

Intermediate inputs from region c, Y_{cnt}^p, or from region r, Y_{rnt}^p, are perfect substitutes in the final good production of region n. The production inputs are produced using labor, and they can be traded with no trade costs:

$$Y_{nt}^p = A_{nt}^p L_{nt}^p, \tag{6}$$

where A_{nt}^p evolves exogenously.

The use of non-solar energy generates GHG emissions affecting the climate cycle. As it is common in the macro-climate literature, deterioration of the climate results in output

damages, $D(S_t)$, which measures the fraction of output lost due to climate change. S_t is the carbon concentration in the atmosphere. Damages take the exponential form $(1 - D(S_t)) = e^{-\epsilon_t(S_t - \bar{S})}$. The climate cycle and the damage function are the same as in Golosov et al. (2014):

$$S_t = \bar{S} + \sum_{s=0}^{t+T} (\phi_L + (1 - \phi_L)\phi_0(1 - \phi)^s)\xi^d E^d_{t-s}. \tag{7}$$

The economy starts at $t = -T$, which is the time of industrialization. $\bar{S}$ is carbon concentration in the pre-industrial time. E^d_t is non-solar energy used in period t by both countries ($E^d_t = E^d_{ct} + E^d_{rt}$). ξ^d measures the carbon intensity of non-solar energy. A fraction ϕ_L of carbon emitted stays in the atmosphere forever. Of the remaining emissions, a share $1 - \phi_0$ exits immediately, and a share ϕ_0 decays at a geometric rate ϕ.

3.1.1 Energy Production

Energy is produced locally using non-solar energy and solar energy, which are combined with an elasticity $\xi > 1$.

$$E_{nt} = (\alpha_d (E^d_{nt})^{\frac{\xi-1}{\xi}} + \alpha_s (E^s_{nt})^{\frac{\xi-1}{\xi}})^{\frac{\xi}{\xi-1}}. \tag{8}$$

Non-solar energy is produced using labor according to:

$$E^d_{nt} = A^d_{nt} L^d_{nt}. \tag{9}$$

The non-solar energy technology level A^d_{nt} evolves at an exogenous rate. We assume that the non-solar energy sector is imperfectly competitive. In particular, firms charge a markup $\frac{\sigma}{\sigma-1}$ over the marginal cost[8]

Solar energy is produced with a continuum of intermediate inputs indexed by the letter i, with an elasticity of substitution $\sigma > 1$:

$$Y^s_{nt} = \left[\int_0^{M^c} \left(\frac{x^i_{cnt}}{\tau_{cn}} \right)^{\frac{\sigma-1}{\sigma}} di + \int_{M^c}^1 \left(\frac{x^i_{rnt}}{\tau_{rn}} \right)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}. \tag{10}$$

Intermediates, x^i_{cnt}, x^i_{rnt} are tradable goods, and each intermediate is produced by only one firm located in one of the two regions. Every region is specialized in producing a set of intermediates. The intermediates indexed by $i \in [0, M^c]$ are produced in China, while intermediates indexed by $i \in (M^c, 1]$ are produced in the rest of the world (RoW).[9] In what follows we use M^r to define the mass of solar intermediate inputs produced in the rest of the world (i.e.

[8] Implicitly, we assume that non-solar energy inputs are produced by combining a continuum of intermediates that are imperfect substitutes with elasticity σ, similarly to the solar production process (see below).

[9] We are currently working on an extension that endogenizes M^c through entry and exit.

$M^r = 1 - M^c$). τ_{cn} are trade costs to ship goods from China to region n, and similarly τ_{rn} are trade costs between the RoW and region n. Trade costs are zero to ship within a region, and positive to ship to another region (i.e., $\tau_{cc} = \tau_{rr} = 1$, $\tau_{cr} > 1, \tau_{rc} > 1$). Trade costs take the iceberg form: Given $i \in [0, M^c]$, if firm i produces x^i_{cnt} units of the intermediate good in China to ship to region n, $\frac{x^i_{cnt}}{\tau_{cn}}$ units will arrive to region n to be used for solar energy production.

The firm produces the intermediate input x^i_t using labor with a productivity level q^i:

$$x^i_t = q^i_t l^i_t. \tag{11}$$

l^i_t is labor used by the firm to produce the intermediate good i for both regions c and r ($x^i_t = x^i_{nrt} + x^i_{nct}$, where n is the country where firm i is located). Finally, we introduce industrial policies through a labor cost subsidy s_{nt}. In our main counterfactual analysis, only China subsidizes the solar industry, therefore $s_{rt} = 0\ \forall t$. Therefore if the firm producing intermediate input x^i_t is located in China, it pays a per unit cost of production $\frac{(1-s_{ct})w_{ct}}{q^i_t}$. If the firm is located in the RoW, it pays a per unit production cost equal to $\frac{w_{rt}}{q^i_t}$.

3.1.2 Innovation

Every period and in each region, entrepreneurs hire workers to attempt to improve the current machines used to produce the solar intermediates. They can choose to innovate on any machine. Successful entrepreneurs improve the quality of the intermediate input machine they have chosen by a factor λ_n, and receive monopoly rights to produce it for one period. If they are not successful, the monopoly rights are randomly allocated to an entrepreneur who uses the current (non-improved) technology to produce the intermediate. The entrepreneur working on machine i decides how many researchers to hire (R^i_t). Because workers can work in production or as researchers in their region, the entrepreneurs must pay them the market wage w_{nt}. The solar technology level in region n, Q^s_{nt}, is defined as the average quality level in the given region.

$$Q^s_{nt} = \Big(\int_0^{M^c} (q^i_t)^{\sigma-1} di \Big)^{\frac{1}{\sigma-1}} \tag{12}$$

$$Q^s_{rt} = \Big(\int_{M^c}^{1} (q^i_t)^{\sigma-1} di \Big)^{\frac{1}{\sigma-1}} \tag{13}$$

$$\tag{14}$$

A researcher in region n has a probability of success of $\eta (R^i_t)^{-\kappa} \left(\frac{Q_{n,t-1}}{q^i_{t-1}} \right)^{\sigma-1}$. η is research productivity. R^i_t is the mass of scientists directing their research to intermediate i, and $\kappa < 1$

is a stepping-on-the-toe externality. $\left(\frac{Q_{n,t-1}}{q^i_{t-1}}\right)^{\sigma-1}$ captures knowledge spillovers.

$$Q_{nt}^{\sigma-1} = ((Q_{nt}^s)^{\sigma-1})^{\zeta}((Q_{ct}^s)^{\sigma-1} + (Q_{rt}^s)^{\sigma-1})^{1-\zeta} \tag{15}$$

There are local knowledge spillovers, which means spillovers across intermediates in the same region, as well as global spillovers, that is across intermediates in different regions. The smaller is ζ, the more important are local spillovers relative to global spillovers.
The law of motion of technology Q_{nt} is the following.

$$Q_{nt}^s = \left(1 + \eta R_{nt}^{1-\kappa} M^n \left(\frac{Q_{n,t-1}}{Q_{n,t-1}^s}\right)^{\sigma-1} ((1+\lambda)^{\sigma-1} - 1)\right)^{\frac{1}{\sigma-1}} Q_{n,t-1}^s \tag{16}$$

3.2 Budget, Resource, and Labor Constraints

Labor market clearing implies that in each region, the P_n workers must be allocated across production (of the final good (L_{nt}^p), the non-solar energy input (L_{nt}^d), or solar intermediates (L_{nt}^s)), and solar innovation.

$$L_{nt}^p + L_{nt}^d + L_{nt}^s + M^n R_{nt} = P_n \tag{17}$$

R_{nt} is the mass of researchers per solar intermediate in region n. M^n is the mass of solar intermediate varieties produced in region n.
The economy resource constraint requires that consumption equals output net of damages.

$$C_{nt} = (1 - D(S_t))Y_{nt} \tag{18}$$

The household receives labor income from workers and profits from the firms producing the solar intermediates. The households in the two regions must satisfy the following budget constraints.

$$p_{ct}Y_{ct} + s_{ct}w_{ct}L_{ct}^s = w_{ct}(L_{ct}^p + L_{ct}^d + L_{ct}^s) + \int_0^{M^c} \pi_t^i di \tag{19}$$

$$p_{rt}Y_{rt} = w_{rt}(L_{rt}^p + L_{rt}^d + L_{rt}^s) + \int_{M^c}^1 \pi_t^i di \tag{20}$$

$s_{ct}w_{ct}L_{ct}^s$ is a tax imposed on the representative household in China to pay for the subsidies to solar intermediate inputs labor costs. Note that the wages paid to researchers do not appear in the budget constraint as they would enter with a positive sign among workers' wages but with a negative sign in the firms' profits.

Finally, the trade balance states that imports must equal exports for both regions.

$$Y^p_{crt} + \int_0^{M_c} p^i_t \frac{x^i_{crt}}{\tau_{cr}} di = Y^p_{rct} + \int_{M_c}^1 p^i_t \frac{x^i_{rct}}{\tau_{rc}} di \tag{21}$$

4 Decentralized Equilibrium

4.1 Optimal Choices of the Final Good Producer, Energy Producers, and Intermediate Input Producers

The production inputs from China and the RoW are perfect substitutes in the final good production of region n. If the price of the production inputs is lower in one of the two regions, the final good producer would buy the production input only in this region. At an interior solution where both regions produce the production inputs, their prices are equalized across regions. Therefore, the demand for the production inputs by the final good producer is determined by the following FOC.

$$p^p_{nt} = p_{nt}(1-\alpha)\left(\frac{Y_{nt}}{Y^p_{rnt} + Y^p_{cnt}}\right)^{\frac{1}{\psi}} \tag{22}$$

where p^p_{nt} is the price of the production input from region n, and p_{nt} is the price of the final good in region n. The demand for energy in region n is determined by the following FOC.

$$p^e_{nt} = p_{nt}\alpha\left(\frac{\beta_e^{\psi-1} Y_{nt}}{E_{nt}}\right)^{\frac{1}{\psi}} \tag{23}$$

where p^e_{nt} is the energy price in region n. The producers of the production input operate in a competitive market. Therefore, they will price at marginal cost.

$$p^p_{nt} = \frac{w_{nt}}{A^p_{nt}} \tag{24}$$

We normalize the production input price to 1, which pins down the wage in both regions to be equal to the technology A^p_{nt}.

Non-solar energy producers charge a markup $\frac{\sigma}{\sigma-1}$ over their marginal cost. Therefore, the price of non-solar energy is

$$p^d_{nt} = \frac{\sigma}{\sigma-1}\frac{w_{nt}}{A^d_{nt}} \tag{25}$$

The energy producer's optimal choices of non-solar and solar energy inputs are determined

by the following expressions.

$$p_{nt}^{d} = p_{nt}^{e}\alpha_d \left(\frac{E_{nt}}{E_{nt}^{d}}\right)^{\frac{1}{\xi}} \quad \text{and} \quad p_{nt}^{s} = p_{nt}^{e}\alpha_s \left(\frac{E_{nt}}{E_{nt}^{s}}\right)^{\frac{1}{\xi}} \tag{26}$$

The solar producer in n decides how many inputs to buy from firms in the two regions, taking into account the trade costs to be paid on imports.

$$\max_{x_{cnt}^{i}, x_{rnt}^{i}} p_{nt}^{s}E_{nt}^{s} - \int_{0}^{M^c} p_{cnt}^{i}\frac{x_{cnt}^{i}}{\tau_{cn}}di - \int_{M^c}^{1} p_{rnt}^{i}\frac{x_{rnt}^{i}}{\tau_{rn}}di \tag{27}$$

p_{cnt}^{i} (p_{rnt}^{i}) is the price that a firm i located in region c (r) charges when selling to the solar energy producer located in region n. The solar energy producer demands the following quantities respectively from the firms in c and in r:

$$x_{cnt}^{i} = (\frac{p_{nt}^{s}}{p_{cnt}^{i}})^{\sigma}E_{nt}^{s}\tau_{cn} \text{ for i} \in [0, M^c] \tag{28}$$

$$x_{rnt}^{i} = (\frac{p_{nt}^{s}}{p_{rnt}^{i}})^{\sigma}E_{nt}^{s}\tau_{rn} \text{ for i} \in (M^c, 1] \tag{29}$$

The firm i located in region c takes into account the demand x_{cnt}^{i} from the solar producer in region n, and sets the price that maximizes its profits.

$$\max_{p_{cnt}^{i}} \pi_{cnt}^{i} = p_{cnt}^{i}\frac{x_{cnt}^{i}}{\tau_{cn}} - (1 - s_{ct})w_{ct}\frac{x_{cnt}^{i}}{q_{t}^{i}} \tag{30}$$

$$p_{cnt}^{i} = \frac{\sigma}{\sigma - 1}(1 - s_{ct})\frac{w_{ct}}{q_{it}}\tau_{cn} \tag{31}$$

The firm sets a price at a constant markup over marginal costs to maximize its profits. By reducing the marginal costs, subsidies have a direct impact on solar intermediate prices. p_{cnt}^{i} is the effective price paid by the solar producer in n, the price paid per unit of intermediate input consumed in n. If firm i is not located in region n, it takes into account that if it produces x_{it}, only $\frac{x_{it}}{\tau_{cn}}$ will arrive in region n.

The firm i located in r solves a similar maximization problem to decide the price at which it wants to sell to the solar energy producer in region n.

$$\max_{p_{rnt}^{i}} \pi_{rnt}^{i} = p_{rnt}^{i}\frac{x_{rnt}^{i}}{\tau_{rn}} - w_{rt}\frac{x_{rnt}^{i}}{q_{t}^{i}} \tag{32}$$

$$p_{rnt}^{i} = \frac{\sigma}{\sigma - 1}\frac{w_{rt}}{q_{it}}\tau_{rn} \tag{33}$$

Even if two firms located in China and the RoW had the same technology and wages were the same in the two regions, the price of the solar intermediate input produced in China would be lower in the case of positive subsidies.

4.2 Optimal Innovation Choice

Firm i located in region n decides how many researchers to hire to maximize its profits.

$$\max_{R_t^i} \eta (R_t^i)^{1-\kappa} \Big(\frac{Q_{n,t-1}}{q_{t-1}^i} \Big)^{\sigma-1} \pi_t^i - R_t^i w_{nt} \tag{34}$$

which gives the following optimal choice.

$$R_t^i = \Big[\frac{\eta(1-\kappa)}{\sigma w_{nt}} \Big((1+\lambda) \frac{\sigma-1}{\sigma} \frac{Q_{n,t-1}}{(1-s_{nt})w_{nt}} \Big)^{\sigma-1} \Big((p_{ct}^s)^\sigma Y_{ct}^s (\tau_{nc})^{1-\sigma} + (p_{rt}^s)^\sigma Y_{rt}^s (\tau_{nr})^{1-\sigma} \Big) \Big]^{\frac{1}{\kappa}} \tag{35}$$

R_t^i does not depend on i, which means that the same number of researchers will be hired for any intermediate i. We call R_{nt} the mass of researchers hired for any intermediate i in region n.

5 Asymptotic Behavior

In this section, we briefly discuss the asymptotic behavior of our model, under the assumption that the production technology A_{nt}^p grows at the same rate in both regions, that is $1 + g_{A_c^p} = 1 + g_{A_r^p}$. We also restrict our analysis to an interior solution, where wages are exogenously determined by $w_{nt} = A_{nt}^p$.

Recall that total output is characterized by the budget constraint

$$Y_{nt} = w_{nt} \frac{\sigma-1}{\sigma \Omega_{nt}} \left(L_{nt}^p + \frac{\sigma}{1-\sigma} L_{nt}^d + \frac{\sigma}{1-\sigma} (1-s_{nt}) L_{nt}^p \right)$$

On a (asymptotic) BGP where both countries produce the production input, labor allocation is constant and the wage grows at rate $1 + g_{A_n^p}$. Hence, the growth rate of output is dictated by the growth rates of the different technology terms, through the wage and the marginal cost Ω_{nt}. In particular, we have that:

$$\lim_{t\to\infty} 1 + g_{\Omega_n} = \left(\min \left\{ 1, \max\{ \frac{1+g_{A_n^d}}{1+g_{A_n^p}}, \max\{ \frac{1+g_{Q_c^s}}{1+g_{A_c^p}}, \frac{1+g_{Q_r^s}}{1+g_{A_r^p}} \} \right\} \right)^{-1}$$

This means that the economy grows asymptotically at rate:

$$\lim_{t\to\infty} 1 + g^z = (1 + g_{A_n^p}) \times \min \left\{ 1, \max\{ \frac{1+g_{A_n^d}}{1+g_{A_n^p}}, \max\{ \frac{1+g_{Q_c^s}}{1+g_{A_c^p}}, \frac{1+g_{Q_r^s}}{1+g_{A_r^p}} \} \right\}$$

In our model, only the solar technology growth rate is endogenous. We next characterize the asymptotic behavior of the innovation effort R_{nt}^s, which determines the asymptotic

growth rate of the solar technology. Whether the economy converges to an asymptotic balanced growth path (BGP), with positive innovation ($R^s_{nt} > 0$), or diverges to a corner solution with no innovation ($R^s_{nt} = 0$)[10] depends on whether it exhibits *path dependence*. Path dependence occurs when the innovation effort increases in Q^s_{nt}. In that case, the economy diverges to a corner solution, and the BGP is unstable. In contrast, without path dependence, innovation effort and the technology level move in opposite directions, bringing and keeping the economy on the BGP, which is stable. Innovation effort is determined by the expected return on innovation, which depends on solar technology through a direct price effect (a higher level of technology decreases the marginal cost of solar, hence decreases its price and its profits) and a market size effect (a higher level of technology decreases the marginal cost of solar, hence increases its demand and its profits). In our model, whether or not there is path dependence depends on the structural parameters, as well as on the initial relative technology levels. We now provide some intuitions on the determining parameters.

Expected returns on innovation depend on the demand for solar intermediates, which is itself determined by the demand for solar energy, which is itself determined by the demand for the energy composite, which, finally, is itself determined by the household's available income. As solar intermediates are substitutes ($\sigma > 1$), and solar and non-solar energy are substitutes ($\xi > 1$), there is path dependence in the upstream production stages. This is because the market size effect dominates the price effect for imperfectly substitutable inputs[11]. However, because the energy composite and the production inputs are weak complements ($\psi < 1$), there is no path dependence at that stage of production. Overall, whether there is path dependence or not depends on the relative importance of each stage in the total demand for intermediates, hence on the expenditure shares of each input. These shares depend on each input's relative technology level, which are determined by the initial technology levels and their equilibrium growth rates.

Intermediate inputs are traded. Therefore, the expected return on innovation depends on both the domestic and the foreign demand. Analogously, the solar technology level of each region affects both regional demand. Therefore, whether there is path dependence must be assessed for both regions separately. On top of these, the knowledge spillovers push for convergence across regions. The smaller ζ is, the stronger this channel. To sum up, our model allows for different asymptotic paths depending on structural parameters and initial values. Therefore, it is an appropriate tool to analyze different industrial policy scenarios, at different points in time characterized by different relative solar technology levels. In particular, the

[10] There cannot be a corner solution with no production and only innovation ($M_n R^s_{nt} = 1$) in *both* regions. Indeed, innovation is effectively financed by the household and, therefore depends on their income, which is null without production.

[11] This is because the substitution effect and the scale effect driving the effect on demand, following a change in prices due to an underlying change in the marginal costs, go in the same direction. Therefore, the market size effect is strong. In contrast, with complementary inputs, the substitution effect and the scale effect go in opposite directions, which weakens the market size effect.

following asymptotic paths are possible:

- **BGP in both regions.** Solar technologies grow at the same rate in both regions, equal to the growth rate of the production technologies: $1+g_{A_c^p} = 1+g_{A_r^p} = 1+g_{Q_c^s} = 1+g_{Q_r^s}$
- **Corner solution: no innovation in both regions.** Solar technologies don't grow, and all workers are hired in production: $1 + g_{Q_c^s} = 1 + g_{Q_r^s} \to 1$
- **Corner solution: no innovation in region n, no production in region n'.** Solar technologies don't grow in region n, and all workers are hired in production: $1+g_{Q_n^s} \to 1$. All workers work in innovation in region n': $1+g_{Q_{n'}^s} \to \left(1 + \eta M^z \left(\frac{Q_{nt}}{Q_{nt}}\right)^{\sigma-1} ((1+\lambda)^{\sigma-1} - 1)\right)^{\frac{1}{\sigma-1}}$. This is a knife-edge case.
- **Corner and interior solutions: no innovation in region n, BGP in region n'.** Solar technologies don't grow in region n, and all workers are hired in production: $1 + g_{Q_n^s} \to 1$. Solar technology in region n grows at the production technologies growth rate: $1 + g_{Q_{n'}^s} = 1 + g_{A_c^p} = 1 + g_{A_r^p}$

Which one will prevail will depend on our data-driven calibration, to which we will come back in section 7.

6 Effects of Solar PV Industrial Policies: Analytical Results

This section discusses how industrial policies, represented by a production subsidy in our model, affect the different variables and, in particular, global emissions. The goal of this section is to highlight the different economic mechanisms that are at play following the implementation of industrial policies, and that can shed light on our empirical findings.
Emissions are generated by the use of non-solar energy. Therefore, we need to understand how non-solar production is affected. We restrict our analysis to an interior solution, where wages are exogenously determined by $w_{nt} = A_{nt}^p$. All the proofs for this section can be found in appendix A.3
As a production subsidy, the direct effect of the policy is to reduce the effective marginal cost in each region. Indeed, since solar intermediates are tradeable and imperfect substitutes, both regions benefit from the cost reduction:

$$\text{China:}\quad \Omega_{ct}^s = \left((\frac{(1-s_{ct})w_{ct}}{Q_{ct}^s})^{1-\sigma} + (\frac{\tau_{rc} w_{rt}}{Q_{rt}^s})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{RoW:}\quad \Omega_{rt}^s = \left((\frac{\tau_{cr}(1-s_{ct}w_{ct}}{Q_{ct}^s})^{1-\sigma} + (\frac{w_{rt}}{Q_{rt}^s})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

Where Ω^s_{nt} is the effective marginal cost of solar intermediates in region n. It is straightforward to see that it directly decreases with s_{ct} in both regions, all else equal.
Moreover, for a given level of technology, Ω^s_{ct} decreases more than Ω^s_{rt}, due to the trade costs. This is because Chinese solar producers benefit more from the subsidy, since they are using *more* of the subsidized inputs, i.e., the Chinese solar intermediates. Indeed, those are not subject to trade costs. In contrast, RoW solar producers use less of the subsidized inputs, as those are subject to a trade cost. Hence, they benefit less from the subsidy.
In the following, we split the total effects into *static* effects, which take the solar technology level as given, and *dynamic* effects, which endogenize the technology level. Static effects are discussed in section 6.1, while dynamic effects are covered in section 6.2.

6.1 Static Effects

From the FOCs of the energy composite profit-maximization problem, we have that

$$Y^s_{nt} = \alpha^\xi_s \left(\frac{p^e_{nt}}{p^s_{nt}}\right)^\xi E_{nt} \qquad \text{and} \qquad Y^d_{nt} = \alpha^\xi_d \left(\frac{p^e_{nt}}{p^d_{nt}}\right)^\xi E_{nt}$$

The static partial equilibrium effects on solar and non-solar production can be decomposed into a substitution effect (through the relative prices) and a scale effect (through Y_{nt} as $E_{nt} = \alpha^\psi \beta_e^{\psi-1} \left(\frac{p_{nt}}{p^e_{nt}}\right)^\psi Y_{nt}$). As the solar marginal costs decrease, the relative price of solar (non-solar) decreases (increases). Therefore, the production of the energy composite substitutes away from non-solar and demands more solar. In parallel, lower marginal costs decrease the total cost of energy production, which scales up. The static general equilibrium effects are determined by the changes in the total available income of the household, that dictate the change in the demand for the final good, hence total production. To simplify exposure, suppose that profits are rebated outside of the regions, and that taxes are not levied on the household. Therefore,

$$p_{nt} Y_{nt} = w_{nt}$$

In that case, Y_{nt} scales up with the subsidy, as the wage is fixed exogenously, and the total price decreases. This reinforces the partial equilibrium scale effect.

Result 1 *Suppose that $\sigma > \xi > 1 > \psi > 0$. At given technology levels, and if profits and taxes are not part of the household total income, solar production increases with the subsidy in both regions.*

The substitution effect and the scale effects go in the same direction. Therefore, solar production increases.

Result 2 *Suppose that $\sigma > \xi > 1 > \psi > 0$. At given technology levels, and if profits and taxes are not part of the household total income, non-solar production decreases with the subsidy in both regions.*

The substitution effect and the scale effects go in opposite directions, but the former dominates. Therefore, non-solar production decreases.

If taxes and profits enter the household budget constraint, the static effect is ambiguous, because the direction and the relative magnitude of the scale effect depend on several effects. First, there is a direct demand effect, that increases the scale effect since the aggregate price in region z decreases as solar costs decrease. Secondly, total income is distorted by the subsidy: as the subsidy increases, it increases the distortion, and even more so if the distorted sector (solar) extends as well. Therefore, total income decreases. Finally, the markup in the solar and non-solar sectors also distorts total income. Therefore, total income varies as labor is reallocated toward or away from a distorted sector. Therefore, the scale effect depends on how labor is reallocated across sectors following the implementation of the subsidy. Since this doesn't allow for a closed-form solution, we will turn to the calibration in section 7 to characterize it.

6.2 Dynamic Effects

In this section, we let the solar technology in each region be endogenously determined, through the innovation decision of the local firms. We analyze the effects of the changes in solar technologies on non-solar production.

First, notice that the effect of solar technologies, A^s_{rt} and A^s_{ct}, also goes through the effective solar marginal cost:

$$\text{China:}\quad \Omega^s_{ct} = \left((\frac{(1-s_{ct})w_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{\tau_{rc}w_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{RoW:}\quad \Omega^s_{rt} = \left((\frac{\tau_{cr}(1-s_{ct}w_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{w_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

By reducing the solar marginal cost, an increase in any of the solar technologies decreases non-solar production, through the same substitution and scale effects discussed above.

To understand how the solar technologies respond to the subsidy, we need to consider the innovation decision of the local firms. Recall that

$$\text{China:}\quad R^i_{ct} = \left[\frac{(1-\kappa)\eta}{1-\sigma} \frac{(1-s_{ct})(Q^s_{c,t-1})^{\sigma-1}}{(1+\lambda)q^\sigma_{i,t-1}} \left(\tau_{cr} \left(\frac{p^s_{rt}}{p^i_{rt}} \right)^\sigma Y^s_{rt} + \left(\frac{p^s_{ct}}{p^i_{ct}} \right)^\sigma Y^s_{ct} \right) \right]^{\frac{1}{\kappa}}$$

$$\text{RoW:}\quad R^i_{rt} = \left[\frac{(1-\kappa)\eta}{1-\sigma} \frac{(1-s_{rt})(Q^s_{r,t-1})^{\sigma-1}}{(1+\lambda)q^\sigma_{i,t-1}} \left(\left(\frac{p^s_{rt}}{p^i_{rt}} \right)^\sigma Y^s_{rt} + \tau_{rc} \left(\frac{p^s_{ct}}{p^i_{ct}} \right)^\sigma Y^s_{ct} \right) \right]^{\frac{1}{\kappa}}$$

Firms base their decisions on the expected profits of producing intermediate inputs, should they succeed in improving the current technology. At a given level of technologies, expected profits depend on the relative price of solar energy, which determines the (identical) demand for intermediates, and on the change in each intermediate's marginal cost. Through the market size effect, the expected profits increase if the relative price of solar energy decreases, since demand increases. Through the direct price effect, expected profits increase if the relative price of solar energy decreases. Finally, if intermediate producers' own marginal cost decreases, expected profits increase, reinforcing the market size effect.
We can show that the market size effect (reinforced with the direct marginal cost effect) dominates the price effect in China, for reasonable expenditure shares value. Hence, expected profits increase if the relative price decreases. In contrast, in the RoW, the price effect dominates the market size effect, because the latter is not reinforced by a change in intermediates' marginal costs.

Intuitively, the relative price of Chinese intermediate inputs decreases with the subsidy. Indeed, they compete against RoW intermediate inputs, which don't benefit from a subsidy. Therefore, at a given level of technologies, innovation effort R^i_{ct} increases in China. Correspondingly, the relative price of RoW intermediate inputs increases with the subsidy. Therefore, at a given level of technologies, innovation effort R^i_{rt} decreases in the RoW.

Recall the law of motion of solar technology:

$$Q^s_{nt} = \left(1 + \eta (R^s_{nt})^{1-\kappa} M^n \left(\frac{Q_{n,t-1}}{Q^s_{n,t-1}}\right)^{\sigma-1} ((1+\lambda)^{\sigma-1} - 1)\right)^{\frac{1}{\sigma-1}} Q^s_{n,t-1}$$

At a given level of technologies, a higher innovation effort increases the success rate of innovation, which in turn, increases the growth rate of technologies. Therefore, as the innovation effort increases (decreases) in China (in the RoW), the growth rate of solar technologies will increase (decrease). In turn, this will affect the innovation decision through the effect of solar technologies on the solar marginal costs, and through the spillovers.

Overall, isolating these effects sheds light on the different mechanisms that are at play when an industrial policy is introduced in our global economy. However, the total impact on emissions depends on the relative strength of these different effects, both static and dynamic. Therefore, we now turn to calibrating our model, in order to quantify that total impact.

7 Effects of Solar PV Industrial Policies: Quantitative Results

The quantitative analysis aims to evaluate the overall impact of the Chinese subsidies in the Solar PV sector on global emissions reduction and welfare. As highlighted by the empirical and theoretical analysis, the subsidies affect the economy through multiple channels with opposite effects on emissions and welfare. The subsidies immediately decrease the price of Chinese solar intermediates, which pushes for larger solar energy adoption in the short run. The larger solar energy market size pushes for more solar innovation in China in the short run. On the other hand, solar innovation in the rest of the world decreases, which might result in slower technological progress and increased emissions in the long run. These are some of the key mechanisms at play.

To quantify which effect prevails, we calibrate the model to key data moments from the US and Chinese economies and energy markets. Section 7.1 describes the calibration strategy and the key data sources. The calibration of the model is still work-in-progress at this stage, therefore this draft does not include the final quantitative results of the calibrated model. Section 7 presents the effects of Solar PV industrial policies under reasonable parameters assumptions. This section is intended to show the key mechanisms through which the subsidies affect the economy, but it does not aim to provide a quantitative assessment of the policy impact. We are currently working on the calibration strategy, and expect to have final quantitative results soon.

7.1 Calibration

A model period corresponds to one year. We currently focus on the US as our RoW region, though we plan to include additional regions in the future. We calibrate our model to match pre-subsidy ($t = 2006$) relevant empirical moments for the US and China. We start by externally calibrating some standard parameters following the literature, then target aggregate variables such as total employment and GDP, and energy-specific variables such as R&D, labor, levelized costs, and output in solar and non-solar energy, to calibrate the key parameters in our model.

7.1.1 Externally Calibrated Parameters

Table 4 in appendix A.2 summarizes the values of the parameters that we calibrate externally. Our specification of the climate cycle and of preferences closely follows Golosov et al. (2014) and Acemoglu et al. (2023). Therefore, we use their parameter values, only modified to accommodate our one-year time period and the composition of our non-solar energy input. We follow the macro-environment literature and calibrate the elasticity of substitution between solar intermediates to be equal to 6, the elasticity of substitution between solar and non-solar energy to be equal to 3, and the elasticity of substitution between energy and the production

input to be equal to 0.9. We follow the recent innovation literature (Akcigit and Kerr (2018), Acemoglu et al. (2018), Bloom et al. (2021)) to calibrate the stepping-on-the-toe externality in innovation κ. We use Liu and Ma (2021)'s estimates of the US and Chinese reliance on domestic patents to calibrate our cross-region spillovers. We exogenously set a growth rate of 2% for the production input and the non-solar energy technologies. Finally, we set the energy weight in the final good production function, α to 0.2 without loss of generality since different values of α can be accommodated by varying β_e.

7.1.2 Internally Calibrated Parameters.

Tables 5 in appendix A.2 summarizes the values of the empirical moments that we target. We deflate all the prices and values to be expressed in 2015 US dollars. In our model, the price of the production input is the numeraire (i.e., $p_p^c = p_p^r = 1$). In contrast, the final good (GDP), is the numeraire in the data. Therefore, when deflating the prices, we need to adjust them to match the model price[12]. We recover the model final good price as $p_{nt} = (1-\alpha)^{\frac{\psi}{1-\psi}}(1-\theta_{nt}^{ey})^{\frac{1}{\psi-1}}$.

Employment. We recover the US and the Chinese total labor force from the World Development Index (WDI) Database of the World Bank. We normalize the labor force in the US to 1. We then measure the workforce employed in the energy sector by aggregating employment across relevant sectors. For the US, we use the US Labor Statistics of the BLS and aggregate employment across mining (oil and gas extraction, coal), manufacturing of semiconductors and other electronic components, manufacturing of Petroleum and coal products, gasoline stations, utilities, and pipeline transportation. For China, we use data from the China Statistical Yearbook and aggregate across mining and washing of coal, extraction of petroleum and natural gas, processing of petroleum, coking, processing of nuclear fuel, production and supply of electric power and heat power, and production and supply of gas.

Number of intermediates. We normalize the total number of solar intermediates to 1, and count the number of Chinese and US solar intermediates firms registered in Orbis IP. This gives us $M^c = 0.82$.

Non-solar energy. Our calibration requires a value for the price p_{nt}^d and output of non-solar energy Y_{nt}^d. For the US, we collect data on the levelized cost of all non-solar energy sources from Lazard. However, to measure p_{nt}^d, we cannot simply use the naive average levelized cost of all energy sources but solar, as this would assume that those different energy sources are perfect substitutes. To aggregate these costs under a more realistic assumption, we instead

[12]Take for instance the price of solar panels. We have that $\frac{p_{nt}^s(model)}{p_{rt}(model)} = \frac{p_{nt}^s(data)}{p_{rt}(data)}$ where $p_{rt}(data) = 1$ for $n = c, r$, therefore $p_{nt}^s(model) = p_{nt}^s(data)p_{rt}(model)$

infer the share of each of the energy sources by assuming that they are aggregated in a CES manner as follows:

$$Y_{rt}^d = \left(\sum_i \kappa_i (Y_{rt}^i)^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}}$$

Where κ_i is the share of source i, and we take ξ to the same elasticity of substitution as between solar and non-solar. From the demand for each source, along with the normalization that $\sum_i \kappa_i = 1$, we obtain a system of equations that identifies all the κ_i:

$$\frac{\kappa_i}{\kappa_j} = (\frac{Y_{rt}^i}{Y_{rt}^j})^{\frac{1}{\xi}} \frac{p_{nt}^i}{p_{rt}^i}$$

With the κ_i identified, we can recover the model-consistent price of other sources of energy:

$$p_{rt}^d = \left(\sum_i \kappa_i^{\xi} (p_{nt}^i)^{1-\xi} \right)^{\frac{1}{1-\xi}}$$

We recover the price of non-solar energy in China once we have estimated α^d (see below) and a measure of the energy price p_{ct}^e. To estimate the latter, we use the Chinese GDP from the World Bank WDI Database, combined with the Chinese energy share of value-added that we compute based on OECD IO tables, as well as the total energy output in China, that comes from the 2024 Statistical Review of World Energy of the Energy Institute. Formally, $p_{ct}^e = \theta_{ct}^{ey} \frac{GDP_{ct}}{Y_{ct}^e}$.

Once we have calibrated A_{nt}^p (see below), we can recover the initial level of non-solar energy technology in both regions as

$$A_{nt}^d = \frac{\sigma}{\sigma - 1} \frac{A_{nt}^p}{p_{nt}^d}$$

Wages. The solar R&D share of GDP, θ_R^s, the total labor force, labor in energy, and total GDP, determine the initial wage (which is equal to $A_p(0)$), using the budget constraint. We measure the R&D share of GDP using the R&D expenditure of our solar firms in Orbis IP. GDP in both regions comes from the World Bank WDI Database.

$$A_{nt}^p = \frac{GDP_{nt}(1 + \theta_R^s)}{L_{nt} + \frac{L_{nt}^e}{\sigma - 1}}$$

Solar energy technology: With A_{nt}^p calibrated, we can recover the initial level of solar energy technology for both regions, using the solar prices. In particular, we use:

$$Q^s_{rt} = \left[\left(\frac{\sigma - 1}{\sigma} p^s_{rt} \right)^{1-\sigma} - (\frac{\sigma}{\sigma - 1})^{\sigma-1} \frac{EXP^s_{ct}}{(p^s_{rt})^\sigma Y^s_{rt}} \right]^{\frac{1}{\sigma-1}} (1 - s_{rt}) A^p_{rt}$$

$$Q^s_{ct} = \left[\left(\frac{\sigma - 1}{\sigma} p^s_{ct} \right)^{1-\sigma} - (\frac{\sigma}{\sigma - 1})^{\sigma-1} \frac{EXP^s_{rt}}{(p^s_{ct})^\sigma Y^s_{ct}} \right]^{\frac{1}{\sigma-1}} (1 - s_{ct}) A^p_{ct}$$

We again use Lazard levelized cost data to measure the price of solar energy in the US, whereas we recover the Chinese price from the International Renewable Energy Agency's *Renewable Power Generation Costs* 2022 report.

Trade costs: We recover the iceberg trade costs using the US Census Bureau trade flows:

$$\tau_{cr} = \left((\frac{\sigma - 1}{\sigma})^{\sigma-1} (p^s_{rt})^\sigma Y^s_{rt} \frac{1}{EXP^s_{ct}} \right)^{\frac{1}{\sigma-1}} \frac{Q^s_{ct}}{(1 - s_{ct}) A^p_{ct}}$$

$$\tau_{rc} = \left((\frac{\sigma - 1}{\sigma})^{\sigma-1} p^c_s(t)^\sigma Y^s_{ct} \frac{1}{EXP^s_{rt}} \right)^{\frac{1}{\sigma-1}} \frac{Q^s_{rt}}{(1 - s_{rt}) A^p_{rt}}$$

Solar and non-solar shares in production: Using the solar and non-solar energy prices and consumption - the latter taken from the 2024 Statistical Review of World Energy of the Energy Institute - along with total energy price and consumption, we can recover:

$$\alpha^s_n = \left(\frac{Y^s_{nt}}{Y^e_{nt}} \right)^{\frac{1}{\xi}} \frac{p^s_{nt}}{p^e_{nt}}$$

$$\alpha^d_n = \left(\frac{Y^d_{nt}}{Y^e_{nt}} \right)^{\frac{1}{\xi}} \frac{p^d_{nt}}{p^e_{nt}}$$

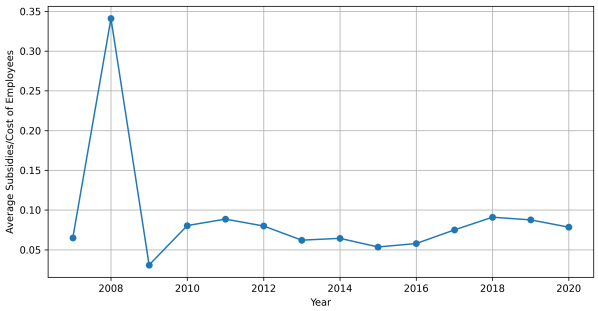
Since we don't have access to non-solar energy prices and output for China in 2006, we impose that $\alpha^d_c = \alpha^d_r$.

Energy share in production: Along with the energy price, that we compute from the solar and non-solar prices, the energy expenditure share of GDP that we measure using the OECD IO tables gives us β^e_n:

$$\beta^e_n = p^e_{nt} \left(\frac{1 - \alpha}{\alpha} \right)^{\frac{\psi}{\psi-1}} \left(\frac{\theta^{ey}_{nt}}{1 - \theta^{ey}_{nt}} \right)^{\frac{1}{\psi-1}}$$

Innovation: Using again the R&D share of GDP, along with GDP and our calibrated wage, we can solve for the initial number of scientists in each region:

Figure 5. Subsidies received by Chinese Publicly listed firms



Notes: This figure reports the evolution of the average subsidies-to-employment-cost ratio in China over the years for publicly listed solar firms. Solar firms are defined as firms with at least one solar PV technology patent. Sources: CSMAR and Orbis IP, based on authors' computations.

$$R^s_{nt} = \frac{\theta^R_{nt} GDP_{nt}}{A^p_{nt} M_{nt}}$$

Finally, using R^s_{nt} and the growth rate of technology that we measure from the one-year growth rate of granted solar patents in PATSTAT, we jointly estimate η and λ:

$$\eta = \frac{(R^s_{nt})^{\kappa}}{\frac{(1-\kappa)}{\sigma w_{nt}} \left(\frac{(1+\lambda)(\sigma-1)Q_{nt-1}}{\sigma(1-s_{nt})w_{nt}} \right)^{\sigma-1} ((p^s_{nt})^{\sigma} Y^s_{nt} + (p^s_{n't})^{\sigma} Y^s_{n't} \tau^{1-\sigma}_{nn'}))}$$

$$(1+\lambda)^{\sigma-1} - 1 = \frac{(g^s_{nt})^{\sigma-1} - 1}{\eta (R^s_{nt})^{1-\kappa} M_{nt} (\frac{Q_{nt-1}}{Q^s_{nt-1}})^{\sigma-1}}$$

Subsidies. We calibrate subsidies by using the China Stock Market & Accounting Research Database (CSMAR). This dataset provides information on the balance sheet of publicly listed firms that are quoted on the stock market in China. Starting from 2007, all quoted firms must report the amount of government subsidies received by the government. The sectoral classification does not allow us to identify only firms that are active in the solar PV sector. By matching the firms with Orbis IP data, we can identify 211 firms with at least one solar photovoltaic technology patent. We build our measure of subsidies by computing the ratio of government subsidies over the costs of employees for this set of firms. Figure 5 shows the evolution of the average level of subsidies across this set of firms over the years. The subsidies peaked in 2008, as a response of the government to the global financial crisis (Branstetter et al., 2023). The average value of subsidies is 0.09, which is the value we take to parametrize the subsidies in our simulations.

7.2 Results

As the model calibration is still work-in-progress, this section presents the impact of the subsidies for sample parameter values with the objective to illustrate the main forces at play in our model. We assume all the technology levels start at 1, both in China and in the RoW. We assume the RoW is more productive in innovation than China ($\eta_r = 1.25$, $\eta_c = 1.2$, $\lambda_r = \lambda_c = 0.6$). This assumption is based on preliminary results from our calibration strategy, which gives larger research productivity in the US (our RoW in the calibration strategy) than in China. The subsidy equals the average subsidy level in the CSMAR data (0.9%) as explained in section 7.1. The economy is simulated for 100 periods, with the introduction of the subsidy in period 20[13].

To highlight the role of endogenous solar innovation, we first simulate the impact of the subsidies with exogenous technological development, keeping the solar technological paths equal to the paths in the absence of subsidies [14]. Secondly, we allow for innovation to respond to the introduction of subsidies.

Figure 6a shows the growth rate of the solar technologies in China and in the RoW, obtained by solving the model in the absence of subsidies. The solar technology growth rate is higher in the RoW than in China. This is partly mechanically driven by the assumption that research productivity is higher in the RoW than in China ($\eta_r > \eta_c$). In addition, given the solar technology grows faster in the RoW, solar energy captures a larger market which incentivizes more solar innovation. The Row is more productive in research, and it has a large number of scientists innovating in the solar sector (see figure 6c). Over time the technology gap grows and eventually, the RoW specializes in solar innovation, while China does not innovate in solar.

In the absence of subsidies, the RoW always produces more solar energy output than China, and also more solar intermediates (see figures 6b and 6d). When the subsidy is introduced, solar intermediates production increases substantially in China, while it decreases in the RoW. On the other hand, solar energy output increases in both regions. The RoW produces less intermediates at home, and it imports more solar intermediates from China. The increase in solar energy output is larger in China than in the RoW, given the benefits of cheaper Chinese solar intermediates are mediated by trade costs for the RoW. Given the RoW innovates more in solar (with the exogenous innovation path), in the long run, the RoW still produces more intermediates than China as it uses more advanced and cheaper technologies. The subsidies do not have any major impacts on output, and slightly decrease emissions.

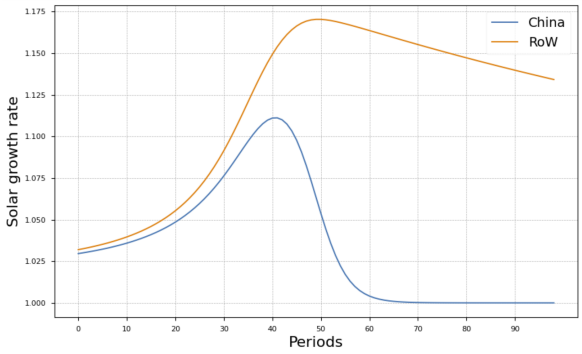
[13] We assume the mass of firms, M, equals 0.5, and the knowledge spillovers parameter, ζ, equals 0.7 in both China and the RoW.

[14] We first simulate the economy in the absence of subsidies. We store how the solar technology evolves in China and the RoW in the absence of subsidies. In the exogenous technology scenario, we assume the solar technologies evolve as in the case with no subsidies.

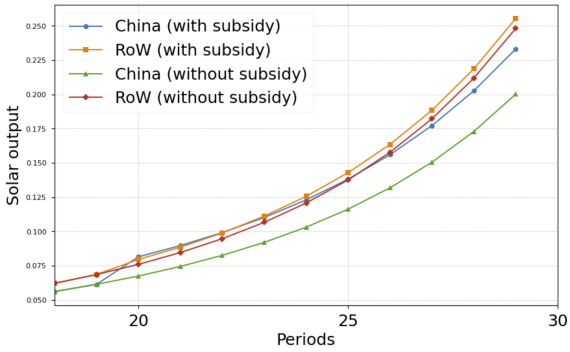
Figure 7a illustrates the solar technology growth rate with endogenous innovation. Subsidies are introduced in the period 20. Before the introduction of subsidies, the growth rate is higher in the RoW given the assumption that the RoW is more productive in innovation. After the introduction of the subsidies, we see a positive jump in Chinese innovation. The production of intermediates shifts away from the RoW towards China (see figure 7d). The larger market size pushes for more innovation in China, and less innovation in the RoW. Now China specializes in both innovation in solar intermediates and production of solar intermediates (see figure 7c). The endogenous innovation response amplifies the effect of the subsidy. With exogenous innovation, the subsidy temporarily shifts intermediates production toward China, but the RoW technology grows faster, and eventually, the production of intermediates moves back to the RoW. However, when considering the endogenous innovation response, the shift of the production of intermediates towards China becomes permanent, given China also specializes in innovation and eventually has a more advanced solar technology than the RoW. Output in China increases after the introduction of the subsidy, while it decreases in the RoW. This is due to higher productivity in the solar sector driven by increased innovation in China, and lower productivity in the solar sector in the RoW due to decreased incentives to innovate. Overall, figure 7e shows the global output is lower with subsidies than in the scenario without subsidies. This result is driven by two channels. First, the production of solar intermediates is moved to the region with an initially less advanced technology. Secondly, solar innovation is moved to the less research-productive region. Figure 7f, finally, shows that the emissions reduction is stronger when considering the endogenous innovation response. The subsidies increase solar energy adoption and the market size of the solar sector, which in turn results in more solar innovation, faster solar technological change, and a faster transition to clean energy.

These results highlight that the subsidies can result in a trade-off between emissions reduction and output growth. Secondly, they show that considering endogenous innovation is key to evaluating the long-run effect of solar PV industrial policies. Additional simulation results for the periods not shown in these graphs can be found in the appendix section A.4.

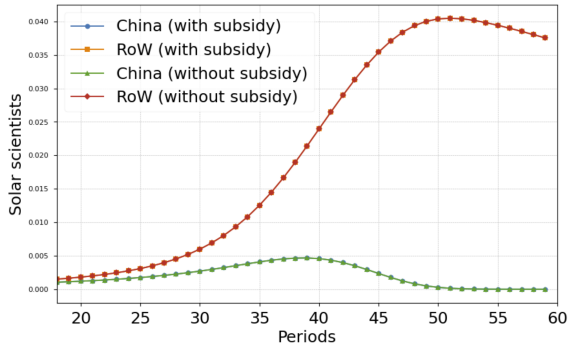
Figure 6. Subsidies Impact with Exogenous Innovation



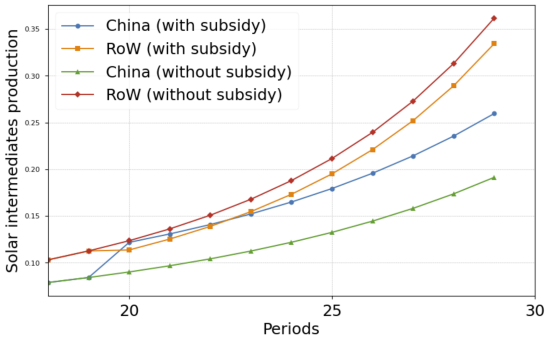
(a) Solar Technology Growth Rate



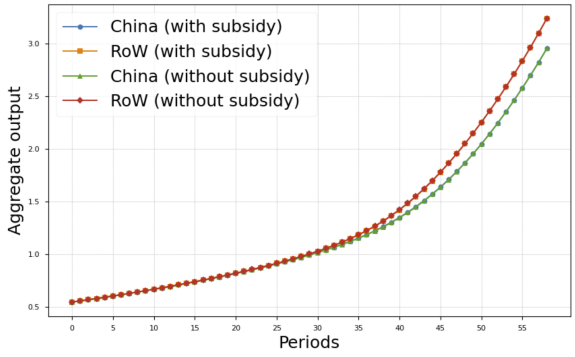
(b) Solar Energy Output



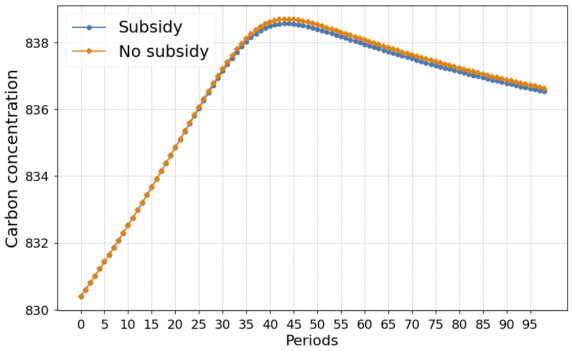
(c) Solar Scientists



(d) Solar Intermediates Production

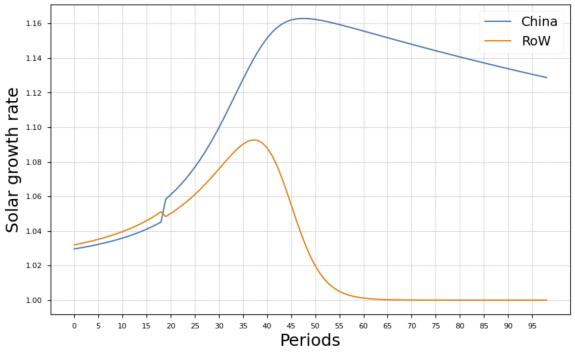


(e) Aggregate Output

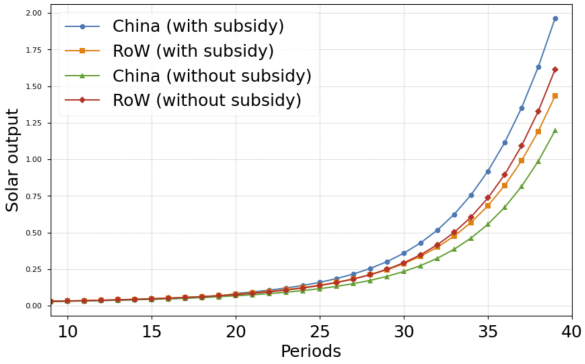


(f) Carbon Concentration

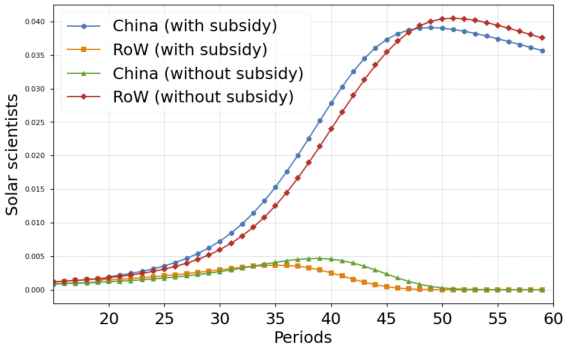
Figure 7. Subsidies Impact with Endogenous Innovation



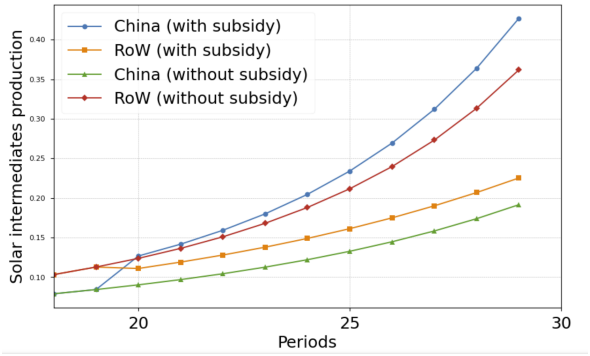
(a) Solar Technology Growth Rate



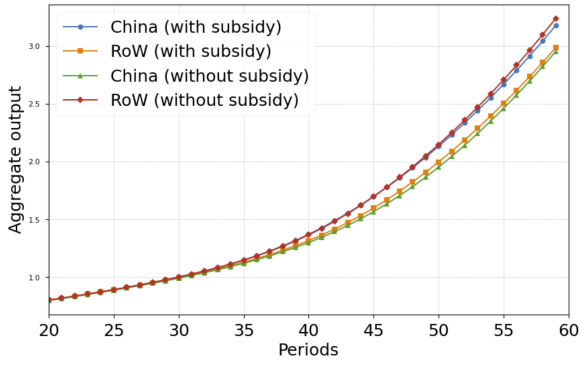
(b) Solar Energy Output



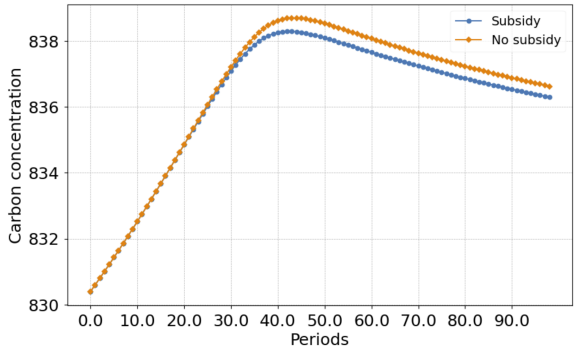
(c) Solar Scientists



(d) Solar Intermediates Production



(e) Aggregate Output



(f) Carbon Concentration

8 Conclusion

This paper studies the impact of the introduction of industrial policies, in the form of subsidies, supporting the solar PV manufacturing sector in China on innovation, emissions reduction, and output at the global level. The policies have helped China to become the major producer of solar cells and a key player in innovation in solar photovoltaic energy technologies. They have also contributed to the massive decline in the costs of solar PV worldwide. However, our empirical analysis using patent data on the universe of solar patenting firms demonstrates that the increase in Chinese competition in the solar PV manufacturing sector had a negative impact on innovation in the rest of the world. Consequently, we develop a tractable but comprehensive theoretical model to evaluate the effects of industrial policies on sectors that are crucial to the energy transition. The model highlights the main mechanisms through which the subsidies affect the economy: it immediately reduces the costs of production in the country implementing the policies, and reallocates market share toward the targeted industry in this country. In the medium-run, it incentivizes innovation in the country but discourages it in the rest of the world. The overall effect on prices, demand and emissions is ambiguous. Therefore, to quantitatively evaluate the overall effect of Chinese industrial policies, we are currently working on calibrating the model. As it is clear from the general formulation above, our model can be used not only for an ex-post evaluation of the effect of the Chinese industrial policies in the solar sector, but also as an ex-ante evaluation tool for the effects of trade and industrial policies that are being implemented in the RoW. Moreover, it also applies to other pivotal sectors of the energy transition. For instance, it is an appropriate tool to predict the development of the global EV industry, as China has more recently targeted this sector with industrial policies similar to the solar sector. The costs, market share and innovation patterns are strikingly similar between the two sectors, but slightly delayed in the EV sector. As both the EU and the US are trying to protect the EV industry through tariffs and domestic content requirements, our model can provide insights on whether these policies will be effective, but also on their implications for emissions reduction and for the clean energy transition.

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A Appendix

A.1 Empirical Results

This section reports our main empirical results. Table 3 reports the coefficients β_{1t} on the interaction terms between the Chinese exposure measure and the time dummies. We find a statistically significant negative impact of being exposed to Chinese competition on solar patents starting from 2013 onwards.

A.2 Calibration

In this section, we provide more details on our calibration. Table 4 reports the values and sources of the parameters that we calibrate externally based on standard values from the literature. Table 5 reports information on the empirical moments we use for our internal calibration.

Table 5: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter identified**
Total L^c	Chinese labor force	774287037	World Bank WDI	$\frac{L^c}{L^r}$
Total L^r	USA labor force	154154002	World Bank WDI	$\frac{L^c}{L^r}$
L_e^r	US Energy labor	2226600	US Labor Statistics	$A_p^r(0)$
L_e^c	Chinese Energy labor	9074300	China Statistical Yearbook	$A_p^c(0)$
$g_s^c(t)$	Chinese one-year solar granted patent growth rate (%)	90%	PATSTAT	λ^c, η^c
$g_s^r(t)$	US one-year solar granted patent growth rate (%)	63.03%	PATSTAT	λ^r, η^r
θ_{ct}^{ey}	Chinese energy share of VA at basic prices (%)	2.83%	OECD IO table	β_e^c, $p_e^c(t)$
θ_{rt}^{ey}	US energy share of VA at basic prices (%)	1.28%	OECD IO table	β_e^r
$GDP^r = p^r Y^r$	US GDP (in 2015 m US$)	15992063	World bank WDI	$A_p^r(0), R_s^r(0)$
$GDP^c = p^c Y^c$	China GDP (in 2015 m US$)	4982879	World bank WDI	$A_p^c(0), R_s^c(0)$
θ_R^c	Chinese R&D expenditure share of GDP (%)	work-in-progress	Orbis	λ^c, η^c

Table 5: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter identified**
θ_R^r	US R&D expenditure share of GDP (%)	work-in-progress	Orbis	λ^r, η^r
Y_s^r	US solar energy generation (TWh)	0.824	Energy Institute - Statistical Review of World Energy (2024)	α_s
Y_s^c	Chinese solar energy generation (TWh)	0.095	Energy Institute - Statistical Review of World Energy (2024)	
Y_e^r	US primary energy consumption (TWh)	26700	Energy Institute - Statistical Review of World Energy (2024)	$p_e^c(t)$
Y_e^c	Chinese primary energy consumption (TWh)	23048	Energy Institute - Statistical Review of World Energy (2024)	$p_e^c(t)$
$Y_{ge}^r(t)$	US geothermal energy consumption (TWh)	226.21	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_{gc}^r(t)$	US gas energy consumption (TWh)	5865.78	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_c^r(t)$	US coal energy consumption (TWh)	6249.68	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_n^r(t)$	US nuclear energy consumption (TWh)	2262.58	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$

Table 5: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter identified**
$Y_w^r(t)$	US wind energy consumption (TWh)	76.42	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_o^r(t)$	US oil energy consumption (TWh)	11072.75	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_h^r(t)$	US hydropower energy consumption (TWh)	812.49	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$Y_b^r(t)$	US biofuel energy consumption (TWh)	131.70	Energy Institute - Statistical Review of World Energy (2024)	$Y_d^c(t)$
$p_s^c(0)$	Price of solar in China (2022 US \$/MWh) (2010)	330	International Renewable Energy Agency - Renewable Power Generation Costs in 2022	$Q_s^r(0), Q_s^c(0)$
$p_s^r(0)$	Price of solar in the USA (US \$/MWh) (2009)	359	Lazard LCOE	$Q_s^r(0), Q_s^c(0)$
$p_{ge}^r(0)$	Levelized cost of geothermal energy in the US (US \$/MWh) (2009)	76	Lazard LCOE	κ_{ge} for $p_d^r(t)$ for $A_d^c(0)$
$p_{gc}^r(0)$	Levelized cost of gas (combined cycle) energy in the US (US \$/MWh) (2009)	83	Lazard LCOE	κ_{gc} for $p_d^r(t)$ for $A_d^c(0)$
$p_c^r(0)$	Levelized cost of coal energy in the US (US \$/MWh) (2009)	111	Lazard LCOE	κ_c for $p_d^r(t)$ for $A_d^c(0)$

Table 5: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter identified**
$p_n^r(0)$	Levelized cost of nuclear energy in the US (US \$/MWh) (2009)	123	Lazard LCOE	κ_n for $p_d^r(t)$ for $A_d^c(0)$
$p_w^r(0)$	Levelized cost of wind energy in the US (US \$/MWh) (2009)	135	Lazard LCOE	κ_w for $p_d^r(t)$ for $A_d^c(0)$
$p_o^r(0)$	West Texas Intermediate Oil price in the US (US \$/MWh) (2009)	36.32	Statista	κ_o for $p_d^r(t)$ for $A_d^c(0)$
M^c	Number of Chinese solar intermediates firms	350	Orbis IP	M^c
M^r	Number of US solar intermediates firms	77	Orbis IP	M^r
EXP_s^c	Chinese solar export (2006 \$)	70551765	US Census Bureau (Imports from China)	τ
EXP_s^r	US solar export (2006 \$)	10423119	US Census Bureau (domestic exports to China)	τ

A.3 Analytical effects of industrial policies

Below, we prove our different results on the effects of the subsidy. We will make repetitive use of the following elasticities:

$$\frac{dlog\Omega_{nt}}{dlog\Omega_{nt}^e} = \alpha^{\psi}\beta_e^{\psi-1}(\frac{\Omega_{nt}}{\Omega_{nt}^e})^{\psi-1} = \frac{p_{nt}^e Y_{nt}^e}{p_{nt}Y_{nt})} > 0$$
$$\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s} = \alpha_s^{\xi}(\frac{\Omega_{nt}^e}{\Omega_{nt}^s})^{\xi-1} = \frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e} > 0$$
$$\frac{dlog\Omega_{nt}^s}{dlogs_{ct}} = -(\Omega_{nt}^s)^{\sigma-1}\left(\frac{\tau_{cn}(1-s_{ct})w_{ct}}{Q_{ct}^s}\right)^{1-\sigma}\frac{s}{1-s} = -\frac{s}{1-s}\frac{\int_c p_i^c(t)x_i^c(t)di}{p_{nt}^s Y_{nt}^s} < 0$$

Chinese solar marginal costs decrease more than RoW solar marginal costs. We have that

$$\frac{dlog\Omega_s^r(t)}{dlogs} - \frac{dlog\Omega_s^c(t)}{dlogs} = \left(\frac{(1-s_{ct})w_{ct}}{Q_{ct}^s}\right)^{1-\sigma}\frac{s}{1-s}\left((\Omega_{ct}^s)^{\sigma-1} - \tau_{cr}^{1-\sigma}(\Omega_{rt}^s)^{\sigma-1}\right)$$

Table 3: Impact of Chinese Exposure on Solar Patents Counts

	All patents	Owners at least 1 biadic	Biadic patents
Intercept	—	—	—
	—	—	—
chinese exp 2009	-0.9618*	-1.7195**	-2.1181
	(0.5693)	(0.7392)	(1.5719)
chinese exp 2010	-0.6127	-1.2100*	-0.4218
	(0.5456)	(0.6626)	(1.8228)
chinese exp 2011	-0.9619	-1.7271*	1.4048
	(0.7605)	(0.9055)	(1.8087)
chinese exp 2012	0.4854	-0.1375	0.6642
	(0.6331)	(0.7962)	(1.8812)
chinese exp 2013	-1.0878*	-1.9322**	-2.5440
	(0.6452)	(0.8306)	(1.8217)
chinese exp 2014	-1.8007**	-3.1960***	-1.4467
	(0.8814)	(1.0391)	(1.9112)
chinese exp 2015	-1.8157**	-3.1165***	-0.9418
	(0.7779)	(0.9762)	(2.0667)
chinese exp 2016	-2.3299***	-3.4246***	-1.1734
	(0.8667)	(1.1346)	(1.5963)
chinese exp 2017	-3.1440***	-4.7418***	-2.0278
	(0.8993)	(1.1870)	(2.2997)
chinese exp 2018	-3.2989***	-4.9963***	1.7753
	(0.8541)	(1.1648)	(4.4939)
chinese exp 2019	-2.5900***	-3.1416***	-3.3395
	(0.8093)	(1.1715)	(2.4897)
Pseudo R-squared	0.9755	0.9995	0.4100
Number of firms	617	236	209
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-year FE	No	No	No

Notes: Standard errors in parentheses: * p<.1, ** p<.05, ***p<.01. Standard errors are clustered at the firm level. This tables shows the coefficients estimated with a Poisson Regression of the main specification, which is given by equation 3. Chinese exposure (year) represents the interaction term between the Chinese exposure measure which varies at the firm level and the year dummy for the given year.

We can show that $(\Omega^s_{ct})^{\sigma-1} - \tau_{cr}^{1-\sigma}(\Omega^s_{rt})^{\sigma-1} > 0$. Indeed,

$$
\begin{aligned}
&(\Omega^s_{ct})^{\sigma-1} - \tau_{cr}^{1-\sigma}(\Omega^s_{rt})^{\sigma-1} > 0 \\
\Rightarrow\ &(\Omega^s_{rt})^{1-\sigma} > \tau_{cr}^{1-\sigma}(\Omega^s_{ct})^{1-\sigma} \\
\Rightarrow\ &(\frac{\tau_{cr}(1-s_{ct})w_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{w_{rt}}{Q^s_{rt}})^{1-\sigma} > (\frac{\tau_{cr}(1-s_{ct})w_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{\tau_{cr}^2 w_{rt}}{Q^s_{rt}})^{1-\sigma} \\
\Rightarrow\ &1 > \frac{1}{\tau_{cr}^{2(\sigma-1)}}
\end{aligned}
$$

Table 4: Externally calibrated parameters

Parameters	Value	Description	Comments
κ	0.5	Return to scale in innovation	Acemoglu et al. (2018), Akcigit and Kerr (2018), Bloom et al. (2021)
σ	6	Elasticity of substitution between intermediates	
ξ	3	Elasticity of substitution between solar and dirty energy	
ψ	0.9	Elasticity of substitution between energy and production inputs	
α	0.2	Share of energy in final good production	WLOG
ζ^r	0.7	Cross-regions spillovers	US reliance on domestic patents from Liu and Ma, 2021
ζ^c	0.4	Cross-regions spillovers	Chinese reliance on domestic patents from Liu and Ma, 2021
g_{A_d}	(1.02, 1.02)	Exogenous growth rate of dirty energy technology	
g_{A_p}	(1.02, 1.02)	Exogenous growth rate of prod. input technology	Equal to the growth rate of wages
ρ	0.01	Social Planner's rate of time preference	Acemoglu et al., 2023
ϑ	1.5	Inverse EIS	Acemoglu et al., 2023
$T(0)$	830	Pre-industrial carbon concentration (in Gtc)	Acemoglu et al., 2023
ι	0.86	Carbon intensity of non-solar energy sources (pounds per kWh)	EIA 2022
ϕ_L	0.2	Permanent emissions share	Acemoglu et al., 2023
ϕ_0	0.3973	Emissions immediately absorbed	Acemoglu et al., 2023
ϕ_d	0.0115	Rate of decay	Acemoglu et al., 2023
χ	0.000053	damage parameter	Acemoglu et al., 2023

Which holds, since $\sigma > 1$.

A.3.1 Static effects

We first consider the static effects, taking the technologies level as given.

Solar production increases with the subsidy in both regions. Recall that

$$\begin{aligned} Y_{nt}^s = \alpha_s^\xi \left(\frac{p_{nt}^e}{p_{nt}^s}\right)^\xi Y_{nt}^e = \alpha_s^\xi \left(\frac{p_{nt}^e}{p_{nt}^s}\right)^\xi \alpha^\psi \left(\frac{p_{nt}}{p_{nt}^e}\right)^\psi Y_{nt} \\ = \alpha_s^\xi \alpha^\psi (\Omega_{nt}^s)^{-\xi} (\Omega_{nt}^e)^{\xi-\psi} (\Omega_{nt})^\psi Y_{nt} \end{aligned}$$

Therefore,

$$\frac{dlogY_{nt}^s}{dlogs} = \underbrace{-\xi \frac{dlog\Omega_{nt}^s}{dlogs} + (\xi-\psi)\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}\frac{dlog\Omega_{nt}^s}{dlogs} + \psi \frac{dlog\Omega_{nt}}{dlog\Omega_{nt}^e}\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}\frac{dlog\Omega_{nt}^s}{dlogs}}_{\text{PE effects}} + \underbrace{\frac{dlogY_{nt}}{dlogs}}_{\text{GE effects}}$$

General equilibrium effects depend on the budget constraint. For now, we suppose that profits are rebated outside of the regions, and that taxes are not levied on the household. Therefore,

$$p_{nt} Y_{nt} = w_{nt}$$

In that case,

$$\frac{dlogY_{nt}}{dlogs} = -\psi \underbrace{\frac{dlog\Omega_{nt}}{dlog\Omega_{nt}^e}}_{>0} \underbrace{\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}}_{>0} \underbrace{\frac{dlog\Omega_{nt}^s}{dlogs}}_{<0} > 0$$

Therefore

$$\frac{dlogY_{nt}^s}{dlogs} = -\underbrace{\frac{dlog\Omega_{nt}^s}{dlogs}}_{<0} \left[\xi - \underbrace{\frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e}}_{<1} \left((\xi-\psi) - (1-\psi) \underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}}}_{<1} \right) \right]$$

Expenditure shares are weakly smaller than 1 and weakly positive. Suppose that $\sigma > \xi > 1 > \psi > 0$. Then,

$$\begin{aligned} \xi - \underbrace{\frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e}}_{\leq 1} \left((\xi-\psi) - (1-\psi) \underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}}}_{\leq 1} \right) \\ \geq \xi - (\xi-\psi) + (1-\psi) \underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}}}_{\leq 1} = \psi + (1-\psi) \underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}}}_{\geq 0} \geq \psi \end{aligned}$$

Therefore, $\frac{dlogY_{nt}^s}{dlogs} \geq 0$.

Fossil fuel production decreases with the subsidy in both regions. Recall that

$$Y_{nt}^d = \alpha_d^\xi \left(\frac{p_{nt}^e}{p_{nt}^d}\right)^\xi Y_{nt}^e = \alpha_d^\xi \left(\frac{p_{nt}^e}{p_{nt}^d}\right)^\xi \alpha^\psi \left(\frac{p_{nt}}{p_{nt}^e}\right)^\psi Y_{nt}$$
$$= \alpha_d^\xi \alpha^\psi (\Omega_{nt}^d)^{-\xi} (\Omega_{nt}^e)^{\xi-\psi} (\Omega_{nt})^\psi Y_{nt}$$

Therefore,

$$\frac{dlogY_{nt}^d}{dlogs} = \underbrace{(\xi-\psi)\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}\frac{dlog\Omega_{nt}^s}{dlogs} + \psi\frac{dlog\Omega_{nt}}{dlog\Omega_{nt}^e}\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}\frac{dlog\Omega_{nt}^s}{dlogs}}_{\text{PE effects}} + \underbrace{\frac{dlogY_{nt}}{dlogs}}_{\text{GE effects}}$$

General equilibrium effects depend on the budget constraint. For now, we suppose that profits are rebated outside of the regions, and that taxes are not levied on the household. Therefore,

$$p_{nt}Y_{nt} = w_{nt}$$

In that case,

$$\frac{dlogY_{nt}}{dlogs} = -\psi \underbrace{\frac{dlog\Omega_{nt}}{dlog\Omega_{nt}^e}}_{>0}\underbrace{\frac{dlog\Omega_{nt}^e}{dlog\Omega_{nt}^s}}_{>0}\underbrace{\frac{dlog\Omega_{nt}^s}{dlogs}}_{<0} > 0$$

Therefore

$$\frac{dlogY_{nt}^d}{dlogs} = \underbrace{\frac{dlog\Omega_{nt}^s}{dlogs}}_{<0}\underbrace{\frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e}}_{<1}\left((\xi-\psi) - (1-\psi)\underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt}Y_{nt}}}_{<1}\right)$$

Expenditure shares are weakly smaller than 1 and weakly positive. Suppose that $\sigma > \xi > 1 > \psi > 0$. Then,

$$(\xi-\psi) - (1-\psi)\underbrace{\frac{p_{nt}^e Y_{nt}^e}{p_{nt}Y_{nt}}}_{\leq 1} \geq (\xi-\psi) - (1-\psi) \geq \xi - 1 > 0$$

Therefore, $\frac{dlogY_{nt}^d}{dlogs} \leq 0$.

A.3.2 Dynamic effects

The firms' decision can be written as

$$(R_{nt}^s)^\kappa = \frac{(1-\kappa)\eta}{(\sigma-1)w_{nt}^\sigma}\left(\frac{(1+\lambda)Q_{nt}}{1-s_{nt}}\right)^{\sigma-1}\left(\frac{(\Omega_{rt}^s)^\sigma}{\tau_{rn}^{\sigma-1}}Y_{rt}^s + \frac{(\Omega_{ct}^s)^\sigma}{\tau_{cn}^{\sigma-1}}Y_{ct}^s\right)$$

For a given level of technology:

$$\frac{dlog((R^s_{nt})^\kappa)}{dlog(s)} = (\sigma-1)\frac{s_{nt}}{1-s_{nt}} + \frac{1}{\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt} + \frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}}$$
$$\times \left[\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt}\left(\left((\sigma-\xi)+\left((\xi-\psi)+\psi\frac{dlog\Omega_{rt}}{dlog\Omega^e_{rt}}\right)\frac{dlog\Omega^e_{rt}}{dlog\Omega^s_{rt}}\right)\frac{dlog\Omega^s_{rt}}{dlogs}+\frac{dlogY_{rt}}{dlogs}\right)+\right.$$
$$\left.\frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}\left(\left((\sigma-\xi)+\left((\xi-\psi)+\psi\frac{dlog\Omega_{ct}}{dlog\Omega^e_{ct}}\right)\frac{dlog\Omega^e_{ct}}{dlog\Omega^s_{ct}}\right)\frac{dlog\Omega^s_{ct}}{dlogs}+\frac{dlogY_{ct}}{dlogs}\right)\right]$$

Assuming that profits are not rebated to the household, and that the tax is not levied on the household, such that $p_{nt}Y_{nt} = w_{nt}$:

$$\frac{dlog((R^s_{nt})^\kappa)}{dlog(s)} = (\sigma-1)\frac{s_{nt}}{1-s_{nt}} + \frac{1}{\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt} + \frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}}$$
$$\times \left[\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt}\left((\sigma-\xi)+\left((\xi-\psi)-(1-\psi)\frac{dlog\Omega_{rt}}{dlog\Omega^e_{rt}}\right)\frac{dlog\Omega^e_{rt}}{dlog\Omega^s_{rt}}\right)\frac{dlog\Omega^s_{rt}}{dlogs}+\right.$$
$$\left.\frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}\left((\sigma-\xi)+\left((\xi-\psi)-(1-\psi)\frac{dlog\Omega_{ct}}{dlog\Omega^e_{ct}}\right)\frac{dlog\Omega^e_{ct}}{dlog\Omega^s_{ct}}\right)\frac{dlog\Omega^s_{ct}}{dlogs}\right]$$

Which we can rewrite in terms of expenditure shares:

$$\frac{dlog((R^s_{nt})^\kappa)}{dlog(s)} = \underbrace{(\sigma-1)\frac{s_{nt}}{1-s_{nt}}}_{=0 \text{ in the RoW}}$$
$$-\frac{\frac{s_{ct}}{1-s_{ct}}}{\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt} + \frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}}$$

$$\times \left[\frac{(\Omega^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt}\left((\sigma-\xi)+\left((\xi-\psi)-(1-\psi)\underbrace{\frac{p^e_{rt}Y^e_{rt}}{p_{rt}Y_{rt}}}_{\leq 1}\right)\underbrace{\frac{p^s_{rt}Y^s_{rt}}{p^e_{rt}Y^e_{rt}}}_{\leq 1}\right)\underbrace{\frac{\int_c p^c_{it}x^c_{it}di}{p^s_{rt}Y^s_{rt}}}_{\leq 1}\right. \tag{36}$$
$$\left.+\frac{(\Omega^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}\left((\sigma-\xi)+\left((\xi-\psi)-(1-\psi)\underbrace{\frac{p^e_{ct}Y^e_{ct}}{p_{ct}Y_{ct}}}_{\leq 1}\right)\underbrace{\frac{p^s_{ct}Y^s_{ct}}{p^e_{ct}Y^e_{ct}}}_{\leq 1}\right)\underbrace{\frac{\int_c p^c_{it}x^c_{it}di}{p^s_{ct}Y^s_{ct}}}_{\leq 1}\right]$$

Expenditures shares are weakly positive and weakly smaller than 1. Therefore, we can identify the upper and lower bounds of the terms in the second to fourth line.

The lower bound is characterized by the following limits for expenditure shares in both

regions:

$$\frac{\int_c p_{it}^c x_{it}^c di}{p_{nt}^s Y_{nt}^s} \to 1 \quad \frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e} \to 1 \quad \frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}} \to 0$$

The upper bound is simply characterized by null Chinese solar intermediates expenditure shares in both regions:

$$\frac{\int_c p_{it}^c x_{it}^c di}{p_{nt}^s Y_{nt}^s} \to 0$$

Therefore,

$$\sigma - \psi \geq \left((\sigma - \xi) + \left((\xi - \psi) - (1 - \psi) \frac{p_{nt}^e Y_{nt}^e}{p_{nt} Y_{nt}} \right) \frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e} \right) \frac{\int_c p_{it}^c x_{it}^c di}{p_{nt}^s Y_{nt}^s} \geq 0 \; \forall n$$

Which implies that

$$\underbrace{(\sigma - 1) \frac{s_{nt}}{1 - s_{nt}}}_{=0 \text{ in the RoW}} \geq \frac{dlog((R_{nt}^s)^\kappa)}{dlog(s)} \geq \underbrace{(\sigma - 1) \frac{s_{nt}}{1 - s_{nt}}}_{=0 \text{ in the RoW}} - (\sigma - \psi) \frac{s_{ct}}{1 - s_{ct}}$$

It immediately follows that $\frac{dlog((R^s rt)^\kappa)}{dlog(s_{ct})} < 0$ (at given technologies). Intuitively, following a change in marginal cost that affects the price, expected profits are impacted positively by the price effect, and negatively by the market size effect. The price effect is however mitigated by the initial change in marginal costs (the first term in equation (36)), as prices negatively comove with the marginal costs. However, in the RoW, the firms' marginal cost is left unchanged. Therefore, the price effect is larger than usual, hence it always dominates the market size effect. In other words, the relative price that the RoW firms charge *increase*, as the price of their competitors from China decreases, while their own marginal cost is left unchanged. Therefore, they lose demand, and the more substitutes their inputs are, the more affected they are by a change in their relative price. The complementarity of the energy and production inputs attenuates the loss, because it decreases the importance of the relative price for the demand of all inputs, but not enough to change the sign.

The case of China is ambiguous, as the inequality becomes

$$(\sigma - 1) \frac{s_{ct}}{1 - s_{ct}} \geq \frac{dlog((R_{ct}^s)^\kappa)}{dlog(s_{ct})} \geq -(1 - \psi) \frac{s_{ct}}{1 - s_{ct}}$$

First, notice that if $\psi > 1$, that is, if the energy composite and the production inputs were substitutes, the innovation effort would unambiguously increase with the subsidy ($\frac{dlog((R_{ct}^s)^\kappa)}{dlog(s)} \geq 0$). This is because the market size effect always dominates the price effect in that case, as explained by Acemoglu et al., 2012. Since the subsidy decreases the price, the market size effect is positive, hence the effect on the innovation effort is positive.
However, in our context, it seems reasonable to assume that $\psi < 1$, that is, the energy

composite and the production inputs are weak complements. In this case, in the limits where Chinese solar intermediates constitute the entire expenditures of solar production ($\frac{\int_c p^c_{it} x^c_{it} di}{p^s_{nt} Y^s_{nt}} \to 1$) in both regions, and solar energy constitutes the entire expenditures of energy production ($\frac{p^s_{nt} Y^s_{nt}}{p^e_{nt} Y^e_{nt}} \to 1$) in both regions, the subsidy would decrease the innovation effort ($\frac{dlog((R^s_{ct})^\kappa)}{dlog(s)} = -\frac{s}{1-s}(1-\psi)(1-\frac{p^e_{nt} Y^e_{nt}}{p_{nt} Y_{nt}})$). This is because the marginal cost of solar and of energy would move one-to-one with the marginal cost of the Chinese intermediate inputs, which means that the subsidy offers no comparative advantage to those inputs. However, as soon as expenditure shares decrease away from these limits, the effect on the innovation effort is likely to turn positive, and the more so, the larger ψ is.

As an illustration, suppose that $\frac{\int_c p^c_{it} x^c_{it} di}{p^s_{nt} Y^s_{nt}} \to 1$ and that $\frac{p^e_{nt} Y^e_{nt}}{p_{nt} Y_{nt}} \to 0$, but that $\frac{p^s_{nt} Y^s_{nt}}{p^e_{nt} Y^e_{nt}} < 1$, equal across regions. In that case,

$$\frac{dlog((R^s_{ct})^\kappa)}{dlog(s)} = \frac{s_{ct}}{1-s_{ct}} \left((\xi - 1) - \frac{p^s_{nt} Y^s_{nt}}{p^e_{nt} Y^e_{nt}} (\xi - \psi) \right)$$

which is likely to be positive if ψ is close to 1, or if $\frac{p^s_{nt} Y^s_{nt}}{p^e_{nt} Y^e_{nt}}$ isn't too large.

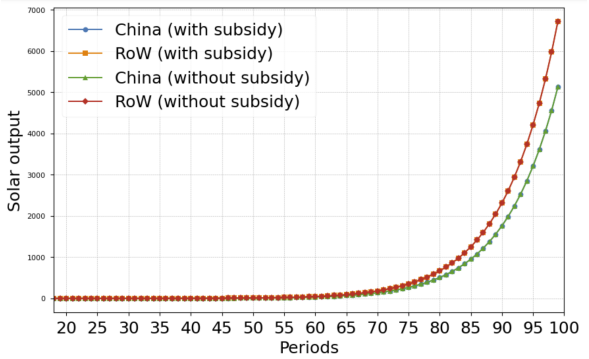
Similarly, suppose that $\frac{p^s_{nt} Y^s_{nt}}{p^e_{nt} Y^e_{nt}} \to 1$ and that $\frac{p^e_{nt} Y^e_{nt}}{p_{nt} Y_{nt}} \to 0$, but that $\frac{\int_c p^c_{it} x^c_{it} di}{p^s_{nt} Y^s_{nt}} < 1$, equal across regions. In that case,

$$\frac{dlog((R^s_{ct})^\kappa)}{dlog(s)} = \frac{s_{ct}}{1-s_{ct}} \left((\sigma - 1) - \frac{\int_c p^c_{it} x^c_{it} di}{p^s_{nt} Y^s_{nt}} (\sigma - \psi) \right)$$

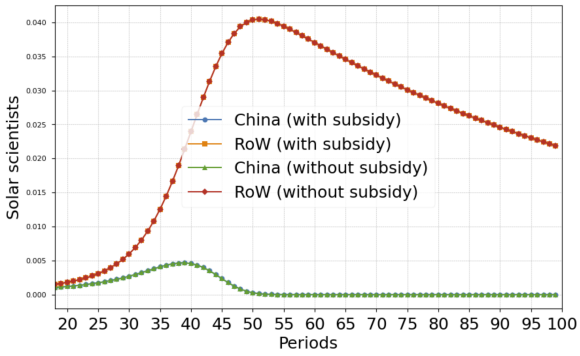
which is likely to be positive if ψ is close to 1, or if $\frac{\int_c p^c_{it} x^c_{it} di}{p^s_{nt} Y^s_{nt}}$ isn't too large.

A.4 Additional simulation results

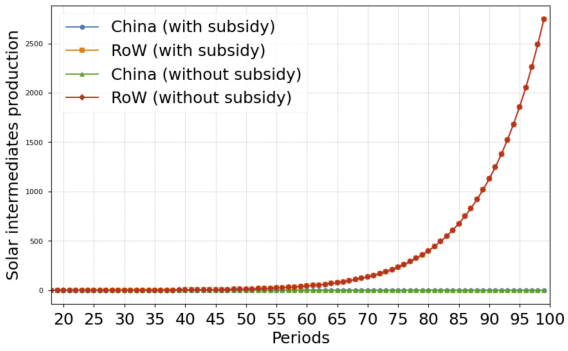
Figure 8. Subsidies Impact with Exogenous Innovation



(a) Solar Energy Output

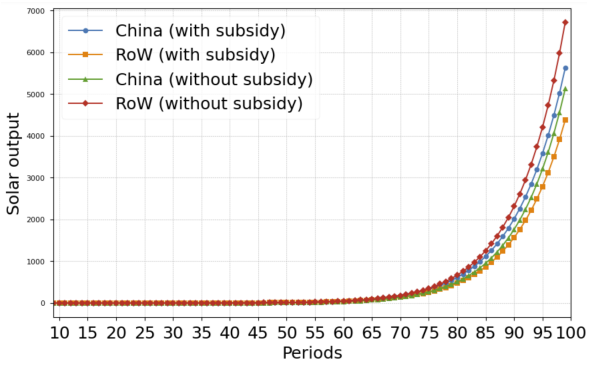


(b) Solar Scientists

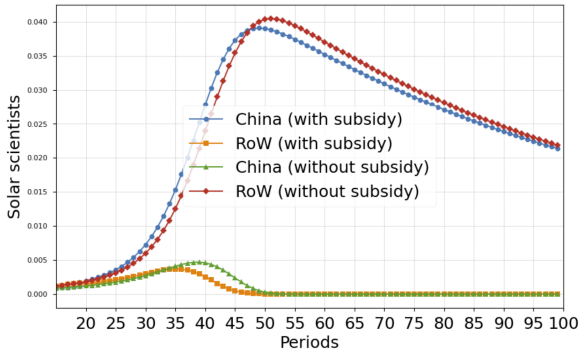


(c) Solar Intermediates Production

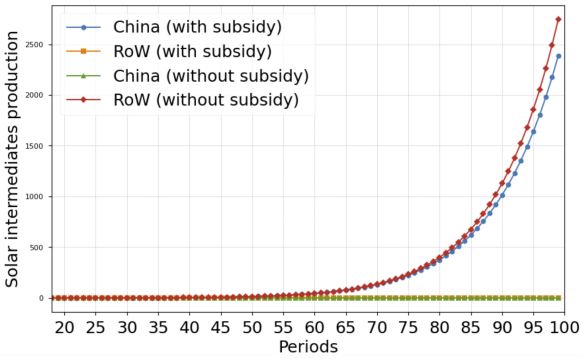
Figure 9. Subsidies Impact with Endogenous Innovation



(a) Solar Energy Output



(b) Solar Scientists



(c) Solar Intermediates Production