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

Claudia Gentile† David Hémous‡ Carole Marullaz§

March, 2025

Preliminary and Incomplete¶

Click here for most recent version

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 and non-solar energy technologies to evaluate the overall effect of Chinese industrial policies on solar panel costs, through their counteracting effects on domestic and foreign innovation, combined with their positive effects on production. Our preliminary calibration using US and Chinese data highlights the crucial role of the global innovation response. In the short run, industrial policies have an unambiguously positive impact on the development of the solar energy sector. However, in the long run, the impact on the solar sector is positive with exogenous technological changes, while it turns negative once the global innovation response is taken into account, delaying the clean transition.

*We thank seminar participants at the University of Zurich, the University of Geneva, the Swiss Workshop on Environmental, Resource and Energy Economics, the London School of Economics, the Bank of Italy, the University of Oslo, the Energy, Trade and Decarbonization Sloan-NBER conference, the Barcelona Summer Forum, the Imperial-LSE Environment Workshop, the Annual Congress of the Swiss Society of Economics and Statistics, and the PSE Green R&D and Industrial Policy in Open Economies Workshop for their helpful comments.

†Assistant Professor, University of Geneva. Email: claudia.gentile@unige.ch

‡Associate Professor, University of Zurich and CEPR. Email: david.hemous@econ.uzh.ch

§PhD Student, University of Zurich. Email: carole.marullaz@econ.uzh.ch

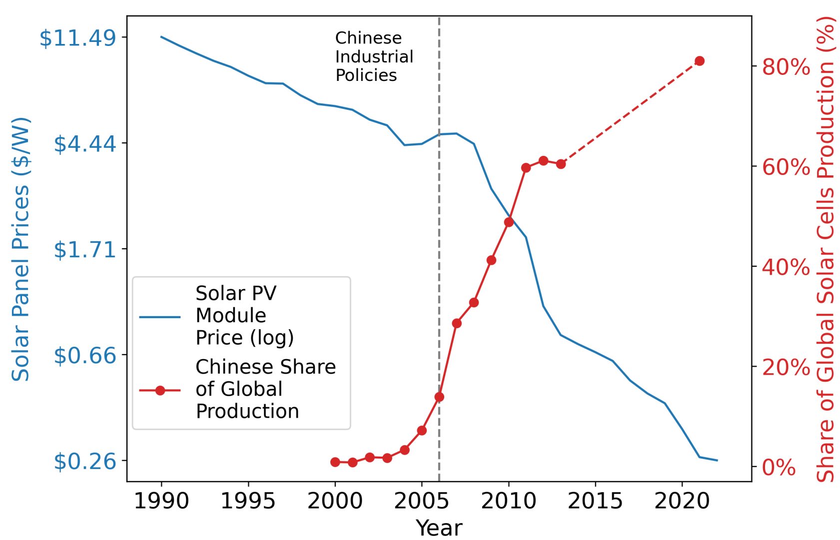
¶This is work in progress, please do not cite the quantitative results of this version.

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% (figure 1). The notable acceleration in cost declines starting in 2007 is concomitant with another important development in the solar PV sector, the outstanding rise of China as a dominant player in global solar manufacturing. In 2006, the Chinese government started introducing a growing number of industrial policies, supporting the solar sector through demand, production, and innovation subsidies (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) and 80% by 2020 (IEA, 2022).

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). Competition with low Chinese prices has eroded the profit margins of foreign producers, potentially damaging incentives to innovate in the rest of the world. Particularly concerning is the marked decline in innovation in solar technologies outside of China over the last decade (figure 2a). 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

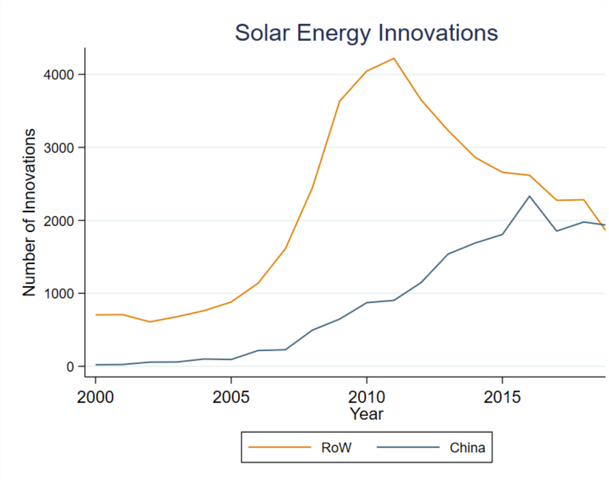


Notes: The blue line shows the solar panel prices in $/W, and the red line displays the Chinese share of global solar cells production. The data sources are, respectively, the International Renewable Energy Agency (2023) and the Earth Policy Institute (2014).

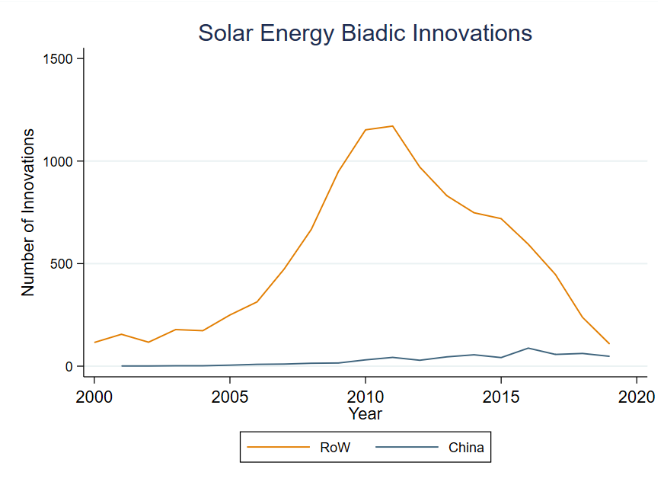
Our contribution is twofold. First, we empirically demonstrate that the increase in Chinese competition harmed innovation in solar technologies in the rest of the world. Using firm-level patent data, we find that a one-standard deviation increase in Chinese competition exposure decreases a firm's expected patent counts by at least 25% from 2013 onward, relative to expected patent counts in 2007. Given this novel empirical evidence, the overall effects of Chinese solar industrial policies on the clean energy transition are ambiguous. On one hand, we expect the policies to have a positive effect on short run emissions reduction, through the direct effects via lower Chinese solar panel prices, and increased innovation in China as documented by Banares-Sanchez et al. (2023). On the other hand, given the negative impact of the policies on incentives to innovate in the rest of the world, the medium and long-run effects of the policies might be negative if global solar technological change slows down.

The second contribution of our paper is thus to develop an open economy growth model with trade and innovation in solar technologies 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. Our preliminary calibration to two regions, China and the US, highlights that considering the endogenous global innovation response is crucial to evaluating the overall effects of industrial policies. In the short run, we find an unambiguously positive impact of industrial policies on the development of solar energy. However, in the long run, the impact on the solar sector is positive with exogenous technological change, while it turns negative once we consider the global innovation response. If policies shift innovation away from the most innovative regions towards the least innovative regions, they can have long-term negative effects on solar technological levels, solar energy deployment, and emissions reduction.

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 uses firm-level patent data on the universe of solar patenting firms from Orbis IP and PATSTAT to 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. We use firms' patent shares as a proxy for market shares, building on the strategy developed by Aghion et al. (2016). A patent grants its owner the right to be the only one to commercially exploit its innovation for a limited period of time. Given patenting in an additional country is costly, firms patent in countries where they expect to sell in the future. 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 2013 onward. An increase in the Chinese exposure measure by 1 standard deviation decreases the expected patent count in 2013 by 25%, relative to the expected patent count in 2007. The magnitude of the effect is increasing over time. 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.

Building on these observations, we develop an open economy growth model with trade and innovation in solar energy technologies, to evaluate the overall effect of Chinese industrial policies on solar energy adoption through their counteracting effects on solar panel prices and domestic and foreign innovation. The economy is composed of two regions: China and the rest of the world (RoW). Every region produces a final good using a production input and an energy input. The energy input is produced using solar and non-solar energy. Solar energy is produced using a continuum of intermediate inputs. Importantly, a fixed fraction of these intermediates is produced in China, while the remainder is produced in the RoW. The two regions trade in the production input and in solar intermediate inputs. Every intermediate input has its own quality level and is produced by a monopolist who sets the price and decides how many researchers to hire to improve its technology. We model incentives to innovate with a model of directed technical change à la Acemoglu et al. (2012). In each region, there is a mass one of scientists who decide to direct their innovation towards improving solar or non-solar technologies. A crucial factor affecting the technological race between China and the RoW is knowledge spillovers. We allow for knowledge spillovers between solar and non-solar technologies, and between our two regions. Finally, non-solar energy use generates CO2 emissions which accumulate in the atmosphere following a climate cycle à la Golosov et al. (2014).

The Chinese industrial policies are introduced in the model as a combination of subsidies to production costs of Chinese solar intermediates producers and subsidies to innovation. The former directly decreases the optimal solar intermediate price charged by the Chinese producers, while the latter indirectly reduces prices of Chinese solar intermediates by incentivizing solar innovation. Analytical results show that the Chinese industrial policies reduce the cost of production of solar PV, increase solar production and innovation in China, and decrease innovation in the RoW. The overall effect on emissions and global welfare is thus ambiguous.

Therefore, we calibrate our model to match pre-subsidy (2002-2006) key empirical moments for the US and China.[1] In particular, we target aggregate macroeconomic variables such as total employment and GDP, as well as electricity sector variables such as levelized costs, and output in solar and non-solar electricity. We calibrate innovation productivity using data on non solar energy cost declines from Lazard (2020), and data on costs decline for solar systems with panels manufactured in China or in the US from the Berkeley Tracking the Sun data. We calibrate cross-country knowledge spillovers using patent citation data from Liu and Ma (2021). We calibrate Chinese solar industrial policies by using subsidies data from 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.

We use the calibrated model to carry out a quantitative analysis of the impact of the Chinese solar industrial policies on solar energy adoption and innovation, emissions reduction, and welfare. The quantitative analysis performs three exercises. First, we study how the economy evolves in the absence of the Chinese solar industrial policies. This exercise is important as it allows us to evaluate how incentives to innovate and solar technologies evolve in the absence of subsidies. In what follows, we define exogenous technological progress as the technological evolution we observe in the absence of subsidies. Secondly, we evaluate the impact of the Chinese solar

[1] We are currently working on extending our calibration to include more countries as the RoW.

industrial policies with exogenous technological progress. Then we allow innovation to respond to the subsidies, and evaluate the impact of the subsidies with endogenous innovation. Finally, we evaluate the impact of US trade policies.

Since we are still refining our calibration, the results of the quantitative analysis should be regarded as preliminary. With exogenous technological progress, the Chinese solar industrial policies unambiguously increase solar energy output both in China and in the US. Solar intermediates production shifts towards China. The calibrated solar technological level and solar innovative productivity are initially higher in the US than in China. The technological gap shrinks over time thanks to an increase in solar innovation in China, and to knowledge spillovers, but the US technological level remains always more advanced. The economy eventually transitions away from non-solar energy towards a long-run equilibrium with solar energy only. The policies accelerate the transition to solar energy, particularly in China.

With endogenous innovation, the policy-driven short-run increase in solar energy adoption is amplified. 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. After the introduction of the subsidies, the R&D resources devoted to the solar sector decrease in the US and increase in China. Thanks to faster technological progress, the Chinese technology catches up with and surpasses US technology by 2020. Technological progress slows down in the US, and the US solar technological level is substantially lower than in the absence of the Chinese solar industrial policies. Solar intermediates production shift towards China, more so than with exogenous technological progress. The calibrated innovative productivity is higher in the US than in China. In turn, even though the Chinese solar technology becomes temporarily more advanced, once the two regions start to transition to solar energy and devote most of their R&D resource to that sector, technological progress is faster in the US than in China.[2] The US become again the solar technological frontier in 2050. Given that technological progress in the US has been slowed down by the Chinese solar industrial policies, the solar technological levels in the long run are lower than what we would see in the absence of policies. In turn, the policies delay the solar transition in the US. They accelerate the transition in China in the medium run, as the transition away from non-solar starts earlier than in the absence of policies. However, the policies also delay the transition in China in the long run, as the solar technology ends up being comparatively less advanced in the long run. Overall, the long-run carbon concentration in the atmosphere is larger with the Chinese industrial policies than in the absence of policies. All in all, the negative effects of the policies on RoW innovation dominate the positive effects. This is explained by the initial research productivity gap estimated between the US and China:

[2] In the short run, even though innovative productivity is higher in the US than in China, China devotes more R&D resources to the solar sector. Therefore, it achieves faster technological progress than the US.

the policies shift innovation away from the most innovative region towards the least innovative region. However, there is no reason to believe that research productivity has stayed constant over time, especially considering the outstanding development of the sector. Therefore, we are currently working on calibrating the evolution of these parameters as well.

Our preliminary results highlight that considering the impact of Chinese industrial policies on innovation incentives is key to evaluating the long-run impact of the policies. With exogenous technological progress the policies have an unambiguously positive impact on the transition to solar energy and emission reductions both in the short run and in the long run. With endogenous technological change, the policies have a positive impact in the short run, while the long-run impact can be negative if China does not catch up sufficiently fast with US research productivity.

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, the incumbents enjoy high profits and do not have incentives to innovate. 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, as the rewards to innovation diminish.[3] The solar PV sector, with a high degree of trade openness, homogeneous products, and a high entry, is a highly competitive sector. 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 in manufacturing and other industrial sectors using firm-level data (Autor et al., 2020; Bloom et al., 2016; Campbell & Mau, 2021) and find mixed results. Our paper contributes to this literature by shedding more light on the empirical relationship between competition and innovation in the solar PV sector. Studying non-Chinese firms patenting in solar photovoltaic technologies, we find that exposure to Chinese competition negatively affects firms' patenting activity.

Secondly, the paper directly relates to the literature studying the impact of firm-level subsidies by the Chinese government. Boeing (2016) finds that Chinese government subsidies are typically directed toward firms recipients of other government grants, with high-quality patents, and with a minority state ownership. Banares-Sanchez et al. (2023) study the impact of Chinese subsidies to the solar PV sector on local outcomes. The authors find that production and innovation subsidies both have a strong positive impact on firms' innovation and production in the regions where the policies are implemented, as well as on the number of firms. This paper contributes to this literature by studying the impact of Chinese solar subsidies on solar energy adoption, solar innovation, and emissions reduction in China as well as in the rest of the world.

[3] When the level of competition is high, a further increase in competition increases innovation, as it decreases the incumbents' profits pushing them to innovate to escape the competition. When competition is high, the economy is composed of incumbents who enjoy moderately low profits and laggards. A further increase in competition is expected to have a negative impact on innovation, as it decreases incumbents profits as well as the reward for laggards in case they are successful at innovating.

Juhász et al. (2022) uses a text based approach to measure the changing importance of industrial policies over time, and the key features of such policies. The authors find an increasing trend in the use of industrial policy. The number of implemented industrial policies doubled through the 2010s, which highlights the importance of understanding the overall implications of such policies. The most frequent measure of industrial policies is composed of subsidies and export promotion measures, targeted to individual firms, which are key characteristics of the Chinese industrial policies we study in this paper. Lane (2020) reviews the empirical evidence on the effects of industrial policy. The paper highlights that empirical studies typically focus on evaluating the impact of industrial policies on investment, employment, and productivity of the treated industry, but lack the instruments to evaluate the overall welfare effects of such policies, which we aim to evaluate in this project.

Finally, our paper is part of a growing literature studying the impact of industrial and trade policies in green sectors (Allcott et al., 2024; Barwick et al., 2025; Bollinger et al., 2024; Houde & Wang, 2023). 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. The novelty of our paper is analyzing the impact of industrial and trade policy, taking into account its effects on domestic as well as foreign firms' incentives to innovate, which is particularly important when evaluating the long-term impact of policies.

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 and 5 describe, respectively, the decentralized model equilibrium and analytical results on the key mechanisms through which a subsidy affects the economy. Section 6 discusses the model simulations to evaluate the impact of the Chinese subsidies on solar innovation, emissions, and output. Finally, Section 7 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.

2.1 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, providing evidence that patent shares in the period 1998–2008 serve as a good proxy for expected market shares in 2008. [4]

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

[4]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.

policies to ensure that this measure is not affected by the policies.[5] Chinese subsidy policies are introduced at the prefecture-level city (admin2) level. The first policies appear in 2007, when 3 cities implemented subsidies.[6] The number of cities adopting policies increases steadily until 2015, after which it stabilizes at around 40 (Banares-Sanchez et al., 2023). For the construction of firm-level weights, we consider the years 2000-2009 as pre-policy period. Given the large growth of the solar sector between 2005 and 2009, including more years in the construction of firm-level weights, allows us to have a larger sample size. 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 market (country) n for firm i:[7]

$$\omega_n^i = \frac{\#Patents_{n,i,2000-2009} * GDP_n^{0.35}}{\sum_m \#Patents_{m,i,2000-2009} * GDP_m^{0.35}}. \tag{1}$$

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 that firm i has applied for in all countries. Similarly, we build the measure of the importance of market (country) n for China as a whole, which is given by the number of patents Chinese firms have applied for patent protection in country n, divided by the total number of patents by Chinese firms.

$$\omega_n^{China} = \frac{\#Patents_{n,China,2000-2009}}{\#Patents_{China,2000-2009}} \tag{2}$$

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.

$$\textbf{Chinese\_exposure}_{\mathbf{i}} = \sum_n \omega_n^i \cdot \omega_n^{China} \tag{3}$$

The Chinese exposure measure is higher for firms that have high market shares in countries 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 foreign firm innovation. Sales to China could be directly affected by other channels than the competition channel we are interested in, so we exclude n = China from our measures ω_n^i and ω_n^{China}. In addition, Chinese firms patent disproportionally in China, so including China

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

[6] The number of cities implementing subsidy policies by 2009 is 6, by 2011 is 11, by 2015 is 36, and by 2019 is 40.

[7] 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).

in our measure would make the Chinese vector close to a China dummy. A China dummy would capture the impact of having a relatively high market share in China on foreign firms's patenting activity. This is not what we are interested in, especially given that for most innovative foreign firms, China is not a particularly important export market[8]. By excluding n = China, we 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.

$$E(Solar\_Patents_{it}) = \exp\left(\beta_0 + \beta_{1,t} \cdot \delta_t \cdot Chinese\_exposure_i + \alpha_i + \gamma_t\right) \tag{4}$$

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. α_i denotes a firm fixed effect and γ_t is a year fixed effect that captures trends affecting all solar innovators equally.

2.2 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.[9] As our measure of Chinese exposure is built using patent data in the years 2000-2009, our dataset is restricted to firms with at least one patent in the $Y02E10/5$ CPC class between 2000 and 2009.

Table 1 provides summary statistics on total solar patent counts at the firm level in our period of analysis. On average a firm applies for patent protection for 8.63 patents between 2000 and 2019. Table 2 provides summary statistics on the firms' country weights, ω_n^i. The left column of panel A reports the average weights for the first, second, and third largest country weights for a firm. On average, the weight for the largest country n for a firm i is 0.26. This means that, on average, 26% 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

[8]Foreign firms have applied for protection in China for only 6% of their patents, which suggests the most relevant markets for foreign innovative firms is outside of China.

[9]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.

respectively 0.18 and 0.16. The right column of panel A reports the three countries with the largest average weight across all firms, with their respective average weights. Panel B instead reports the value of the Herfindahl–Hirschman Index (HHI) of the firm-level country weights. The mean HHI is 0.66. At least half of the firms have an HHI of 1, meaning they patent in only one country n, which is associated with ω_n^i=1. At least one quarter of firms have an HHI smaller than or equal to 0.25, meaning their patenting activity is not concentrated in one country but in multiple countries. 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, the US, Japan, 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 Switzerland, 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 firm-level variables

	Patents Count	Chinese Exposure
mean	8.63	0.36
std	44.74	0.20
25%	1.00	0.20
50%	2.00	0.34
75%	4.00	0.49
count	5774.00	5774.00

Notes: This table reports summary statistics for the total number of solar patents (patents count) applied for by firms in our sample in the whole period of analysis (2000-2019) and the firm-level Chinese exposure measure. Our sample is composed of firms with at least one patent in the weights construction period 2000-2009. Solar patents are defined with the Y02E10/5 CPC code.

2.3 Main Results

Column (1) in table 3 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. In the interest of space, this table only reports the coefficients of the interaction term after 2008. The earlier coefficients can be found in the Appendix table 5. We find a statistically significant negative impact of being exposed to Chinese competition on solar patents in 2009, 2011, and from 2013 onwards at the 5% significance level. Figure 4 reports the transformed coefficients (β_{1t}^T)[10] which are easier to interpret. An increase in the Chinese exposure measure

[10] All coefficient of the Poisson regression are transformed using $\beta_{1t}^T = exp(\Delta Chinese\_exposure_i * \beta_{1t}) - 1$. The transformed coefficient displays the percentage change in patents count for a change $\Delta Chinese\_exposure_i$ in the Chinese exposure measure.

Table 2: Summary statistics of firms' country weights

Panel A: Average weights of the three largest markets

Country	Average weight	Country	Average weight
First largest	0.26	United States	0.24
Second largest	0.18	South Korea	0.18
Third largest	0.16	Japan	0.18

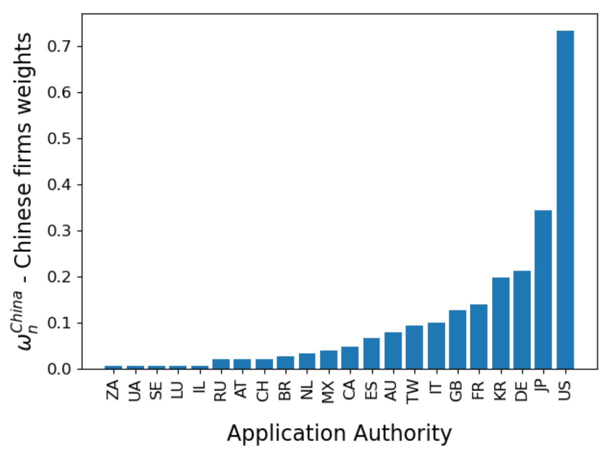
Notes: This panel reports statistics on the firms' country weights, ω_n^i, as defined in equation (1). It reports the average weight of the firms' three largest markets (the average is computed among firms patenting in at least three countries), and the average weight of the three countries with the largest average weights across all firms (United States, South Korea, and Japan).

Panel B: HHI

	HHI
mean	0.66
std	0.38
25%	0.25
50%	1.00
75%	1.00
count	5774.00

Notes: This panel reports statistics on the firms' country weights, ω_n^i, as defined in equation (1). Panel B reports summary statistics on the Herfindahl–Hirschman Index (HHI) of the firm-level country weights.

Figure 3. Chinese weights

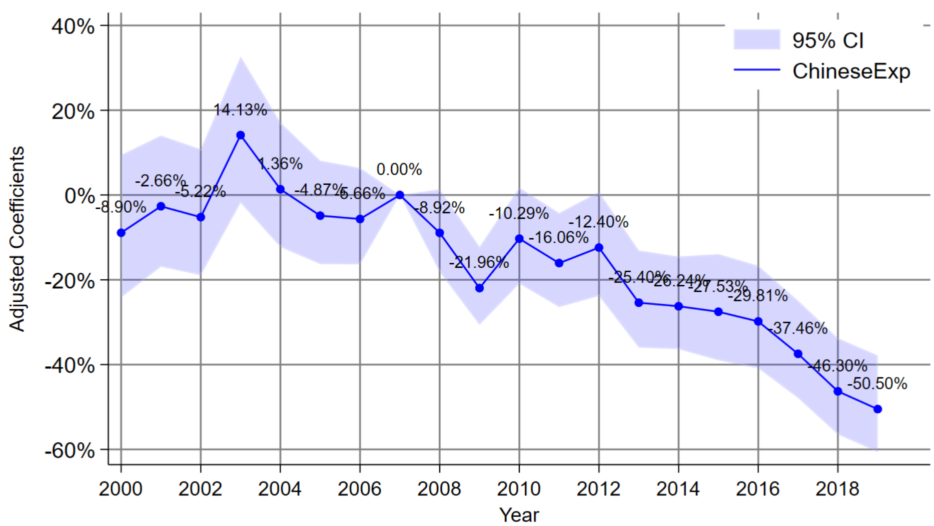


Notes: This figure reports the importance of a country n for China, that is, ω_n^{China} as defined in equation (2), for the most important countries (excluding China). This importance is measured as the number of Chinese patents applied for in a country, divided by the total number of Chinese patents.

by 1 standard deviation decreases the expected patent count in 2013 by 25%, relative to the expected patent count in 2007. 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 46% and 50%, respectively, relative to patenting activity in 2007.

One might rightly wonder why the negative effect of Chinese competition is continuously significant only from 2013 onward, when the first policies that increased Chinese competitiveness were introduced in 2007. First, Chinese subsidy policies were initially introduced in 2007, but the number of implemented policies has steadily increased up to 2015 (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, especially for the early years of the decline. Other factors such as the rise of shale gas, as highlighted by Acemoglu et al. (2023), played a significant role.

Figure 4. Impact of Chinese Exposure on Solar Innovation



Notes: This figure shows the main coefficient of interest, β_{1t}, for the regression in equation 4 with a 95% confidence interval. The coefficient is transformed using $\beta_{1t}^{T} = exp(\Delta Chinese\_exposure_i * \beta_{1t}) - 1$. The transformed coefficient displays the percentage change in patents count for a 1 standard deviation change in the Chinese exposure measure. The number of firms in the regression is 5774. The standard deviation of the Chinese exposure variable is 0.2.

2.4 Robustness exercises

We perform a series of robustness exercises. First, we investigate whether the results are robust to focusing on high quality patents. We use two measures of high quality patents. We first restrict the attention to biadic patents, which are patents for which the owner has applied for patent protection in at least two application authorities, which is considered a sign of a high-quality innovation (Aghion et al., 2016). Secondly, we restrict the attention to patents with at least one non-self citation. In both cases the coefficients show the same sign. As columns (3)-(4) of Table 3 show, results are still negative and statistically significant starting from 2014 in both specifications. The results in the biadic-only specification are significant only at the 10% level,

Table 3: Impact of Chinese Exposure on Solar Patents Counts

	(1) Baseline	(2) At Least 1 Biadic	(3) Biadic	(4) Non-Self Citation	(5) Country FEs
chinese_exp_2008	-0.4740	-0.1076	0.2836	-0.3902	-0.0077
	(0.2764)	(0.3394)	(0.4096)	(0.2771)	(0.2828)
chinese_exp_2009	-1.2577***	-0.9758*	0.2196	-0.9820**	-0.3925
	(0.3045)	(0.4164)	(0.4262)	(0.3006)	(0.3231)
chinese_exp_2010	-0.5510	-0.9425*	0.9931*	-0.5958	0.0905
	(0.3258)	(0.4523)	(0.4460)	(0.3092)	(0.3689)
chinese_exp_2011	-0.8884**	-1.6586***	0.0208	-0.9862**	-0.1263
	(0.3409)	(0.4721)	(0.5077)	(0.3330)	(0.3896)
chinese_exp_2012	-0.6715	-1.5168**	0.4707	-0.6676	-0.2873
	(0.3610)	(0.4924)	(0.5557)	(0.3575)	(0.4202)
chinese_exp_2013	-1.4862***	-2.3526***	-0.4901	-1.3664***	-0.8254
	(0.3956)	(0.5516)	(0.6670)	(0.3970)	(0.5116)
chinese_exp_2014	-1.5437***	-2.5276***	-1.9711**	-1.5927***	-1.0358
	(0.3821)	(0.5233)	(0.6789)	(0.3944)	(0.5360)
chinese_exp_2015	-1.6336***	-2.6080***	-1.4874*	-1.5305***	-1.5315**
	(0.4451)	(0.6132)	(0.7194)	(0.4465)	(0.5355)
chinese_exp_2016	-1.7957***	-2.8037***	-1.5451*	-1.6843***	-1.4844*
	(0.4437)	(0.6144)	(0.6854)	(0.4748)	(0.6026)
chinese_exp_2017	-2.3809***	-3.6287***	-2.2346**	-2.5292***	-1.5606*
	(0.4727)	(0.6547)	(0.6942)	(0.5276)	(0.6339)
chinese_exp_2018	-3.1544***	-4.2903***	-2.0481*	-2.9734***	-2.3567**
	(0.5428)	(0.7666)	(0.8536)	(0.6154)	(0.7491)
chinese_exp_2019	-3.5673***	-4.8435***	-1.9865*	-3.3583***	-3.1489***
	(0.5898)	(0.8367)	(0.9250)	(0.7223)	(0.7500)
Observations	115480	61300	61300	109440	99054
Unique Firms	5774	3065	3065	5472	5100
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	No
Country-Year FEs	No	No	No	No	Yes

Standard errors clustered at the firm level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors in parentheses: * p<.1, ** p<.05, ***p<.01. Standard errors are clustered at the firm level. This table shows the coefficients estimated with a Poisson Regression of the main specification, which is given by equation 4. 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.

which is likely related to the smaller sample size. Given not all firms have biadic patents, the number of firms drops in this specification from 5774 to 3065. Column (5) of Table 3 reports an additional specification where we include country-year fixed effects, in order to test whether our results are driven by a specific country. One might be concerned the Chinese industrial policies happen at the same time as the introduction (or the phase out) of other renewable energy incentives in a specific country in our sample. If that is the case, firms from such country might change their innovation investments reacting to the domestic policies in a way that would be correlated with the increase in Chinese competition. In column (5), the impact of domestic policies is captured by country-year fixed effects. Results remain statistically significant at the 10 and 5% level from 2015.

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,[11] innovation in solar and non-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 L_n. The representative household is composed of production workers and scientists. Its utility is given by

$$U_0 = \sum_{t=0} \beta^t \frac{((1 - D(S_t))C_{nt})^{1-\vartheta}}{1 - \vartheta}$$

β is the rate of time preference. $(1-D(S_t))C_{nt}$ is consumption in region n, net of climate damage (see below). ϑ is the inverse elasticity of intertemporal substitution.

[11] For comparability across electricity sources, we will focus on energy used for electricity generation in our calibration.

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

$$Y_{nt} = \left((1-\alpha)^{\frac{1}{\psi}}(Y^p_{nrt} + Y^p_{nct})^{\frac{\psi-1}{\psi}} + \alpha^{\frac{1}{\psi}}(B^e_n Y^e_{nt})^{\frac{\psi-1}{\psi}}\right)^{\frac{\psi}{\psi-1}}$$

Production inputs from region c, Y^p_{nct}, or from region r, Y^p_{nrt}, are perfect substitutes in the final good production of region n. They are traded with no trade costs. Energy is purchased on the domestic market only. The production inputs are produced using labor and the final good as an input:[12]

$$Y^p_{nt} = A^p_{nt}(\frac{L^p_{nt}}{\nu})^{\nu}(\frac{Y^{input_p}_{nt}}{1-\nu})^{1-\nu}$$

where the technology A^p_{nt} 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 consumed output lost due to climate change.[13] 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):

$$S_t = \bar{S} + \sum_{s=0}^{t+T}(\phi_L + (1-\phi_L)\phi_0(1-\phi)^s)\iota^d_{t-s}Y^d_{t-s}$$

The economy starts at $t = -T$, which is the time of industrialization. $\bar{S}$ is carbon concentration in the pre-industrial time. Y^d_t is non-solar energy used in period t by both countries ($Y^d_t = Y^d_{ct} + Y^d_{rt}$). ι^d_t 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 $\xi > 1$.

$$Y^e_{nt} = \left(\alpha_d^{\frac{1}{\xi}}(Y^d_{nt})^{\frac{\xi-1}{\xi}} + \alpha_s^{\frac{1}{\xi}}(Y^s_{nt})^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}$$

[12]The production input is effectively produced by aggregating a continuum of mass 1 of domestic intermediate inputs that are produced by combining labor and the final good in a Cobb-Douglas manner ($y^i_{pt} = a^i_{pt}(\frac{l^{p,i}_{nt}}{\nu})^{\nu}(\frac{Y^{input_p,i}_{nt}}{1-\nu})^{1-\nu}$). These intermediate inputs are aggregated through a CES with elasticity σ, and their producers are monopolistically competitive. Therefore, they charge a markup $\frac{\sigma}{\sigma-1}$ over their marginal cost.

[13]To focus on the effect of emissions on welfare, and avoid feedback effects on productivity, we assume that emissions only affect the household consumption, and not the final good used as an input in production.

Non-solar energy is produced by aggregating labor and the final good as an intermediate input, according to:

$$Y_{nt}^{d} = A_{nt}^{d}\left(\frac{L_{nt}^{d}}{\nu}\right)^{\nu}\left(\frac{Y_{nt}^{input_d}}{1-\nu}\right)^{1-\nu}$$

The non-solar energy technology level A_{nt}^{d} evolves endogenously through innovation (see below). 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.[14]

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

$$Y_{nt}^{s} = \left[\int_{0}^{M_c} (x_{nct}^{i})^{\frac{\sigma-1}{\sigma}} di + \int_{M_c}^{1} (x_{nrt}^{i})^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}}$$

Intermediates, x_{nct}^{i}, x_{nrt}^{i} 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).[15] In what follows we use M_r to define the mass of solar intermediate inputs produced in the rest of the world (i.e. $M_r = 1 - M_c$). Solar intermediates are subject to iceberg trade costs. τ_{nc} are trade costs to ship goods from China to region n, and similarly τ_{nr} 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 y_{nct}^{i} units of the intermediate good in China to ship to region n, $x_{nct}^{i} = \frac{y_{nct}^{i}}{\tau_{nc}}$ units will arrive to region n to be used for solar energy production.

A firm produces the intermediate input y_{nt}^{i} by aggregating labor and the final good as an intermediate input, with a productivity level $q_{nt}^{s,i}$:

$$y_{nt}^{i} = q_{nt}^{s,i}\left(\frac{l_{it}^{s}}{\nu}\right)^{\nu}\left(\frac{Y_{it}^{input_s}}{1-\nu}\right)^{1-\nu}$$

y_{nt}^{i} is the quantity of intermediate good i produced for both regions c and r ($y_{nt}^{i} = y_{rnt}^{i} + y_{cnt}^{i}$, where n is the country where firm i is located). Finally, we introduce industrial policies through a production cost subsidy s_{nt}. In our main counterfactual analysis, only China subsidizes the solar industry, so that $s_{rt} = 0 \ \forall t$. Therefore, if the firm producing intermediate input y_{t}^{i} is located in China, it pays a per unit cost of production $\frac{(1-s_{ct})w_{ct}^{\nu}p_{ct}^{1-\nu}}{q_{ct}^{s,i}}$. If the firm is located in the RoW, it pays a per unit production cost equal to $\frac{w_{rt}^{\nu}p_{rt}^{1-\nu}}{q_{rt}^{s,i}}$.[16]

[14] Implicitly, we assume that non-solar energy inputs are produced by combining a continuum of domestic intermediates that are imperfect substitutes with energy σ, similarly to the production input.

[15] We are currently working on an extension that endogenizes M_c through entry and exit, and that includes multi-national firms.

[16] We also allow for time-varying tax credits and demand subsidies in both regions, that we model through a

3.1.2 Innovation

Every period and in each region, solar and non-solar intermediate input producers hire scientists to improve their current machines. Successful scientists improve the quality of their intermediate input technology by a factor λ_n^f, for $f = s, d$. If they are not successful, the current (non-improved) technology is used to produce. Producer i decides how many scientists (R_{it}^f for $f = s, d$)[17] to hire. The solar technology level in region n, Q_{nt}^s, is defined as the aggregate quality level of intermediate inputs produced in the given region.

$$Q_{ct}^s = \Big(\int_0^{M_c} (q_{nt}^{s,i})^{\sigma-1} di \Big)^{\frac{1}{\sigma-1}}$$
$$Q_{rt}^s = \Big(\int_{M_c}^{1} (q_{nt}^{s,i})^{\sigma-1} di \Big)^{\frac{1}{\sigma-1}}$$

The non-solar technology is defined similarly:

$$A_{nt}^d = \Big(\int_0^{1} (a_{nt}^{d,i})^{\sigma-1} di \Big)^{\frac{1}{\sigma-1}}$$

We define the following aggregates that will capture knowledge spillovers. First, because we are modeling an open economy model, we consider cross-regional knowledge spillovers. In particular,

$$(Q_{nt}^{s,spill})^{(\sigma-1)} = \left(\frac{(Q_{nt}^s)^{\sigma-1}}{M_n} \right)^{\zeta} (Q_{world,t}^s)^{(\sigma-1)(1-\zeta)}$$
$$(A_{nt}^{d,spill})^{(\sigma-1)} = (A_{nt}^d)^{(\sigma-1)\zeta} (A_{world,t}^d)^{(\sigma-1)(1-\zeta)}$$

Where $Q_{world,t}^s = \big((Q_{ct}^s)^{\sigma-1} + (Q_{rt}^s)^{\sigma-1}\big)^{\frac{1}{\sigma-1}}$ and $A_{world,t}^d = \big((A_{ct}^d)^{\sigma-1} + (A_{rt}^d)^{\sigma-1}\big)^{\frac{1}{\sigma-1}}$. 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 larger is ζ, the more important are local spillovers relative to global spillovers. Secondly, we allow for cross-technology knowledge spillovers, parametrized by $1 > \gamma > 0$. In particular, we define

$$A_{nt}^{e,spill} = \Big((A_{nt}^{d,spill})^{(\sigma-1)} + (Q_{nt}^{s,spill})^{(\sigma-1)} \Big)^{\frac{1}{\sigma-1}}$$

subsidy $s_{nt}^{p_s}$ on the aggregate solar price p_{nt}^s.

[17] R_{it}^f should be interpreted in units of human capital employed. The total mass of scientists has N_n units of human capital at disposal.

This yields the following total knowledge spillover term for each sector respectively:

$$\left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s}_{it-1}}\right)^{(\sigma-1)}$$
$$\left(\frac{(A^{d,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{a^{d}_{it-1}}\right)^{(\sigma-1)}$$

A high value of γ lowers the spillovers across solar and non-solar technologies.

Taken together, this means that R^{f}_{it} scientists in region n have a probability of success of $\eta^{s}_{n}(R^{s,i}_{nt})^{1-\kappa_n}\left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}}\right)^{(\sigma-1)}$ if they work on a solar ($f = s$) machine $i \in M_n$, while they will succeed with probability $\eta^{d}_{n}(R^{d,i}_{nt})^{1-\kappa_n}\left(\frac{(A^{d,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{a^{d,i}_{nt-1}}\right)^{(\sigma-1)}$ if they work on a non-solar machine ($f = d$). η^{f}_{nt}, for $f = s, d$ is research productivity. R^{f}_{it} is the amount of human capital of scientists directing their research to intermediate i, and $\kappa_n < 1$ is a stepping-on-the-toe externality, which parametrizes the elasticity of R&D with respect to its costs. The last term captures the knowledge spillovers. Finally, because Chinese solar industrial policies include subsidies to R&D (Banares-Sanchez et al., 2023), we include a research subsidy s^{RD}_{nt} that reduces the wages paid to scientists working on a solar intermediate input.

The law of motion of individual solar and non-solar intermediate input technology are the following:

$$q^{s,i}_{nt} = \begin{cases} (1+\lambda^{d}_{n})q^{s,i}_{nt-1} & \text{with prob. } \eta^{s}_{n}(R^{s,i}_{nt})^{1-\kappa_n}\left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}}\right)^{(\sigma-1)} \\ q^{s,i}_{nt-1} & \text{with prob. } 1-\eta^{s}_{n}(R^{s,i}_{nt})^{1-\kappa_n}\left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}}\right)^{(\sigma-1)} \end{cases}$$
$$a^{d,i}_{nt} = \begin{cases} (1+\lambda^{d}_{n})a^{d,i}_{nt-1} & \text{with prob. } \eta^{d}_{n}(R^{d,i}_{nt})^{1-\kappa_n}\left(\frac{(A^{d,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{a^{d,i}_{nt-1}}\right)^{(\sigma-1)} \\ a^{d,i}_{nt-1} & \text{with prob. } 1-\eta^{d}_{n}(R^{d,i}_{nt})^{1-\kappa_n}\left(\frac{(A^{d,spill}_{n,t-1})^{\gamma}(A^{e,spill}_{n,t-1})^{(1-\gamma)}}{a^{d,i}_{nt-1}}\right)^{(\sigma-1)} \end{cases} \tag{5}$$

3.2 Budget, Resource, and Labor Constraints

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

$$L^{p}_{nt} + L^{d}_{nt} + L^{s}_{nt} = L_n$$

The economy resource constraint requires that the national output equals the sum of household consumption and of the solar and non-solar sector demand for the final good.

$$C_{nt} + Y_{nt}^{input_s} + Y_{nt}^{input_d} + Y_{nt}^{input_p} = Y_{nt}$$

Where $Y_{nt}^{input_s} = \int_0^{M^n} Y_{nt}^{input_s,i} di$ and $Y_{nt}^{input_k} = \int_0^1 Y_{nt}^{input_k,i} di$ for $k = p, d$. The household receives labor income from workers and profits from the firms producing the solar and non-solar intermediates. It consumes and finances the subsidies through a lump-sum tax T_{nt}. Therefore, the following budget constraint must be satisfied in each region:

$$p_{nt}C_{nt} + T_{nt} = w_{nt}(L_{nt}^p + L_{nt}^d + L_{nt}^s) + \int_0^{M_n} \pi_{nt}^{s,i} di + \int_0^1 \pi_{nt}^{d,i} di + \int_0^1 \pi_{nt}^{p,i} di$$

Where $T_{nt} = s_{nt}\left(w_{nt}L_{ct}^s + p_{nt}Y_{nt}^{input_s}\right) + s_{nt}^{RD} w_{nt}^R R_{nt}^s + s_{nt}^{p_s} p_{nt}^s Y_{nt}^s$ is a lump-sum tax imposed on the representative household to finance the subsidies to solar intermediate inputs costs, solar prices and to the solar R&D sector. In our main counterfactual analysis, only China uses R&D and production subsidies. Therefore, $T_{rt} = s_{rt}^{p_s} p_{rt}^s Y_{rt}^s$.
Finally, the trade balance states that imports must equal exports for both regions.

$$p_{rct}^p Y_{rct}^p + \int_0^{M_c} p_{rct}^i x_{rct}^i di = p_{crt}^p Y_{crt}^p + \int_{M_c}^1 p_{crt}^i x_{crt}^i di$$

4 Decentralized Equilibrium

This section characterizes the decentralized equilibrium of our model. More details and additional proofs are provided in appendix B.1. In the next section, we discuss some analytical results on the key mechanisms through which a subsidy affects the economy.

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

As our model doesn't include savings, the household is hand-to-mouth and the budget constraint determines the demand for the final good.

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.

$$p_{nt}^p = p_{nt}(1-\alpha)^{\frac{1}{\psi}} \left(\frac{Y_{nt}}{Y_{nrt}^p + Y_{nct}^p}\right)^{\frac{1}{\psi}}$$

where p^p_{nt} is the price of the production input in 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.

$$p^e_{nt} = p_{nt}\alpha^{\frac{1}{\psi}}\left(\frac{(B^e_n)^{\psi-1}Y_{nt}}{Y^e_{nt}}\right)^{\frac{1}{\psi}}$$

where p^e_{nt} is the energy price in region n. The producers of the production input intermediates are monopolistically competitive. Therefore, they charge a markup $\frac{\sigma}{\sigma-1}$ over their marginal cost. This results in the following unit cost for the aggregate production input:

$$mc^p_{nt} = \frac{\sigma}{\sigma-1}\frac{w^{\nu}_{nt}p^{1-\nu}_{nt}}{A^p_{nt}}$$

The aggregate production inputs are perfectly substitutable across regions. Therefore, they are perfectly competitive and price at marginal cost ($p^p_{nt} = mc^p_{nt}$), and the production input prices are equalized across regions ($p^p_{ct} = p^p_{rt}$). We normalize it to 1, which pins down the wage and final good price Cobb-Douglas aggregate in both regions to the technology A^p_{nt}: $\frac{\sigma}{\sigma-1}w^{\nu}_{nt}p^{1-\nu}_{nt} = A^p_{nt}$.

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

$$p^d_{nt} = \frac{\sigma}{\sigma-1}\frac{w^{\nu}_{nt}p^{1-\nu}_{nt}}{A^d_{nt}} = \frac{A^p_{nt}}{A^d_{nt}}$$

The energy producer's optimal choices of non-solar and solar energy inputs are determined by the following expressions.

$$p^d_{nt} = p^e_{nt}\alpha_d^{\frac{1}{\xi}}\left(\frac{Y_{nt}}{Y^d_{nt}}\right)^{\frac{1}{\xi}} \quad \text{and} \quad (1-s^{p^s}_{nt})p^s_{nt} = p^e_{nt}\alpha_s^{\frac{1}{\xi}}\left(\frac{Y_{nt}}{Y^s_{nt}}\right)^{\frac{1}{\xi}}$$

The solar producer in n decides how many inputs to buy from firms in the two regions.

$$\max_{x^i_{nct},x^i_{nrt}} p^s_{nt}Y^s_{nt} - \int_0^{M^c} p^i_{nct}x^i_{nct}di - \int_{M^c}^1 p^i_{nrt}x^i_{nrt}di$$

p^i_{nct} (p^i_{nrt}) 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:

$$x^i_{nct} = (\frac{p^s_{nt}}{p^i_{nct}})^{\sigma}Y^s_{nt} \text{ for i} \in [0, M^c]$$
$$x^i_{nrt} = (\frac{p^s_{nt}}{p^i_{nrt}})^{\sigma}Y^s_{nt} \text{ for i} \in (M^c, 1]$$

Firm i located in region $z = c, r$ chooses its input demand from cost minimization. The Cobb-

Douglas aggregate yields the usual marginal cost $c_{zt} = (1 - s_{zt})w_{zt}^{\nu}p_{zt}^{1-\nu}$. The firm then takes into account the demand x_{nzt}^i from the solar producer in region n, and sets the price p_{nzt}^i that maximizes its profits.

$$\max_{p_{nzt}^i} \pi_{nt}^{i\in z} = p_{nzt}^i x_{nzt}^i - (1 - s_{zt})w_{zt}^{\nu}p_{zt}^{1-\nu}\frac{y_{nzt}^i}{q_{zt}^{s,i}} \quad \text{s.t. } x_{nzt}^i = (\frac{p_{nt}^s}{p_{nzt}^i})^{\sigma}Y_{nt}^s$$
$$\Rightarrow p_{nzt}^i = \frac{\sigma}{\sigma - 1}(1 - s_{zt})\frac{w_{zt}^{\nu}p_{zt}^{1-\nu}}{q_{zt}^{s,i}}\tau_{nz} = (1 - s_{zt})\frac{A_{zt}^p}{q_{zt}^{s,i}}\tau_{nz}$$

The firm sets a price at a constant markup over marginal costs, taking the trade costs into account, to maximize its profits. By reducing the marginal costs, subsidies have a direct impact on solar intermediate prices. $p_{nt}^{i\in z}$ is the effective price paid by the solar producer in n, i.e., the price paid per unit of intermediate input consumed in n. If firm i is located in region $z \neq n$, it takes into account that if it produces y_{zt}^i, only $x_{nzt}^i = \frac{y_{nzt}^i}{\tau_{nz}}$ will arrive in region n. In our baseline counterfactual, $s_{rt} = 0$. Therefore, 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 will be lower thanks to the positive subsidies.

4.2 Optimal Innovation Choice

We suppose that intermediate input producers are myopic. Therefore, they only consider the one-period profits when taking their innovation decision.[18] This means that a solar intermediate firm i located in region n decides how many researchers to hire to maximize:

$$\begin{aligned}\max_{R_{nt}^{s,i}} \quad & \eta_n^s(R_{nt}^{s,i})^{1-\kappa_n}\left(\frac{(Q_{n,t-1}^{s,spill})^{\gamma}(A_{n,t-1}^{e,spill})^{(1-\gamma)}}{q_{nt-1}^{s,i}}\right)^{(\sigma-1)}\pi_{nt}^i((1+\lambda_n^s)q_{nt-1}^{s,i}) \\ & + \left(1 - \eta_n^s(R_{nt}^{s,i})^{1-\kappa_n}\left(\frac{(Q_{n,t-1}^{s,spill})^{\gamma}(A_{n,t-1}^{e,spill})^{(1-\gamma)}}{q_{nt-1}^{s,i}}\right)^{(\sigma-1)}\right)\pi_{nt}^i(q_{nt-1}^{s,i}) \\ & - (1 - s_{nt}^{RD})w_{nt}^{R_s}R_{nt}^{s,i}\end{aligned}$$

And similarly for a non-solar intermediate firm. Scientists are paid their outside option, which is the expected marginal profits of working in the other sector. Therefore, the firm's scientists hiring decision is characterized by comparing the expected marginal profits in the two sectors. This gives the following optimal choice (the proof can be found appendix B.3):

$$\frac{R_{nt}^{s,i}}{R_{nt}^{d,i}} = \frac{R_{nt}^s}{R_{nt}^d} = \Big[\frac{\eta_n^s((1+\lambda_n^s)^{\sigma-1} - 1)}{(1 - s_{nt})^{\sigma-1}(1 - s_{nt}^{RD})\eta_n^d((1+\lambda_n^d)^{\sigma-1} - 1)}\Big(\frac{Q_{n,t-1}^{s,pill}}{A_{n,t-1}^{s,spill}}\Big)^{\gamma(\sigma-1)}\frac{(p_{ct}^s)^{\sigma}Y_{ct}^s(\tau_{cn})^{1-\sigma} + (p_{rt}^s)^{\sigma}Y_{rt}^s(\tau_{rn})^{1-\sigma}}{(p_{nt}^d)^{\sigma}Y_{nt}^d}\Big]^{\frac{1}{\kappa_n}} \tag{6}$$

[18]This generates the standard innovation distortion, because the firn doesn't fully internalize the returns from their innovation.

$R_{nt}^{s,i}$ does not depend on i, which means that the same number of researchers will be hired for any intermediate $i \in n$. Therefore, we define $R_{nt}^{s,i}$ as the mass of researchers hired for any solar intermediate i in region n, and $M_n R_{nt}^s$ is the total mass of scientists working in solar in a firm located in region n.

5 Effects of Solar PV Industrial Policies: Analytical Results

This section discusses how Chinese industrial policies, represented by a production and an R&D subsidies in our model,[19] 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. The model doesn't allow for a closed-form solution for all the analytical results. Therefore, we restrict our attention to illustrative cases and high-level discussions on the mechanisms at play. We next turn to a data-driven calibration in section 6 to evaluate the overall effect of the industrial and trade policies.

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, so that marginal costs are determined by $w_{nt}^{\nu} p_{nt}^{1-\nu} = \frac{\sigma-1}{\sigma} A_{nt}^p$. We start by analyzing the effect of the production subsidy in the next section. We split the total effects into *static* effects, which maintain the technologies level constant, and *dynamic* effects, which follow the changes in solar and non-solar technologies. Finally, we briefly discuss the effect of the research subsidy in section 5.2. All the proofs for this section can be found in appendix B.4.

5.1 Production subsidy

5.1.1 Static Effects

As a production subsidy, the direct effect of the policy is to reduce the effective marginal cost of solar in each region. Indeed, since solar intermediates are tradeable and imperfect substitutes, both regions benefit from the cost reduction. In contrast, since A_{nt}^p is exogenous and pins down the factor prices Cobb-Douglas aggregate given our choice of numeraire, the non-solar marginal

[19] We focus on industrial policies that only apply to the solar production in one region, to study the reallocation of production and innovation across regions. In our model, it means subsidies to intermediate input production (s_{nt}) and subsidies to R&D (s_{nt}^{RD}). In contrast, solar price subsidies ($s_{nt}^{p_s}$) benefit both the domestic and the foreign components and won't distort the regional allocation.

cost is not affected by the subsidy.

$$\text{China: } p^s_{ct} = \left((\frac{(1-s_{ct})A^p_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{\tau_{cr}A^p_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{RoW: } p^s_{rt} = \left((\frac{\tau_{rc}(1-s_{ct})A^p_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{A^p_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{Non-solar (both): } p^d_{nt} = \frac{A^p_{nt}}{A^d_{nt}}$$

Where $\frac{\sigma-1}{\sigma}p^s_{nt}$ 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, we can show that p^s_{ct} decreases more than p^s_{rt}, due to the trade costs. This is because Chinese solar producers use relatively more of the subsidized inputs, i.e., the Chinese solar intermediates, because those are not subject to trade costs for them. Therefore, Chinese terms of trade deteriorate.

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

$$Y^s_{nt} = \alpha_s \left(\frac{p^e_{nt}}{(1-s^{p^s}_{nt})p^s_{nt}} \right)^{\xi} Y^e_{nt} \qquad \text{and} \qquad Y^d_{nt} = \alpha_d \left(\frac{p^e_{nt}}{p^d_{nt}} \right)^{\xi} Y^e_{nt}$$

The static 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}, since $Y^e_{nt} = \alpha(B^e_n)^{\psi-1}\left(\frac{p_{nt}}{p^e_{nt}}\right)^{\psi} Y_{nt}$). As the solar marginal costs decrease, the relative price of solar versus non-solar decreases. 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 scale effects are determined by the changes in the total available income of the household, that dictates the change in the demand for the final good, hence total production. The direction and the relative magnitude of the scale effect depend on several effects. First, there is a direct demand effect, which is positive since the aggregate price in region n 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) expands as well. Therefore, total income decreases. Since solar intermediates are traded, the scale effect depends on the response of the solar sector in both regions. Overall, the scale effect cannot be characterized in closed-form. In this discussion, we focus the analysis on small subsidies, which carry the main mechanisms. We use our calibration to discuss the general equilibrium effects for larger subsidy changes.

Result 1 *Suppose that $\sigma > \xi > 1 > \psi > 0$. At given technology levels and for a small subsidy, solar production increases with the subsidy in both regions.*

Solar production increases as energy production substitutes away from the non-solar sector toward the solar sector. In the RoW, it is amplified by the scale effect, as the final good demand increases following the price decrease. In China, the scale effect is however mitigated by the subsidy distortion, that results in inefficiently low production. In particular, if ν is not too small[20] - a condition that holds true in our data -, the scale effect is negative. However, providing that the share of Chinese solar intermediate exports of total output is not too large, a condition that again, holds true in our date, the substitution effect always dominates the scale effect, and the effect of the subsidy on Chinese solar output is positive as well. The effect is stronger if ν is smaller and $\psi < 1$ is larger. Indeed, a small ν implies a higher multiplier effect through the decrease in the final good price, which serves as an input in production of all sectors with a share $1 - \nu$: this amplifies the positive effect on total output, boosting the scale effect. In contrast, a small ψ implies more complementarity between the production input and energy in the final good production, which mitigates the effect of the solar price decrease on total energy demand.

Result 2 *Suppose that $\sigma > \xi > 1 > \psi > 0$ and that ν is not too small. At given technology levels, and for a small subsidy, non-solar production decreases with the subsidy in both regions.*

In the RoW, the substitution effect and the scale effects go in opposite directions, but the former dominates if ν is not too small.[21] Therefore, non-solar production decreases. In China, the two effects go in the same direction, therefore non-solar production always decrease with the subsidy.

For larger subsidies, the static effect is ambiguous, as input reallocation across distorted sectors might become of first order for the scale effect. Since this case doesn't allow for a closed-form solution, we will turn to the calibration in section 6 to characterize it.

5.1.2 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 effects of solar technologies, Q^s_{nt}, and non-solar technology, A^d_{nt}, also

[20] ν amplifies the price effect on total output, through roundabout production. Therefore, if ν is small, the multiplier effect is larger as production relies more on the final good. If solar constitutes a large share of production, which implies that the effect on total price is large, the subsidy could increase total output. Intuitively, this channel arises because the monopoly distortions imply that the economies are producing too little, meaning that they are using too little final good in production. The subsidy partially corrects for that distortion by boosting production. However, since it is only applied to the solar sector, it creates inter-sectoral distortions. The larger the solar sector, the closer to the efficient correction, which would cover all producing sectors, the subsidy will be.

[21] Small ν would imply large multiplier effect that could result in the scale effect dominating the substitution effect.

act through the effective solar and non-solar marginal costs:

$$\text{Solar (China): } p^s_{ct} = \left((\frac{(1-s_{ct})A^p_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{\tau_{rc}A^p_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{Solar (RoW): } p^s_{rt} = \left((\frac{\tau_{cr}(1-s_{ct})A^p_{ct}}{Q^s_{ct}})^{1-\sigma} + (\frac{A^p_{rt}}{Q^s_{rt}})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$\text{Non-solar (both): } p^d_{nt} = \frac{A^p_{nt}}{A^d_{nt}}$$

By reducing the solar (non-solar) marginal cost, an increase in any of the solar (non-solar) technologies decreases (increases) 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

$$\text{China: } \frac{R^s_{ct}}{R^d_{ct}} = \Big[\frac{\eta^s_c((1+\lambda_s)^{\sigma-1}-1)}{(1-s_{ct})^{\sigma-1}(1-s^{RD}_{ct})\eta^d_c((1+\lambda_d)^{\sigma-1}-1)} \Big(\frac{Q^{s,spill}_{c,t-1}}{A^{d,spill}_{c,t-1}}\Big)^{\gamma(\sigma-1)} \frac{(p^s_{ct})^\sigma Y^s_{ct} + (p^s_{rt})^\sigma Y^s_{rt}(\tau_{cr})^{1-\sigma}}{(p^d_{ct})^\sigma Y^d_{ct}}\Big]^{\frac{1}{\kappa_c}}$$

$$\text{RoW: } \frac{R^s_{rt}}{R^d_{rt}} = \Big[\frac{\eta^s_r((1+\lambda_s)^{\sigma-1}-1)}{\eta^d_r((1+\lambda_d)^{\sigma-1}-1)} \Big(\frac{Q^{s,spill}_{r,t-1}}{A^{d,spill}_{r,t-1}}\Big)^{\gamma(\sigma-1)} \frac{(p^s_{ct})^\sigma Y^s_{ct}(\tau_{rc})^{1-\sigma} + (p^s_{rt})^\sigma Y^s_{rt}}{(p^d_{rt})^\sigma Y^d_{rt}}\Big]^{\frac{1}{\kappa_n}}$$

Firms base their decisions on the expected marginal profits of producing intermediate inputs in one sector or the other, 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 solar profits increase if the relative price of solar energy decreases, since demand increases. Through the direct price effect, expected solar profits increase if the relative price of solar energy increases. Finally, if intermediate producers' own marginal cost decreases, expected profits increase, reinforcing the market size effect. We can show that, in the solar sector, the market size effect (reinforced with the direct marginal cost effect) dominates the price effect in China. Hence, expected solar 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, Chinese (RoW) solar intermediate input producers gain (lose) market share, which increases (decreases) their expected profits. At the same time, expected non-solar profits decrease in both region with a relative solar price decrease. Indeed, non-solar demand decreases as the economy substitute non-solar with solar energy (as $\xi > 1$), while the subsidy doesn't affect the non-solar price directly.

Because $\sigma > \xi$, RoW solar intermediate input producers are more affected by the competition from the Chinese solar intermediate than the non-solar sector under (empirically) reasonable solar expenditure shares. Therefore, the negative effect on the non-solar sector is smaller, in magnitude, than the negative effect on the solar sector in the RoW: solar innovation effort decreases on impact, for a given level of technologies. The effect is stronger, the more comparative advantage in solar intermediate input production China has, as the effect on solar is relatively more important than on non-solar. In contrast, Chinese solar intermediate input producers benefit from the subsidy while both their solar and non-solar competitors lose market shares. Therefore, if comparative advantages are not too extreme, Chinese solar innovation effort increases on impact, for a given level of technologies.

Recall the law of motion of aggregate solar technology:

$$Q^s_{nt} = \left(1 + \eta^s_n (R^s_{nt})^{1-\kappa} M^n \left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma} (A^{e,spill}_{n,t-1})^{(1-\gamma)}}{(Q^s_{n,t-1})}\right)^{\sigma-1} ((1+\lambda)^{\sigma-1} - 1)\right)^{\frac{1}{\sigma-1}} Q^s_{n,t-1} \quad (7)$$

For 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. The solar prices in both regions are negatively (positively) affected by the higher (lower) growth rate of solar technology in China (in the RoW). However, prices are relatively more affected by changes in the domestic growth rate, since the domestic intermediates are used relatively more as they are not subject to trade costs.

5.2 R&D subsidy

The effects of the R&D subsidy are more straightforward. They only have a dynamic effect by changing the innovation decision. By increasing the expected marginal profits of solar innovation in China, they directly increase the number of scientists hired by the solar intermediate input sector, taking away scientists from the non-solar sector. On impact, they don't affect the RoW. However, as Chinese solar innovation, hence Chinese solar technology, increases, the solar price decreases in both regions, increasing (decreasing) solar (non-solar) demand. However, it also makes Chinese solar intermediate input producers more competitive, reallocating market share away from RoW solar intermediate input producers. In turn, this change in relative prices and demand, but also on spillovers, will affect the RoW innovation decision in the medium-term.

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.

6 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 electricity markets. Section 6.1 describes the calibration strategy and the key data sources. More details are provided in appendix A.2. Section 6.3 presents the results of the simulations. They should be understood as preliminary, as the calibration is still work-in-progress.

6.1 Calibration

A model period corresponds to five years. 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 electricity-specific variables such as levelized costs and output generation in solar and non-solar electricity, to calibrate the key parameters in our model.

6.1.1 Externally Calibrated Parameters

Table 6 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 if needed to accommodate our five-year time period[22] and the composition of our non-solar electricity input. Non-solar electricity is an aggregate of geothermal, gas, coal, nuclear, wind and oil. We

[22] In particular, we adapt some climate cycle parameters from Acemoglu et al., 2023, itself based on Golosov et al., 2014's calibration, to fit the length of our periods. For a period of length $\tilde{t}$, we use $\rho = (1 + 0.01)^{1/\tilde{t}} - 1$ to match a Social Planner's rate of time preference of 0.01 per year. Moreover, Golosov et al., 2014 target an atmospheric half-life of 300 years to calibrate their rate of decay ϕ_d. This implies that our rate of decay must be set at $\phi_d = 1 - 0.5^{\frac{1}{300/\tilde{t}}}$. Finally, for the share of emissions that is absorbed within a decade, ϕ_0, Golosov et al., 2014 use the empirical observation that approximately half of CO_2 emissions exits the atmosphere after 30 years. In our setting, this means that $\frac{\phi_0=0.3}{0.8(1-\phi_d)^{\tilde{t}}}$.

calibrate the elasticity of substitution between solar intermediates to be equal to 4.[23] Following the macro-environment literature, we calibrate the elasticity of substitution between solar and non-solar electricity to be equal to 3, accounting for recent work that endogenizes it Gentile (2024) and Jo and Miftakhova (2022),[24] and the elasticity of substitution between electricity and the production input to be equal to 0.9 Adeyemi and Hunt (2014). We recover the US and the Chinese total labor force from the World Development Index (WDI) Database of the World Bank and normalize the labor force in the US to 1. We set the labor share in production to $\nu = 0.43$ in both regions, based on the markup-adjusted US GDP to US total output ratio.[25] 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 set λ to 0.05 without loss of generality, since different values of λ can be accommodated by varying η. We use Liu and Ma (2021)'s estimates of the US and Chinese reliance on domestic patents to calibrate our cross-region spillovers to 0.7 and 0.4, respectively. We set the cross-technology spillover parameter $\gamma = 0.97$ to match the growth rate of solar output in the 2006-2018 period. We exogenously set a growth rate of the production input technology, A_t^p, consistent with a long-run economic growth of 2%.[26] Finally, we set the electricity 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 B_n^e.

6.1.2 Internally Calibrated Parameters.

This section summarizes our strategy to calibrate the remaining parameters. Section A.2.1 in appendix A.2 describes it in more details, and tables 7 and 8 in the same appendix report respectively the values of the empirical moments that we target, and the resulting calibrated parameters.

We deflate all the prices and values to be expressed in 2015 US dollars.[27] After having imposed that the production processes of solar and non-solar electricity are symmetric across regions, meaning that $\alpha_c^d = \alpha_r^d$ and that $\alpha_c^s = \alpha_r^s$, we are left with the following parameters to calibrate:

$$\{M_n, A^d_{n,2006}, A^p_{n,2006}, Q^s_{n,2006}, \tau_{rc}, \tau_{cr}, \alpha^s, \alpha^d, B_{n^e}, \eta^s_n, \eta^d_n, \iota\}$$

[23] We are working on using our empirical results to calibrate this parameter.

[24] Due to endogeneity problems, empirically identifying the elasticity of substitution is challenging. Macro climate papers use a range of different values. For instance, Hassler et al. (2022) use an elasticity of 0.95, following the metastudy of Stern (2012). Other papers (e.g., **acemoglu2023<empty citation>**) assume a substitutability larger than one, following Papageorgiou et al., 2017, who empirically estimate the elasticity of substitution finding values around 2 for the electricity-generating sector and close to 3 for the non-energy industries. Recent literature has worked on endogenizing the elasticity of substitution. Gentile (2024) finds a CES production function with an elasticity of 2 to behave most similarly to a micro-founded model of the energy sector, where the substitutability between clean and dirty energy is determined by microdata on the degree of intermittency and technological change in energy technologies.

[25] In particular, in our model $\nu = \frac{GDP}{tot\_output}\frac{\sigma}{\sigma-1} - \frac{1}{\sigma-1}$.

[26] This means that the yearly growth factor of A_t^p is $(1.02)^{\nu}$.

[27] n 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 is the numeraire in the data. Therefore, when deflating the prices, we adjust them to match the model price using the model final good price.

We count the number of Chinese and US solar intermediates firms registered in Orbis IP to calibrate M_n. Our calibration requires a value for the price p^d_{nt} and output of non-solar electricity Y^d_{nt}. We collect data on the levelized cost of all non-solar electricity sources from Lazard, and on the electricity they generated from the Statistical Review of World Energy (2024) of the Energy Institute. We combine the different sources into a non-solar electricity aggregate through a CES, which is more realistic than a simple average that would assume perfect substitution across sources, and infer the CES shares from the equilibrium conditions. We combine the non-solar price and output with the solar price, recovered from the International Renewable Energy Agency's *Renewable Power Generation Costs* report, and output, to calibrate the solar and non-solar shares in production α^s, α^d. This allows us to recover the electricity aggregate and its price, from which we can estimate the final good price (since the production input price is the numeraire), and the electricity-biased technology B^e_n. Using the total labor force[28] (from the World Bank WDI Database) total output (from the OECD IO tables), and solar production, we pin down the wage, using the budget constraint. This allows us to recover the initial production input technology $A^p_{n,2006}$ in both regions. With $A^p_{n,2006}$, we can calibrate the initial non-solar technology $A^d_{n,2006}$. The initial solar technology $Q^s_{n,2006}$ additionally requires values on exports, which we recover from the US Census Bureau.[29] Equipped with $Q^s_{n,2006}$, we can estimate the trade costs τ_{rc} and τ_{cr} using the same export values.[30] We estimate a time-varying emission intensity ι_t as a weighted average of the emission factor of each electricity source from the Energy Information Administration, based on the fuel mix in the calibration years 2006 to 2023. For the years following 2023, we use the weights based on the empirical fuel mix in 2023. Finally, we identify the innovation parameters η^s_n and η^d_n using the growth rate of the solar technology, which we build using data on solar intermediate input price from the Berkeley Tracking the Sun Database.[31]

[28]We first remove the number of solar and non-solar scientists from the total labor force. We compute this number as the number of R&D scientists (from the World Bank WDI Database) multiplied by its share of electricity to total patents filed in our calibration year (from PATSTAT).

[29]As documented by Bollinger et al. (2024), Chinese firms have delocalized production in other South-East Asian countries to avoid US tariffs. In order to consider this re-routing of trade via third countries, when computing Chinese exports to the US we also consider a portion of exports from Thailand, Taiwan, Malaysia, Cambodia, and Vietnam as part of exports from China to the US. In order to compute which share of exports from these countries come from Chinese firms we consider the mean yearly value of exports between an upper bound and a lower bound. The upper bound attributes all exports from the 5 South East Asian countries as coming from Chinese firms. The lower bound is based on data on the share of Chinese firms' production that is done abroad (defined as foreign share), as reported by Bollinger et al. (2024). We could assume exporting firms produce a share of their exports abroad that is equivalent to the foreign share, that is the share of production abroad of all Chinese firms. This is likely a lower bound, given that a good share of production facilities abroad has likely been predominantly built by exporting firms to ship to the US in order to circumvent tariffs. In the lower bound of exports we compute the Chinese exports as exports from China plus exports from China multiplied by the foreign share.

[30]We calibrate the trade costs in 2006, as well as in the second period, covering 2007-2011, to capture change in trade policies.

[31]There is no reason to believe that the innovative productivity has remained constant during our period, especially considering the outstanding development of the solar sector. Therefore, we are currently working on calibrating these parameters dynamically to capture their potential evolution.

Subsidies. We calibrate the Chinese 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. In addition to direct subsidies in the form of government grants, which would be reported on firms' balance sheets, the Chinese industrial policies implemented other subsidies in multiple forms. Other major measures introduced to subsidize firms are loans at discounted rates, and export subsidies introduced in the form of export tax rebates. The export tax rebate rate is 13%. In our best effort to quantify all of these measures into a single subsidy rate, we focus on the measures that are the most easily quantifiable. We therefore consider a subsidy rate of 22%, by summing the average subsidy rate reported by firms in the CSMAR data, with the 13% export subsidy. The 22% subsidy rate is applied both to production costs subsidies and R&D subsidies.[32]

We also include demand subsidies in the form of solar price subsidies $s_{nt}^{p_s}$ in both the USA and China. In addition to the Chinese solar industrial policies, China introduced several measures, like feed-in-tariffs, demand subsidies, and renewable portfolio standards, in the aim to increase solar energy use.[33] Similarly, the US introduced a 30% Investment Tax Credit for solar energy installations and other programs like renewable portfolio standards. We introduce these subsidies as a subsidy on the final solar energy price p_{nt}^{s}, given that these measures decreased the costs of generating solar energy. We treat these subsidies separately from the Chinese solar industrial policies. Indeed, these subsidies do not discriminate between domestic and foreign producers, which is a key feature of the Chinese solar production and R&D subsidies affecting in a different way the incentives to innovate of domestic and foreign producers. We calibrate the US subsidies using estimates from Lazard LCOE cost analysis. Lazard provides solar energy LCOE estimates including and excluding the subsidies measures provided by the US government. We compare the two estimates to calibrate the solar price subsidy value. The estimated values of solar price subsidies start at 38% in 2007-2011, decline to 23% and 6% respectively in the 2012-2016, and

[32] Our measure is comparable to Banares-Sanchez et al., 2023 that compute an R&D subsidy of 16% and a production subsidy of 15%.

[33] Feed-in-tariffs were in place between 2009 and 2020, in order to provide a stable source of revenues to solar energy producers and to incentivize solar energy installations. Renewable portfolio standards were introduced in several provinces, which required utilities to generate a minimum amount of electricity from solar energy sources. The Golden Sun Program (2009–2013) and Poverty Alleviation Solar Program (2014–2020), respectively, provided subsidies for rooftop and distributed solar, and supported rural households installing small-scale solar systems.

2017-2021 periods, before increasing again to 22% with the introduction of the IRA.[34] We keep solar price subsidies constant to 22% up to 2035, which is the year in which the IRA subsidies are currently planned to be phased out. After 2035 all subsidies fall to zero. In China we have not currently been able to find a similar quantification of an overall subsidy measure. We calibrate Chinese solar price subsidies in order to match the Chinese solar output in 2018. The subsidies are calibrated to 25% between 2007 and 2021.[35] Between 2022 and 2035 we adopt the same subsidy rate as in the US of 22%.

Trade Policy. The trade costs in the first two periods of the simulations (2002-2006, 2007-2011) are estimated as described in our calibration strategy for the internally calibrated parameters (see section A.2.1 in the appendix). In the following periods, we start from the baseline trade costs estimated in the last pre-trade-policy period (2007-2011), and we add to these baseline trade costs the US trade policies. The US trade policies consist of three measures: anti-dumping duties, countervailing duties, and safeguard measures. The anti-dumping and countervailing duties on Chinese imports were introduced already in 2012. These duties were introduced with a manufacturer specific duty. We compute the value of the duties by taking the average value across the different manufacturers as reported in the US Federal Register, which gives 25% duties. The 301 Investigation introduced safeguard measures on imports from China corresponding to a 25% tariff introduced in 2018, recently raised to 60% in 2025.[36] All the tariffs apply in a multiplicative way. Chinese firms delocalized part of their production to other South-East-Asian countries in order to avoid tariffs (Bollinger et al., 2024). In order to consider this re-routing of trade via third countries, we take into account both the tariffs imposed on China, as well as on other South-East-Asian countries. A preliminary investigation introduces tariffs of 117%, 49.54%, 58%, and 162%, respectively, for imports from Cambodia, Malaysia, Thailand, and Vietnam, as reported in the US Federal Register. The investigation is still under revision, so the effective rates are subject to change. For now, we consider these preliminary rates coming into effect in 2025. We compute an overall tariff measure weighted by the respective trade flows of the two regions to the US. Table 4 reports the resulting trade costs including US trade policy tariffs.

[34] Given the recent developments which make uncertain whether production subsidies designed in the IRA will be continued, our 22% subsidy measure does not include production subsidies, but only the Investment Tax Credit and the Energy Community Adder

[35] In the late 2000s, the Chinese government implemented a series of demand-pull policies to support the domestic deployment of solar PV following the 2005 Renewable Energy Law. For instance, the Concession Program for Large-Scale Solar PV Power Plants, the 2009 Solar Rooftop Subsidy Program, and the 2009 Golden Sun Demonstration Program provide subsidies up to $50-70\%$ of the total investment cost (Shubbak (2019), IEA Policy Database).

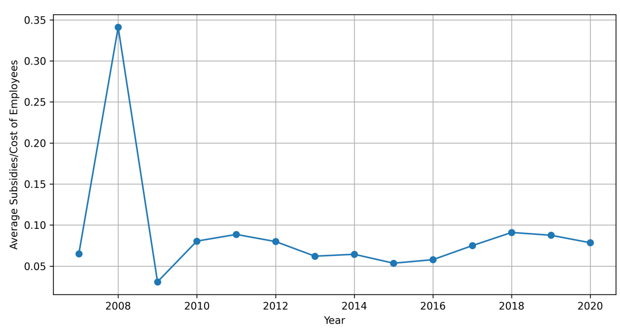
[36] The 201 Investigation introduced additional duties on imports of solar panels from all countries, excluding a list of developing countries. These duties exclude bifacial panels, which are now the majority of imports to the US. As such, we do not include these duties in the trade policy measures.

Table 4: Calibrated trade costs with tariffs

Trade costs		
Period	τ_{cr}	τ_{rc}
2002-2006	1.57	2.38
2007-2011	1.20	1.81
2012-2016	1.37	1.81
2017-2021	1.31	1.81
2022-2026	1.67	1.81
2027-onwards	2.34	1.81

Notes: We calibrate trade costs using data on solar output, exports, and prices. We calibrate trade costs in the first two periods of the model simulations. For the following 5-year periods, trade costs equal trade costs in the 2007-2011 periods plus US tariffs on imports from China and other South-East-Asian countries.

Figure 5. Subsidies received by Chinese Publicly listed firms

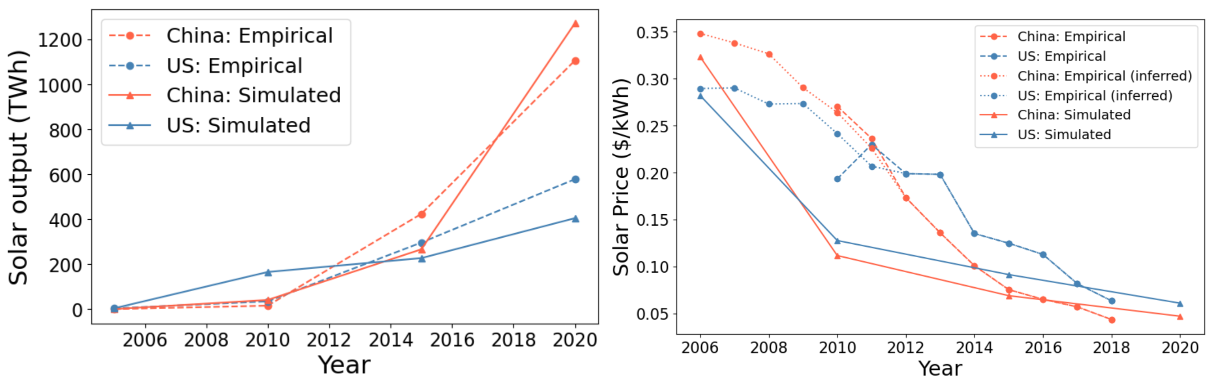


Notes: This figure reports the evolution of the average subsidies-to-employment-cost ratio in China over the years for publicly listed solar firms. Solar firms are defined as firms with at least one solar PV technology patent. Sources: CSMAR and Orbis IP, based on authors' computations.

6.2 Model Fit to the Data

We first compare the results of our calibration to the empirical moments that we observe over the period 2006 to 2018. We calibrate the solar price subsidies in China, and the solar to non-solar spillovers to match solar output in 2018, therefore the model matches by construction solar output in 2018. Given the fact that our calibration is based on static, 2006 empirical moments, the model matches well the untargeted observed price decline between 2010 and 2019, and it also matches the solar price reversal whereby solar energy in China becomes cheaper than in the US. We are working on calibrating the evolution of the innovation parameters as well, which will further improve the trends fit.

Figure 6. Model Fit to the Data



(a) Solar Output

(b) Solar Prices

Notes: The figures plot the evolution of solar output (left panel) and solar prices (right panel) in our simulation (solid line) and in the data (dashed and dotted lines). Because solar prices are only observed starting in 2010, we infer the 2006 prices (dotted line) using the growth rate of the capacity-weighted price of Chinese and US solar intermediate inputs sold in the US. We adjust the growth rate to fit our model price, which is a CES aggregate of the solar intermediate input price.

6.3 Results

To highlight the role of endogenous solar innovation, we first simulate the impact of the Chinese industrial policies[37] with exogenous technological development, keeping the solar technological paths equal to the paths in the absence of subsidies.[38] Secondly, we allow for innovation to respond to the introduction of subsidies. This exercise highlights the importance of considering the effects of the innovation response when evaluating the impact of industrial policies on the clean energy transition. Both scenarios with and without subsidies include the trade policies implemented in the US.

6.3.1 Subsidies Impact with Exogenous Innovation

Figure 7a shows how the solar technology evolves in the absence of subsidies. As estimated in our calibration strategy, the solar technology is initially higher in the US than in China. The US is also more productive in solar innovation than China, so it always remains the technological frontier. The technological gap between the US and China decreases over time due to increased innovation in China and knowledge spillovers.

[37]Our counterfactual analysis focuses on industrial policies that only apply to the solar production in one region (favor domestic relative to foreign producers), to study the reallocation of production and innovation across regions. In our model, it means subsidies to intermediate input production (s_{nt}) and subsidies to R&D (s_{nt}^{RD}). In contrast, solar price subsidies ($s_{nt}^{p_s}$) benefit both the domestic and the foreign manufacturers and won't distort the regional allocation.

[38]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.

Solar output increases thanks to the subsidies. It increases more in China than in the US, because trade costs on imports of Chinese solar intermediates dampen the impact on the US solar output. Solar intermediates production decreases slightly in the US, and it increases substantially in China. The policy-driven increase in solar output in both China and the US is satisfied with an increase in intermediates production in China.

As solar output increases and solar technology becomes more advanced, incentives to innovate on solar technologies gradually increase over time. Eventually, the economy transitions away from fossil fuels towards an equilibrium with solar energy only, in which all researchers innovate in solar. Non-solar energy output peaks in both countries around 2030. In the long run, the economy innovates only in solar technologies, and the non-solar energy output goes to zero. Subsidies accelerate the transition towards solar energy, particularly in China.

6.3.2 Subsidies Impact on Solar Innovation and Solar Energy Adoption

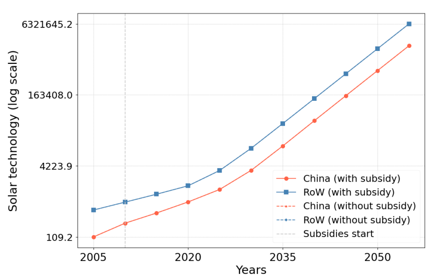
Figure 8 shows the impact of the Chinese solar subsidies including the endogenous innovation response. The introduction of the subsidies, which include both subsidies to solar intermediates production costs, as well as to solar R&D, increases incentives to innovate on solar technologies in China while it decreases incentives to innovate on solar technologies in the US (figure 8b).

Thanks to increased innovation and knowledge spillovers, China catches up with the US solar technology by 2020. By 2020, the Chinese technological level is more advanced than the US. Technological progress is initially faster in China than what we would see in the absence of subsidies. In contrast, the US technological progress is substantially slower than what we would see in the absence of policies. Eventually, the US catches up with the Chinese technological level by 2040. Given that the US is more productive in innovation, in the long-run equilibrium in which both countries use only solar energy and innovate only in solar energy, the technological frontier is the US technology, and the gap between the two technologies is constant. In the long run, the technological level is lower than what we would observe in the absence of subsidies in both countries.

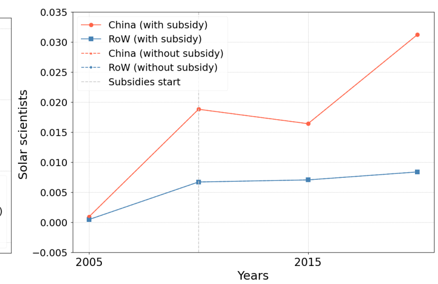
The endogenous response of innovation amplifies the impact of the subsidies on solar output and solar intermediates production. Solar output increases both in China and in the US in the short run. Solar intermediates production in the US decreases substantially, due to an increase in imports from China and slower US technological progress. The short run increase in solar output in both China and the US is sustained through higher solar intermediates production in China.

Importantly, the subsidies delay the transition to solar energy in the long run. Non solar energy use in the US peaks in 2040, while it would peak 10 years earlier, in 2030 in the absence of subsidies. In China, the non-solar energy peak is delayed by only 5 years. In the longer run, the speed of the transition depends on technological progress at the frontier, which is slowed down by the subsidies. Therefore, in the long run, the subsidies result in a higher CO2 concentration

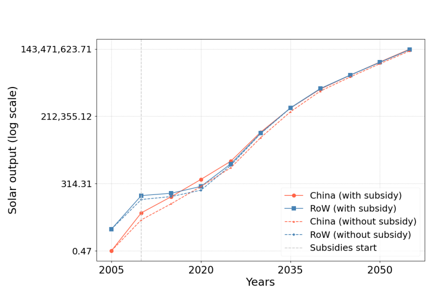
Figure 7. Subsidies Impact with Exogenous Innovation



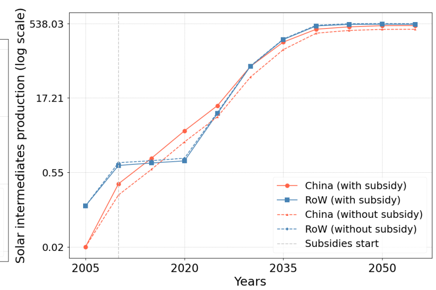
(a) Solar Technology



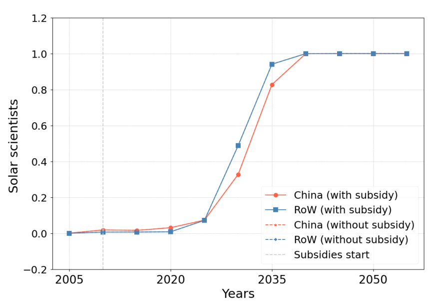
(b) Solar Scientists (Short-Run)



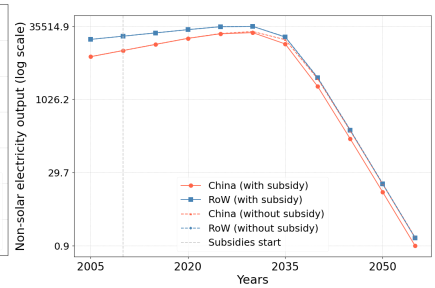
(c) Solar Energy Output



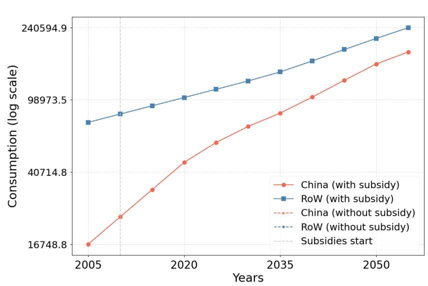
(d) Solar Intermediates Production



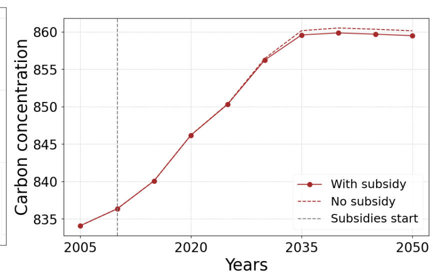
(e) Solar Scientists (Long-Run)



(f) Non-Solar Energy Output



(g) Consumption

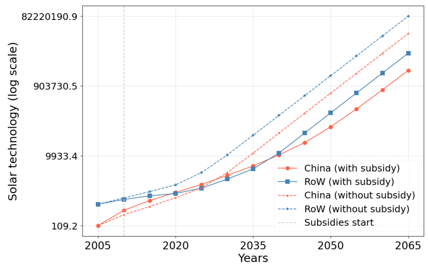


(h) Carbon Concentration

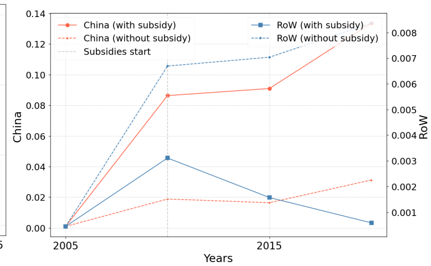
Notes: These figures show the impact of Chinese solar industrial policies (subsidies to R&D an production costs of domestic producers) on solar energy adoption, innovation, emissions, and consumption with exogenous innovation. The technological levels are kept fixed to the level we would observe in the absence of the policy. We are currently calibrating the model to two regions: China and US (RoW in the figures).

due to a delayed transition to solar energy.

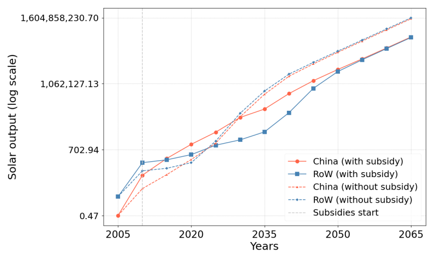
Figure 8. Subsidies Impact with Endogenous Innovation



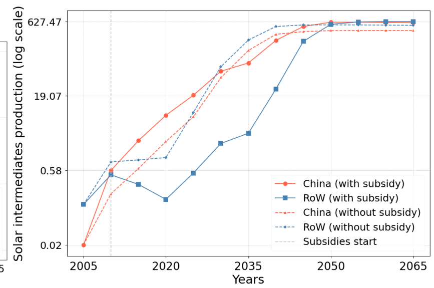
(a) Solar Technology



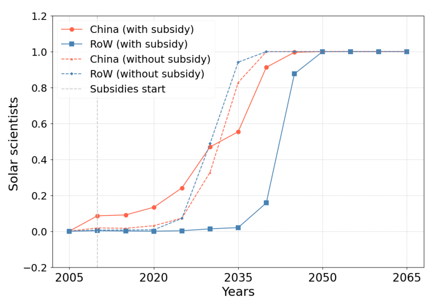
(b) Solar Scientists (Short-Run)



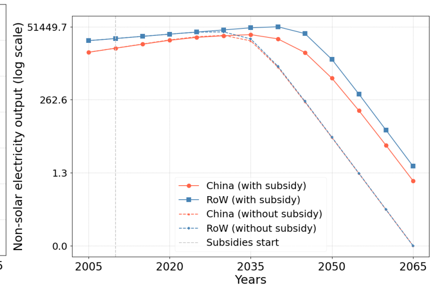
(c) Solar Energy Output



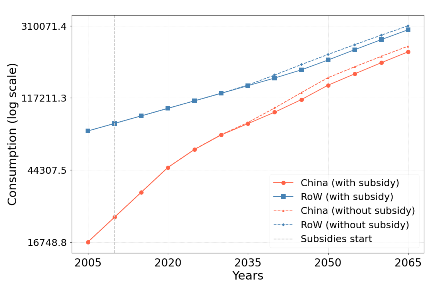
(d) Solar Intermediates Production



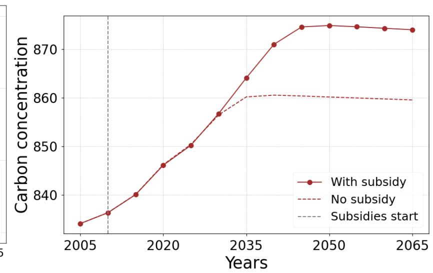
(e) Solar Scientists (Long-Run)



(f) Non-Solar Energy Output



(g) Consumption



(h) Carbon Concentration

Notes: These figures show the impact of Chinese solar industrial policies (subsidies to R&D an production costs of domestic producers) on solar energy adoption, innovation, emissions, and consumption with endogenous innovation. Innovation endogenously respond to policies. We are currently calibrating the model to two regions: China and US (RoW in the figures).

7 Conclusion

This paper studies the impact 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 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 has also had a negative impact on innovation in the rest of the world. A priori, the overall effect of the Chinese industrial policies is therefore ambiguous.

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 subsidizing country but discourages it in the rest of the world. The overall effect on prices, demand, and emissions is ambiguous.

Our preliminary calibration to two regions, China and the US, highlights that considering the endogenous global innovation response is crucial to evaluating the overall effects of industrial policies. In the short run, we find an unambiguously positive impact of industrial policies on the development of the solar energy sector. However, in the long run, the impact on the solar sector is positive with exogenous technological change, while it turns negative when the global innovation response is taken into account, delaying the clean transition. This is because the policies shift innovation away from the most innovative regions towards the least innovative regions. In the long-run, even though Chinese solar technology has become temporarily more advanced, technological progress is sill faster in the US than in China once the two regions start to transition to solar energy and devote most of their R&D resource to that sector. Given that technological progress in the US has been slowed down by the Chinese solar industrial policies, the solar technological levels, in the long run, are lower than what we would observe in the absence of policies.

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. Our model 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 valuable insights on whether these policies will be effective, but also on their implications for emissions reduction and for the clean energy transition.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hémous, D. (2012). The environment and directed technical change. *American economic review*, *102*(1), 131–66.

Acemoglu, D., Aghion, P., Barrage, L., & Hémous, D. (2023). *Climate change, directed innovation, and energy transition: The long-run consequences of the shale gas revolution* (tech. rep.). National Bureau of Economic Research.

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., & Kerr, W. (2018). Innovation, reallocation, and growth. *American Economic Review*, *108*(11), 3450–3491.

Adeyemi, O. I., & Hunt, L. C. (2014). Accounting for asymmetric price responses and underlying energy demand trends in oecd industrial energy demand. *Energy Economics*, *45*, 435–444.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-u relationship. *Quarterly Journal of Economics*, *120*(2), 701–728.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, *124*(1), 1–51.

Akcigit, U., & Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy*, *126*(4), 1374–1443.

Allcott, H., Kane, R., Maydanchik, M., Shapiro, J., & Tintelnot, F. (2024). *The effects of "buy american": Electric vehicles and the inflation reduction act* [Working Paper].

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights*, *2*(3), 357–374.

Banares-Sanchez, I., Burgess, R., Laszlo, D., Simpson, P., Van Reenen, J., & Wang, Y. (2023). *Ray of hope? china and the rise of solar energy.* [Working paper].

Barwick, P. J., Kwon, H.-S., Li, S., & Zahur, N. B. (2025). *Drive down the cost: Learning by doing and government policies in the global ev battery industry* (tech. rep.). National Bureau of Economic Research Working Paper.

Bloom, N., Draca, M., & Van Reenen, J. (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *The review of economic studies*, *83*(1), 87–117.

Bloom, N., Romer, P., Terry, S. J., & Van Reenen, J. (2021). Trapped factors and china's impact on global growth. *The Economic Journal*, *131*(633), 156–191.

Boeing, P. (2016). The allocation and effectiveness of china's r&d subsidies-evidence from listed firms. *Research policy*, *45*(9), 1774–1789.

Bollinger, B., Gerarden, T., Gillingham, K., Vollmer, D., & Yi Xu, D. (2024). *Strategic avoidance and the welfare impacts of solar panel tariffs* [Working paper].

Branstetter, L. G., Li, G., & Ren, M. (2023). Picking winners? government subsidies and firm productivity in china. *Journal of Comparative Economics*, *51*(4), 1186–1199.

Campbell, D. L., & Mau, K. (2021). On "trade induced technical change: The impact of chinese imports on innovation, it, and productivity". *The Review of Economic Studies*, *88*(5), 2555–2559.

Coelli, F., Moxnes, A., & Ulltveit-Moe, K. H. (2022). Better, faster, stronger: Global innovation and trade liberalization. *Review of Economics and Statistics*, *104*(2), 205–216.

Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N., & Ménière, Y. (2011). Invention and transfer of climate change–mitigation technologies: A global analysis. *Review of environmental economics and policy.*

Earth Policy Institute. (2015). *Annual solar photovoltaics cell production by country, 1995-2013.* https://www.earth-policy.org/data_center/c23

Eaton, J., Kortum, S., & Kramarz, F. (2011). An anatomy of international trade: Evidence from french firms. *Econometrica*, *79*(5), 1453–1498. https://doi.org/https://doi.org/10.3982/ECTA8318

EIA, U. (2018). *Electric power annual 2018* (tech. rep.) (Electric Power Annual).

Gentile, C. (2024). *Relying on intermittency: Clean energy, storage, and innovation in a macro climate model* (tech. rep.). Working Paper.

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, *82*(1), 41–88.

Hassler, J., Krusell, P., & Olovsson, C. (2022). Finite resources and the world economy. *Journal of International Economics*, *136*, 103592.

Hemous, D., Olsen, M., Zanella, C., & Dechezlepretre, A. (forthcoming). Induced automation innovation: Evidence from firm-level patent data. *Journal of Political Economy.*

Houde, S., & Wang, W. (2023). *The incidence of the us-china solar trade war* [Working Paper].

IEA. (2022). *World energy employment report.* https://iea.blob.core.windows.net/assets/a0432c97-14af-4fc7-b3bf-c409fb7e4ab8/WorldEnergyEmployment.pdf

Jo, A., & Miftakhova, A. (2022). *How constant is constant elasticity of substitution? endogenous substitution between clean and dirty energy.*

Juhász, R., Lane, N., Oehlsen, E., & Pérez, V. C. (2022). *The who, what, when, and how of industrial policy: A text-based approach* [Working paper.].

Lane, N. (2020). The new empirics of industrial policy. *Journal of Industry, Competition and Trade*, *20*(2), 209–234.

Lazard. (2020). *Levelized cost of storage analysis (lcos 6.0)*. https://www.lazard.com/research-insights/levelized-cost-of-energy-levelized-cost-of-storage-and-levelized-cost-of-hydrogen-2020/

Liu, E., & Ma, S. (2021). *Innovation networks and r&d allocation* (tech. rep.). National Bureau of Economic Research.

Papageorgiou, C., Saam, M., & Schulte, P. (2017). Substitution between clean and dirty energy inputs: A macroeconomic perspective. *Review of Economics and Statistics*, *99*(2), 281–290.

Shubbak, M. H. (2019). The technological system of production and innovation: The case of photovoltaic technology in china. *Research Policy*, *48*(4), 993–1015.

Stern, D. I. (2012). Interfuel substitution: A meta-analysis. *Journal of Economic Surveys*, *26*(2), 307–331.

A Empirical Appendix

A.1 Main Results

Table 5: Impact of Chinese Exposure on Solar Patents Counts - Other years

	(1) Baseline	(2) At Least 1 Biadic	(3) Biadic	(4) Non-Self Citation	(5) Country FEs
chinese_exp_2000	-0.4731	-1.1909	-0.8673	-0.6807	-0.9193
	(0.4750)	(0.6689)	(0.8865)	(0.4585)	(1.1095)
chinese_exp_2001	-0.1367	-0.6574	0.1545	-0.1071	-0.6426
	(0.4093)	(0.5650)	(0.7449)	(0.3952)	(0.7299)
chinese_exp_2002	-0.2720	-1.0527	-1.1967	-0.3712	-0.3180
	(0.4040)	(0.5409)	(0.8044)	(0.4025)	(0.7116)
chinese_exp_2003	0.6706	-0.4411	-1.0567	0.6061	0.0024
	(0.3899)	(0.5371)	(0.6971)	(0.3891)	(0.6412)
chinese_exp_2004	0.0684	-0.6044	0.1686	-0.0679	-0.1727
	(0.3735)	(0.4955)	(0.6030)	(0.3638)	(0.5361)
chinese_exp_2005	-0.2534	-0.8452^{*}	-0.2450	-0.2731	-0.9526^{*}
	(0.3312)	(0.4244)	(0.5264)	(0.3255)	(0.3886)
chinese_exp_2006	-0.2953	-0.3190	0.4475	-0.1895	-0.8179^{*}
	(0.3110)	(0.4033)	(0.5092)	(0.3093)	(0.3434)
Observations	115480	61300	61300	109440	99054
Unique Firms	5774	3065	3065	5472	5100
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	No
Country-Year FEs	No	No	No	No	Yes

Standard errors clustered at the firm level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors in parentheses: * p<.1, ** p<.05, ***p<.01. Standard errors are clustered at the firm level. This table shows the coefficients estimated with a Poisson Regression of the main specification, which is given by equation 4. 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.

A.1.1 Robustness exercises: Country-year FEs and Biadic-only

Figure 9. This figure reports the main coefficient of interest, β_{1t}, over time in the regression specification with country-year FEs.

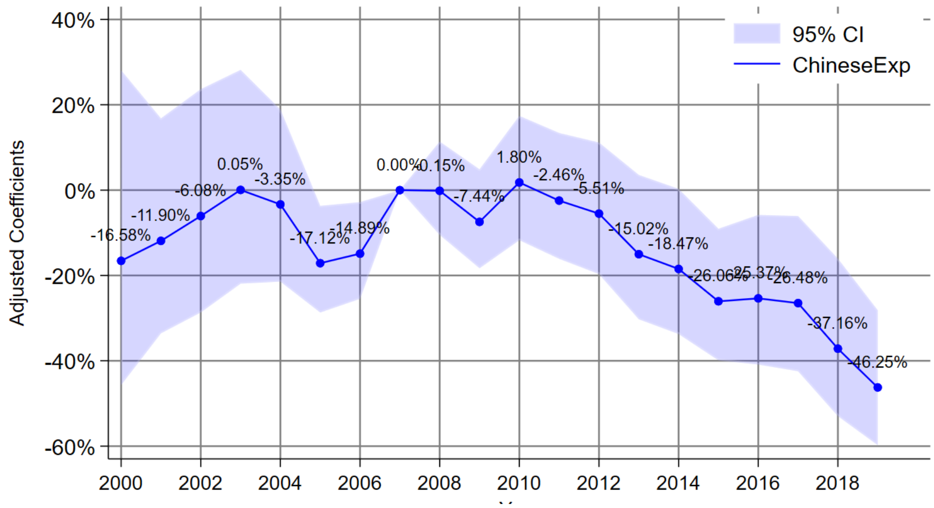
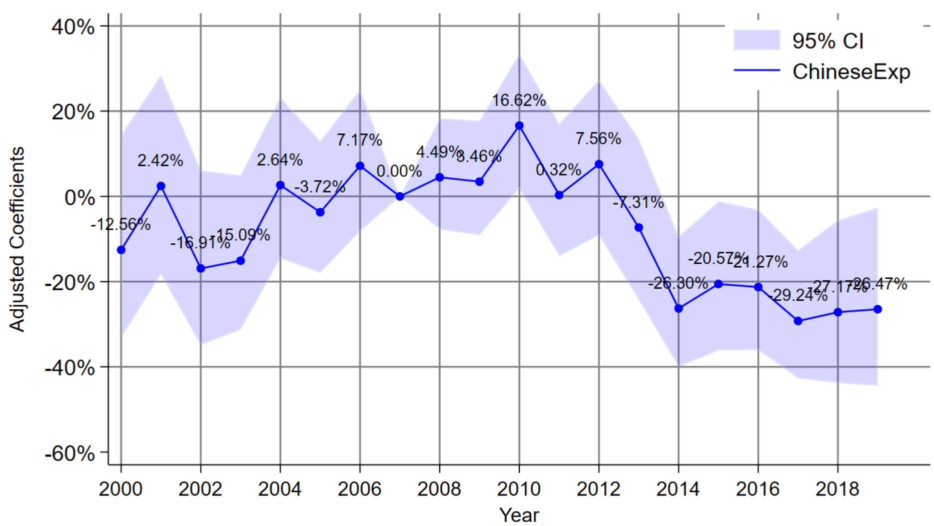


Figure 10. This figure reports the main coefficient of interest, β_{1t}, over time in the regression specification which restricts the sample of patents to biadic patents



A.2 Calibration

In this section, we provide more details on our calibration. Table 6 reports the values and sources of the parameters that we calibrate externally based on standard values from the literature. In subsection A.2.1, we provide more details on our calibration strategy. Table 7 reports information on the empirical moments that we use for our internal calibration. Table 8 report the resulting calibrated parameters

Table 6: Externally calibrated parameters

Parameters	**Value**	**Description**	**Comments**
κ	0.4	Return to scale in innovation	Acemoglu et al. (2018), Akcigit and Kerr (2018), Bloom et al. (2021)
σ	4	Elasticity of substitution between intermediates	
ξ	3	Elasticity of substitution between solar and non-solar electricity	
ψ	0.9	Elasticity of substitution between electricity and production inputs	
ν	0.43	Labor share of production	Markup-adjusted US GDP (World Bank WDI) to US total output (OECD IO tables): $\nu = \frac{GDP_r}{tot\_output_r}\frac{\sigma}{\sigma-1} - \frac{1}{\sigma-1}$
α	0.2	Share of electricity in final good production	WLOG
λ	0.05	Innovation step	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
γ	0.97	Cross-technology spillovers (solar-non solar)	Match the growth rate of solar output in the 2006-2018 period
$g_r^{A_p}$	1.02	US exogenous growth rate of prod. input technology	
$g_{c,06}^{A_p}$	1.07	$2006-2019$ exogenous growth rate of prod. input technology	
$g_{c,19}^{A_p}$	1.05	$2019-2023$ exogenous growth rate of prod. input technology	
$g_{c,24}^{A_p}$	1.04	$2024-2030$ exogenous growth rate of prod. input technology	
$g_{c,30}^{A_p}$	1.03	$2030-2050$ exogenous growth rate of prod. input technology	
$g_{c,50}^{A_p}$	1.02	> 2050 exogenous growth rate of prod. input technology	

Table 6: Externally calibrated parameters

Parameters	Value	Description	Comments
M_c	350	Number of Chinese solar intermediates firms	Orbis IP
M_r	77	Number of US solar intermediates firms	Orbis IP
ρ	0.019	Social Planner's rate of time preference	Adapted from Acemoglu et al., 2023; Golosov et al., 2014
ϑ	1.5	Inverse EIS	Adapted from Acemoglu et al., 2023; Golosov et al., 2014
$T(0)$	830	Pre-industrial carbon concentration (in Gtc)	Adapted from Acemoglu et al., 2023; Golosov et al., 2014
ϕ_L	0.2	Permanent emissions share	Adapted from Acemoglu et al., 2023; Golosov et al., 2014
ϕ_0	0.3973	Emissions immediately absorbed	Acemoglu et al., 2023; Golosov et al., 2014
ϕ_d	0.0115	Rate of decay	Adapted from Acemoglu et al., 2023; Golosov et al., 2014
χ	0.000053	damage parameter	Adapted from Acemoglu et al., 2023; Golosov et al., 2014

A.2.1 Calibration method

We impose that the production processes of solar and non-solar electricity are symmetric across regions, meaning that $\alpha_c^d = \alpha_r^d$ and that $\alpha_c^s = \alpha_r^s$. Moreover, $\alpha_n^d = 1 - \alpha_n^s$. 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 is the numeraire in the data. Therefore, when deflating the prices, we need to adjust them to match the model price[39]. We recover the model final good price based on the electricity expenditure share of total output ($\theta_{nt}^{ey} = \frac{p_{nt}^e Y_{nt}^e}{tot\_output_{nt}}$), where total output $tot\_output_{nt} = p_{nt} Y_{nt}$ is computed from the OECD input-output tables,[40] using $p_{nt} = (1-\alpha)^{\frac{1}{1-\psi}} (1-\theta_{nt}^{ey})^{\frac{1}{\psi-1}}$.

Number of solar intermediate input varieties. We normalize the total number of solar intermediates to 1, and count the number of Chinese and US solar intermediates firms registered

[39]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 $p_{nt}^s(model) = p_{nt}^s(data) p_{rt}(model)$

[40]To be consistent with our calibration, we recover θ_{nt}^{ey} from the calibrated $p_{nt}^e Y_{nt}^e$, which we obtained after having calibrated α_s, α_d and the κ_i. Those parameters are model-consistent, even if based on data prices that haven't been normalized yet, because they are based on price ratio.

in Orbis IP. This gives us $M_c = 0.82$.

Non-solar electricity. Our calibration requires a value for the price p^d_{nt} and output of non-solar electricity Y^d_{nt}. For the US, we collect data on the levelized cost of all non-solar electricity sources from Lazard, and on the electricity they generated from the Statistical Review of World Energy (2024) of the Energy Institute. However, to measure p^d_{nt}, we cannot simply use the naive average levelized cost of all electricity sources but solar, as this would assume that those different electricity sources are perfect substitutes. To aggregate these costs under a more realistic assumption, we instead infer the share of each of the electricity sources by assuming that they are aggregated in a CES manner as follows:

$$Y^d_{rt} = \left(\sum_f \kappa_f^{\frac{1}{\xi}} (Y^f_{rt})^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}}$$

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

$$\frac{\kappa_f}{\kappa_j} = \frac{Y^f_{rt}}{Y^j_{rt}} \left(\frac{p^f_{nt}}{p^i_{rt}} \right)^{\xi}$$

With the κ_f identified, we can recover the model-consistent price of other sources of electricity:

$$p^d_{rt} = \left(\sum_f \kappa_f (p^f_{nt})^{1-\xi} \right)^{\frac{1}{1-\xi}}$$

Finally, we also use the κ_f to compute the non-solar growth factor of $g^{p_d}_{nt}$ as a function of the growth rate of the LCOE of the different non solar electricity sources.

$$g^{p_d}_{nt} = \left(\frac{\sum_f \kappa_f (p^f_{nt})^{1-\xi} (g^{p_f}_{nt})^{1-\xi}}{\sum_f \kappa_f (p^f_{nt})^{1-\xi}} \right)^{\frac{1}{1-\xi}}$$

From which we obtain the growth factor of non-solar technology:

$$g^d_{nt} = \frac{g^{A_p}_{nt}}{g^{p_d}_{nt}} \tag{8}$$

Finally, the κ_f allows us to compute the model-consistent total electricity generation from non-solar sources in both China and in the US, assuming that the κ^f are identical across countries:

$$Y^d_{nt} = \left(\sum_f \kappa_f^{\frac{1}{\xi}} (Y^f_{nt})^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}$$

We can then recover the price of non-solar electricity in China once we have estimated α^d (see below). Using non-solar electricity consumption, we compute $p^d_{ct} = \left(\frac{Y^s_{ct}}{Y^d_{ct}} \frac{\alpha^d}{\alpha^s}\right)^{\frac{1}{\xi}} p^s_{ct}$

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

$$A^d_{nt} = \frac{A^p_{nt}}{p^d_{nt}}$$

Solar and non-solar shares in production: Using the solar and non-solar electricity prices and consumption - the latter taken from the 2024 Statistical Review of World Energy of the Energy Institute - along with the normalization that $\alpha^d + \alpha^s = 1$, we can recover:

$$\alpha^s = \left(1 + \frac{Y^d_{rt}}{Y^s_{rt}} \left(\frac{p^d_{rt}}{p^s_{rt}}\right)^{\xi}\right)^{-1} \quad \text{and} \quad \alpha^d = 1 - \alpha^s$$

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

Electricity expenditure share of output: From the solar and non-solar prices, we obtain the electricity price:

$$p^e_{nt} = \left(\alpha^d_n (p^d_{nt})^{1-\xi} + \alpha^s_n ((1 - s^{p^s}_{nt}) p^s_{nt})^{1-\xi}\right)^{\frac{1}{1-\xi}}$$

And from output, we similarly retrieve Y^e_{nt}:

$$Y^e_{nt} = \left(\alpha_d^{\frac{1}{\xi}} (Y^d_{nt})^{\frac{\xi-1}{\xi}} + \alpha_s^{\frac{1}{\xi}} (Y^s_{nt})^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}$$

Which allows us to compute the electricity expenditure share of GDP

$$\theta^{ey}_{nt} = \frac{p^e_{nt} Y^e_{nt}}{tot\_output_{nt}}$$

At this stage, we use θ^{ey}_{nt} to compute the final good price, such that we can normalize all our prices variables to make them model-consistent, since it matters for parameters such as A^p_{nt}, τ, B^e_n and by extension, η^s.

Electricity-biased technology: The electricity price and the electricity expenditure share of total output give us B^e_n:

$$B_n^e = p_{nt}^e \left(\frac{1-\alpha}{\alpha}\right)^{\frac{1}{\psi-1}} \left(\frac{\theta_{nt}^{ey}}{1-\theta_{nt}^{ey}}\right)^{\frac{1}{\psi-1}}$$

Emission intensity. We estimate ι as a weighted average of the emission intensity of each electricity source, based on the fuel mix in the calibration years 2006 to 2023. For the years following 2023, we use the weights based on the empirical fuel mix in 2023. From our specification of non-solar output Y_{nt}^d, we have that

$$emissions_{nt} = \iota Y_{nt}^d = \sum_f \iota_f Y_{nt}^f = \sum_f \iota_f \kappa_f Y_{nt}^d \left(\frac{p_{nt}^d}{p_{nt}^f}\right)^{\xi} \Rightarrow \iota = \sum_f \iota_f \kappa_f \left(\frac{p_{nt}^d}{p_{nt}^f}\right)^{\xi}$$

Wages. The total labor force,[41] total output, solar electricity generation and exports determine the initial wage, using the budget constraint. Total output produced in both regions comes from the OECD IO tables, while exports come from the US Census Bureau trade flows. We use solar electricity generation, imports and exports to recover solar intermediate input revenues (see equation (9) in the appendix).

$$w_{nt} = \frac{tot\_output_{nt} + \frac{s_{nt}}{1-s_{nt}}(p_{nt}^s Y_{nt}^s - EXP_{ft}^s + EXP_{nt}^s) + s_{nt}^{p_s} p_{nt}^s Y_{nt}^s}{\frac{\sigma}{(\sigma-1)\nu} popW_{nt}}$$

Where $f \neq n$ is the foreign country. We can then use $p_{nt}$to calibrate the production technology:

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

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

$$Q_{rt}^s = \left[(p_{rt}^s)^{1-\sigma} - \frac{EXP_{ct}^s}{(p_{rt}^s)^{\sigma} Y_{rt}^s}\right]^{\frac{1}{\sigma-1}} (1-s_{rt}) A_{rt}^p$$
$$Q_{ct}^s = \left[(p_{ct}^s)^{1-\sigma} - \frac{EXP_{rt}^s}{(p_{ct}^s)^{\sigma} Y_{ct}^s}\right]^{\frac{1}{\sigma-1}} (1-s_{ct}) A_{ct}^p$$

Since Lazard only reports value for the US, we take the price of solar electricity from the International Renewable Energy Agency's *Renewable Power Generation Costs* 2022 report.

[41] We first remove the number of solar and non-solar scientists from the total labor force. We compute this number as the number of R&D scientists (from the World Bank WDI Database) multiplied by its share of electricity to total patents filed in our calibration year (from PATSTAT).

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

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

Innovation: Using the growth rate of the solar technology (equation (7)), we can identify η^s_n and η^d_n. For this, we first re-arrange the scientists' equilibrium decision (equation (6)) to replace R^f_{nt}in the growth rate. We get:

$$\eta^s_n = \frac{1-\frac{g^{p^{s,i}}_{nt}}{g^{A_p}_{nt}}}{(1+\lambda_n)^{\sigma-1}\lambda M_n N_n^{1-\kappa}} \frac{(Q^s_{nt})^{\sigma-1}}{(Q^{s,spill}_{nt})^{(\sigma-1)\gamma_n}(K^e_{nt})^{((\sigma-1)(1-\gamma_n)}} \times$$
$$\left((1-s^{RD}_{nt})(1-s_{nt})^{(\sigma-1)}\left(\frac{(p^d_{nt})^\sigma Y^d_{nt}}{\frac{(p^s_{ft})^\sigma}{\tau^{\sigma-1}_{fn}}Y^s_{ft}+(p^s_{nt})^\sigma Y^s_{nt}}\right)\left(\frac{((g^d_{nt})^{\sigma-1}-1)M_n(1+\lambda_n)^{\sigma-1}\lambda}{(1-\frac{g^{p^{s,i}}_{nt}}{g^{A_p}_{nt}})((1+\lambda_n)^{\sigma-1}-1)}\right)\left(\frac{A^d_{nt-1}}{Q^s_{nt-1}}\right)^{(\sigma-1)}+M_n\right)^{1-\kappa_n}$$

$$\eta^d_n = \eta^s_n\left(\frac{((g^d_{nt})^{\sigma-1}-1)M_n(1+\lambda_n)^{\sigma-1}\lambda_n}{(1-\frac{g^{p^{s,i}}_{nt}}{g^{A_p}_{nt}})((1+\lambda_n)^{\sigma-1}-1)}\right)^{-\kappa_n}\left(\frac{Q^s_{nt-1}}{A^d_{nt-1}}\right)^{-(\sigma-1)\kappa}\left(\frac{A^{d,spill}_{nt-1}}{Q^{s,spill}_{nt-1}}\right)^{-\gamma_n(\sigma-1)} \times$$
$$(1-s^{RD}_{nt})^{1-\kappa_n}(1-s^z(t))^{(\sigma-1)(\kappa_n-1)}\left(\frac{(p^d_{nt})^\sigma Y^z_d(t)}{\frac{(p^s_{ft})^\sigma}{\tau^{\sigma-1}_{fn}}Y^s_{nt}+(p^s_{nt})^\sigma Y^s_{nt}}\right)^{\kappa_n-1}$$

Where $f \neq n$ indexes the foreign country. In the data, we don't observe the growth factor of solar and non-solar technology g^s_{nt} directly. However, we can relate it to the growth factor of prices, which we observe. We have already recovered the growth factor of the non-solar technology in equation (8). For the solar technology, we use the mean capacity-weighted price of solar intermediate inputs from the Berkeley Tracking the Sun Dataset. This dataset reports the capacity and the price of grid-connected, distributed solar photovoltaic systems in the United States, by year and supplier. We build our Chinese and US aggregate solar intermediate input price as the average price across all solar systems produced by a Chinese or US firm, respectively, weighted by their installed capacity ($p^{s,CW}_{rt} = \int_{M_n} p^i_{rnt}\frac{x^i_{rnt}}{\int_{M_n} x^j_{rnt}d_j}di$). We then measure the growth factor of solar intermediate input price $g^{p^{s,i}}_{nt}$ as the average annualized growth rate over the period $2006-2019$, which we then adjust to fit our $5-$year period. We then relate it to the technology growth factor as follows. Since the average capacity-weighted price at $t+1$ is

$$p^{s,CW}_{rt+1} = \frac{\int_{M_n}(p^i_{rn,t+1})^{1-\sigma}di}{\int_{M_n}(p^i_{rn,t+1})^{-\sigma}d_i} = (1-s_n)A^p_{nt+1}\tau_{mn}\frac{\int_{M_n}(q^{s,i}_{rn,t+1})^{\sigma-1}di}{\int_{M_n}(q^{s,i}_{rn,t+1})^{\sigma}d_i}$$

We use the law of motion of the individual solar technology $q^{s,i}_{rn,t+1}$ (equation (5)) to rearrange this expression, assuming that the within-region heterogeneity in individual technology is small. We obtain:

$$g^{p^{s,i}}_{nt} = \frac{p^{s,CW}_{rt+1}}{p^{s,CW}_{rt}} = g^{A_p}_{nt}\left[1 - M_n\left(1+\lambda_n\right)^{\sigma-1}\lambda_n\eta^s_n(R^{s,i}_{nt+1})^{1-\kappa}\left(\frac{(Q^{s,spill}_{nt})^{\gamma_n}(A^{e,spill}_{nt-1})^{1-\gamma_n}}{Q^s_{nt}}\right)^{\sigma-1}\right]$$

Therefore, we can relate the growth factor of solar technology (g^s_{nt}) to the growth factor of the capacity-weighted intermediate input price ($g^{p^{s,i}}_{nt}$) as follow:

$$\begin{aligned} g^s_{nt} = \frac{Q^s_{nt+1}}{Q^s_{nt}} &= \left(1 + \eta_s(R^s_{nt})^{1-\kappa}M_{nt}\left(\frac{(Q^{s,spill}_{nt-1})^{\gamma_n}(A^{e,spill}_{nt-1})^{1-\gamma_n}}{Q^s_{nt-1}}\right)^{\sigma-1}((1+\lambda_n)^{\sigma-1}-1)\right)^{\frac{1}{\sigma-1}} \\ &= \left(1 + \frac{1-\frac{g^{p^{s,i}}_{nt}}{g^{A_p}_{nt}}}{\lambda_n(1+\lambda_n)^{\sigma-1}}((1+\lambda_n)^{\sigma-1}-1)\right)^{\frac{1}{\sigma-1}} \end{aligned}$$

Tables 7 and 8 summarize respectively the values of the empirical moments that we target, and the resulting calibrated parameters.

Table 7: Target moments (2006)

Moment	Variable	Value	Source	Parameter(s) identified
$popW_{ct}$	Chinese labor force to US labor force ratio	5.02	World Bank WDI	$w_{ct} = A^p_{ct}$
$g^{p^{s,i}}_{ct}$	Annualized growth rate of capacity weighted solar system prices in China (2006-2009)	0.9159	Berkeley Tracking the Sun Data	η^s_c
$g^{p^{s,i}}_{rt}$	Annualized growth rate of capacity weighted solar system prices in the US (2006-2009)	0.9676	Berkeley Tracking the Sun Data	η^s_r
$tot\_output_{ct} = p_{ct}Y_{ct}$	China total production over 2002-2006 (in 2015 bio US$)	31317.56	OECD IO table	$w_{ct} = A^p_{ct}, \theta^{ey}_{ct} \Rightarrow B^e_c$
$tot\_output_{rt} = p_{rt}Y_{rt}$	US total production over 2002-2006 (in 2015 bio US$)	1131068.5	OECD IO table	$w_{rt} = A^p_{rt}, \theta^{ey}_{rt} \Rightarrow B^e_r$

Table 7: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter(s) identified**
R_{ct}	Chinese R&D scientists to total US labor force	0.0079519	World bank WDI	$R^s_{ct}, R^d_{ct} \Rightarrow w_{ct}$
R_{rt}	US R&D scientists to total US labor force	0.0069408	World bank WDI	$R^s_{rt}, R^d_{rt} \Rightarrow w_{rt}$
$sp^s_{rt} = \frac{Npatents^s_{rt}}{Npatents_{rt}}$	RoW share of solar to total patents	0.001961	PATSTAT	$R^s_{rt} \Rightarrow w_{rt}$
$sp^s_{ct} = \frac{Npatents^s_{ct}}{Npatents_{ct}}$	China share of solar to total patents	0.003478	PATSTAT	$R^s_{ct} \Rightarrow w_{ct}$
$sp^d_{rt} = \frac{Npatents^d_{rt}}{Npatents_{rt}}$	RoW share of non solar to total patents	0.010534	PATSTAT	$R^d_{rt} \Rightarrow w_{rt}$
$sp^d_{ct} = \frac{Npatents^d_{ct}}{Npatents_{ct}}$	China share of non solar to total patents	0.03856	PATSTAT	$R^d_{ct} \Rightarrow w_{ct}$
R^s_{ct}	China solar R&D scientists to total US labor force	0.0000276598	$sp^s_{ct} \times R_{ct}$	$w_{ct} = A^p_{ct}$
R^s_{rt}	US solar R&D scientists to total US labor force	0.0000136138	$sp^s_{ct} \times R_{ct}$	$w_{ct} = A^p_{ct}$
R^d_{ct}	China non-solar R&D scientists to total US labor force	0.000306596	$sp^d_{ct} \times R_{ct}$	$w_{ct} = A^p_{ct}$
R^d_{rt}	US non-solar R&D scientists to total US labor force	0.0000731138	$sp^d_{rt} \times R_{rt}$	$w_{rt} = A^p_{rt}$
Y^s_{ct}	Chinese solar electricity generation over 2002-2006 (TWh)	0.367	Energy Institute - Statistical Review of World Energy (2024)	$\tau_{rc}, Q^s_{ct}, \eta^s_c, \eta^s_r,\ p^d_{ct} \Rightarrow A^d_{ct}, \theta^{ey}_{ct} \Rightarrow B^e_c$
Y^s_{rt}	US solar electricity generation over 2002-2006 (TWh)	3.484	Energy Institute - Statistical Review of World Energy (2024)	$\alpha_s, \tau_{cr}, Q^s_{rt}, \eta^s_c, \eta^s_r, \theta^{ey}_{rt} \Rightarrow B^e_r$
Y^{ge}_{ct}	Chinese geothermal electricity generation over 2002-2006 (TWh)	20.065	Energy Institute - Statistical Review of World Energy (2024)	$Y^d_{ct}, p^d_{ct} \Rightarrow A^d_{ct}, \theta^{ey}_{nt} \Rightarrow B^e_n$

Table 7: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter(s) identified**
Y_{rt}^{ge}	US geothermal electricity generation over 2002-2006 (TWh)	360.747	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{ge} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{ct}^{gc}	Chinese gas electricity generationover 2002-2006 (TWh)	52.77	Energy Institute - Statistical Review of World Energy (2024)	$Y_{ct}^d, p_{ct}^d \Rightarrow A_{ct}^d, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{rt}^{gc}	US gas electricity generation over 2002-2006 (TWh)	3901.521	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{gc} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{ct}^{c}	Chinese coal electricity generation over 2002-2006 (TWh)	8807.526	Energy Institute - Statistical Review of World Energy (2024)	$Y_{ct}^d, p_{ct}^d \Rightarrow A_{ct}^d, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{rt}^{c}	US coal electricity generation over 2002-2006 (TWh)	10708.073	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{c} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{ct}^{n}	Chinese nuclear electricity generation over 2002-2006 (TWh)	226.869	Energy Institute - Statistical Review of World Energy (2024)	$Y_{ct}^d, p_{ct}^d \Rightarrow A_{ct}^d, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{rt}^{n}	US nuclear electricity generation over 2002-2006 (TWh)	4106.874	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{n} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{ct}^{w}	Chinese wind electricity generation over 2002-2006 (TWh)	.770	Energy Institute - Statistical Review of World Energy (2024)	$Y_{ct}^d, p_{ct}^d \Rightarrow A_{ct}^d, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{rt}^{w}	US wind electricity generation over 2002-2006 (TWh)	80.894	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{w} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{ct}^{o}	Chinese oil electricity consumption (TWh)	259.493	Energy Institute - Statistical Review of World Energy (2024)	$Y_{ct}^d, p_{ct}^d \Rightarrow A_{ct}^d, \theta_{nt}^{ey} \Rightarrow B_n^e$
Y_{rt}^{o}	US oil electricity consumption over 2002-2006 (TWh)	560.763	Energy Institute - Statistical Review of World Energy (2024)	$\kappa_{w} \Rightarrow p_{rt}^d, Y_{rt}^d \Rightarrow \alpha_s, \theta_{nt}^{ey} \Rightarrow B_n^e$

Table 7: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter(s) identified**
p^s_{ct}	Price of solar in China (2015 US $/MWh)	296	International Renewable Energy Agency - Renewable Power Generation Costs in 2022[42]	$\tau_{rc}, Q^s_{ct}, \eta^s_c, \eta^s_r, \theta^{ey}_{ct} \Rightarrow B^e_c, p^d_{ct} \Rightarrow A^d_{ct}$
p^s_{rt}	Price of solar in the USA (2015 US $/MWh)	239	International Renewable Energy Agency - Renewable Power Generation Costs in 2022[42]	$\alpha_s, \tau_{cr}, Q^s_{rt}, \eta^s_c, \eta^s_r, \theta^{ey}_{rt} \Rightarrow B^e_r$
p^{ge}_{rt}	Levelized cost of geothermal electricity in the US (US $/MWh)	76.23	Lazard LCOE[43]	$\kappa_{ge} \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s, \theta^{ey}_{nt} \Rightarrow B^e_n, g^{p_d}_{rt} = g^{p_d}_{ct}$
p^{gc}_{rt}	Levelized cost of gas (combined cycle) electricity in the US (US $/MWh)	105.2	Lazard LCOE	$\kappa_{gc} \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s, \theta^{ey}_{nt} \Rightarrow B^e_n, g^{p_d}_{rt} = g^{p_d}_{ct}$
p^c_{rt}	Levelized cost of coal electricity in the US (US $/MWh)	134.8	Lazard LCOE	$\kappa_c \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s, \theta^{ey}_{nt} \Rightarrow B^e_n, g^{p_d}_{rt} = g^{p_d}_{ct}$
p^n_{rt}	Levelized cost of nuclear electricity in the US (US $/MWh)	120.4	Lazard LCOE	$\kappa_n \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s, \theta^{ey}_{nt} \Rightarrow B^e_n, g^{p_d}_{rt} = g^{p_d}_{ct}$
p^w_{rt}	Levelized cost of wind electricity in the US (US $/MWh)	196.3	Lazard LCOE	$\kappa_w \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s, \theta^{ey}_{nt} \Rightarrow B^e_n, g^{p_d}_{rt} = g^{p_d}_{ct}$
p^o_{rt}	West Texas Intermediate Oil price in the US (US $/MWh)	18.51	Saint-Louis Fed	$\kappa_o \Rightarrow p^d_{rt}, Y^d_{rt} \Rightarrow \alpha_s$

[42]The data starts in 2010. Therefore, we retrieve the 2006 value by imputing the growth rate of solar price from the growth rate of solar intermediate input prices coming from the Berkeley Tracking the Sun Data.

[43]The Lazard data starts in 2009. Therefore, for all prices, we retrieve the 2006 value using the growth rate of the prices between 2009 and 2010.

Table 7: Target moments (2006)

Moment	**Variable**	**Value**	**Source**	**Parameter(s) identified**
$g_{rt}^{ge}(0)$	US Geothermal LCOE average 5-year growth rate over 2009-2019 (US $/MWh)	1.0954	Lazard LCOE	$g_{rt}^{p_d} = g_{ct}^{p_d}$
g_{rt}^{gc}	Gas LCOE average 5-year growth rate over 2009-2019 (US $/MWh)	0.86695	Lazard LCOE	$g_{rt}^{p_d} = g_{ct}^{p_d}$
g_{rt}^{c}	Coal LCOE average 5-year growth rate over 2009-2019 (US $/MWh)	0.9048	Lazard LCOE	$g_{rt}^{p_d} = g_{ct}^{p_d}$
g_{rt}^{n}	Nuclear LCOE average 5-year growth rate over 2009-2019 (US $/MWh)	1.1226	Lazard LCOE	$g_{rt}^{p_d} = g_{ct}^{p_d}$
g_{rt}^{w}	Wind LCOE average 5-year growth rate over 2009-2019 (US $/MWh) (2009-2024)	0.7556	Lazard LCOE	$g_{rt}^{p_d} = g_{ct}^{p_d}$
g_{rt}^{o}	West Texas Intermediate Oil price average 5-year growth rate over 2009-2019 (US $/MWh)	2.15651	Saint-Louis Fed	$g_{rt}^{p_d} = g_{ct}^{p_d}$
ι_{ge}	Emission factor geothermal (kg CO2 to mio BtU)	7.71	EIA, 2018	ι
ι_{gc}	Emission factor gas (kg CO2 to mio BtU)	53.07	EIA, 2018	ι
ι_{c}	Emission factor coal (kg CO2 to mio BtU)	93.30	EIA, 2018	ι
ι_{n}	Emission factor nuclear (kg CO2 to mio BtU)	0	EIA, 2018	ι
ι_{w}	Emission factor wind (kg CO2 to mio BtU)	0	EIA, 2018	ι
ι_{o}	Emission factor oil (kg CO2 to mio BtU)	73.16	EIA, 2018	ι

Table 7: Target moments (2006)

Moment	Variable	Value	Source	Parameter(s) identified
EXP^s_{ct}	Chinese solar export over 2002-2006 (US 2015 bio $)	0.059251	US Census Bureau (Imports from China)	τ_{cr}, Q^s_{rt}
EXP^s_{rt}	US solar export over 2002-2006 (US 2015 bio $)	0.01148	US Census Bureau (domestic exports to China)	τ_{rc}, Q^s_{ct}

Table 8: Internally calibrated parameters for 2006

Parameters	Value	Description	Moment targeted
M_c	0.82	Ratio of Chinese solar firms	Nb. of firms in Orbis IP
$A^p_{c,06}$	4.7155	Level of Chinese production technology	Total output and total labor force
$A^p_{r,06}$	16.8041	Level of US production technology	Total output and total labor force
$A^d_{c,06}$	383.122	Level of Chinese non-solar technology	Non-solar levelized costs
$A^d_{r,06}$	1024.445	Level of US non-solar technology	Non-solar levelized costs
$Q^s_{c,06}$	101.565	Level of Chinese solar technology	Solar levelized costs, output and exports
$Q^s_{r,06}$	440.127	Level of US solar technology	Solar levelized costs, output and exports
τ_{rc}	1.577	Trade costs from China to the US	Solar levelized costs, output and exports
τ_{cr}	2.38	Trade costs from the US to China	Solar levelized costs, output and exports
α_s	0.00218086	Solar share in the electricity composite	Solar and non-solar levelized costs and output
$\alpha(B^e_c)^{\psi-1}$	0.03178338	Chinese electricity share	Electricity expenditure shares of total output
$\alpha(B^e_r)^{\psi-1}$	0.02253678	US electricity share	Electricity expenditure shares of total output

Table 8: Internally calibrated parameters for 2006

Parameters	Value	Description	Moment targeted
$((1+\lambda)^{\sigma-1}-1)\eta_c^s(M_c R_{c,06}^s)^{1-\kappa}$	0.06174746	Chinese solar innovation rate	Solar and non-solar technology growth rates and revenues
$((1+\lambda)^{\sigma-1}-1)\eta_r^s(M_r R_{r,06}^s)^{1-\kappa}$	0.28938579	US solar innovation rate	Solar and non-solar technology growth rates and revenues
$((1+\lambda)^{\sigma-1}-1)\eta_c^d(R_{c,06}^d)^{1-\kappa}$	0.00062574	Chinese non-solar innovation rate	Solar and non-solar technology growth rates and revenues
$((1+\lambda)^{\sigma-1}-1)\eta_r^d(R_{c,06}^d)^{1-\kappa}$	0.00393042	US non-solar innovation rate	Solar and non-solar technology growth rates and revenues
ι	0.000293305	Non-solar emission factor	Non-solar electricity sources' emission factor

B Theoretical Appendix

B.1 Derivations

This section prove some of the decentralized equilibrium results exposed in the main text.

B.2 Solar intermediate input production

Firm i located in region $z = c, r$ chooses its input demand from cost minimization. The Cobb-Douglas aggregate yields the usual marginal cost $c_{zt} = (1 - s_{zt})w_{zt}^{\nu} p_{zt}^{1-\nu}$. The firm then takes into account the demand x_{nzt}^i from the solar producer in region n, and sets the price p_{nzt}^i that maximizes its profits.

$$\max_{p_{nzt}^i} \pi_{nt}^{i\in z} = p_{nzt}^i x_{nzt}^i - (1 - s_{zt})w_{zt}^{\nu} p_{zt}^{1-\nu} \frac{y_{nzt}^i}{q_{zt}^{s,i}} \quad \text{s.t. } x_{nzt}^i = (\frac{p_{nt}^s}{p_{nzt}^i})^{\sigma} Y_{nt}^s$$
$$\Rightarrow p_{nzt}^i = \frac{\sigma}{\sigma-1}(1 - s_{zt})\frac{w_{zt}^{\nu} p_{zt}^{1-\nu}}{q_{zt}^{s,i}}\tau_{nz} = (1 - s_{zt})\frac{A_{zt}^p}{q_{zt}^{s,i}}\tau_{nz}$$

The firm sets a price at a constant markup over marginal costs, taking the trade costs into account, to maximize its profits.

The same firm i located in region $z = c, r$, produces output y_{nzt}^i for region n, and uses l_{nzt}^i

and $Y_{nzt}^{inputs_s,i}$ of each input, respectively, for this part of production:

$$y_{nzt}^{i} = (p_{nt}^{s})^{\sigma} Y_{nt}^{s} \tau_{nz} \left(\frac{\sigma-1}{\sigma} \frac{q_{zt}^{s,i}}{\tau_{nz}(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma}$$

$$l_{nzt}^{i} = \frac{\nu}{(1-s_{zt}) w_{zt}} (p_{nt}^{s})^{\sigma} Y_{nt}^{s} \left(\frac{\sigma-1}{\sigma} \frac{q_{zt}^{s,i}}{\tau_{nz}(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma-1}$$

$$Y_{nzt}^{inputs_s,i} = \frac{1-\nu}{(1-s_{zt}) p_{zt}} (p_{nt}^{s})^{\sigma} Y_{nt}^{s} \left(\frac{\sigma-1}{\sigma} \frac{q_{zt}^{s,i}}{\tau_{nz}(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma-1}$$

Therefore, it makes the following profits π_{nzt}^{i} from selling to region n:

$$\begin{aligned} \pi_{nzt}^{i} &= p_{nzt}^{i} x_{nzt}^{i} - \frac{(1-s_{zt}) w_{nt}^{\nu} p_{nt}^{1-\nu}}{q_{zt}^{s,i}} y_{nzt}^{i} = p_{nzt}^{i} \frac{y_{nzt}^{i}}{\tau_{nz}} - \frac{(1-s_{zt}) w_{nt}^{\nu} p_{nt}^{1-\nu}}{q q_{zt}^{s,i}} y_{nzt}^{i} \\ &= \frac{1}{\sigma} (p_{nt}^{s})^{\sigma} Y_{nt}^{s} \left(\frac{\sigma-1}{\sigma} \frac{q_{zt}^{s,i}}{\tau_{nz}(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma-1} \end{aligned}$$

Therefore, firm i located in region $z = c, r$ makes total profits

$$\pi_{zt}^{i} = \frac{1}{\sigma} \left(\frac{(p_{rt}^{s})^{\sigma}}{\tau_{rz}^{\sigma-1}} Y_{rt}^{s} + \frac{(p_{ct}^{s})^{\sigma}}{\tau_{cz}^{\sigma-1}} Y_{ct}^{s} \right) \left(\frac{\sigma-1}{\sigma} \frac{q_{zt}^{s,i}}{(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma-1}$$

This means that total profits from the solar sector in region z can be expressed as:

$$\int_{0}^{M_n} \pi_{zt}^{i} di = \frac{1}{\sigma} \left(\frac{(p_{rt}^{s})^{\sigma}}{\tau_{rz}^{\sigma-1}} Y_{rt}^{s} + \frac{(p_{ct}^{s})^{\sigma}}{\tau_{cz}^{\sigma-1}} Y_{ct}^{s} \right) \left(\frac{\sigma-1}{\sigma} \frac{Q_{zt}^{s}}{(1-s_{zt}) w_{zt}^{\nu} p_{zt}^{1-\nu}} \right)^{\sigma-1} = \frac{1}{\sigma} p_{zt}^{s} X_{zt}^{s}$$

Where $p_{zt}^{s} X_{zt}^{s} = \int_{0}^{M_n} p_{zt}^{i} x_{zt}^{i} di$ is the total sales of solar intermediate from region z. In a two-region model, total sales from region z are equal to solar electricity generation in region z, $p_{zt}^{s} Y_{zt}^{s}$ plus solar intermediate exports of region n, minus solar intermediate imports of region n:

$$p_{zt}^{s} X_{zt}^{s} = p_{zt}^{s} Y_{zt}^{s} + EXP_{zt}^{s} - EXP_{ft}^{s} \quad \text{for } f \neq z \tag{9}$$

B.3 Optimal Innovation Choice

Solar intermediate firm i located in region n decides how many researchers to hire to maximize:

$$
\begin{aligned}
\max_{R^{s,i}_{nt}} \quad & \eta^s_n (R^{s,i}_{nt})^{1-\kappa_n} \left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma} (A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}} \right)^{(\sigma-1)} \pi^i_{nt}((1+\lambda^s_n) q^{s,i}_{nt-1}) \\
& + \left(1 - \eta^s_n (R^{s,i}_{nt})^{1-\kappa_n} \left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma} (A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}} \right)^{(\sigma-1)} \right) \pi^i_{nt}(q^{s,i}_{nt-1}) \\
& - (1 - s^{RD}_{nt}) w^{R_s}_{nt} R^{s,i}_{nt}
\end{aligned}
$$

And similarly for a non-solar intermediate firm. Solar intermediate producers' profits are

$$
\pi^i_{nt}(q^{s,i}_{nt}) = \left(\frac{q^{s,i}_{nt}}{(1-s_{nt}) w^{\nu}_{nt} p^{1-\nu}_{nt}} \right)^{\sigma-1} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \frac{1}{\sigma-1} \left(\frac{(p^s_{rt})^{\sigma}}{\tau^{\sigma-1}_{rn}} Y^s_{rt} + \frac{(p^s_{ct})^{\sigma}}{\tau^{\sigma-1}_{cn}} Y^s_{ct} \right)
$$

Therefore, we can rewrite the maximization problem as

$$
\begin{aligned}
\max_{R^{s,i}_{nt}} \quad & \left(1 + \eta^s_n (R^{s,i}_{nt})^{1-\kappa_n} \left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma} (A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}} \right)^{(\sigma-1)} ((1+\lambda^s_n)^{\sigma-1} - 1) \right) \times \\
& \left(\frac{q^{s,i}_{nt-1}}{(1-s_{nt}) w^{\nu}_{nt} p^{1-\nu}_{nt}} \right)^{\sigma-1} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \frac{1}{\sigma-1} \left(\frac{(p^s_{rt})^{\sigma}}{\tau^{\sigma-1}_{rn}} Y^s_{rt} + \frac{(p^s_{ct})^{\sigma}}{\tau^{\sigma-1}_{cn}} Y^s_{ct} \right) \\
& - (1 - s^{RD}_{nt}) w^{R_s}_{nt} R^{s,i}_{nt}
\end{aligned}
$$

Hence, the first-order condition yields

$$
\begin{aligned}
(1 - s^{RD}_{nt}) w^{R_s}_{nt} =& (1-\kappa_n) \eta^s_n (R^{s,i}_{nt})^{-\kappa_n} \left(\frac{(Q^{s,spill}_{n,t-1})^{\gamma} (A^{e,spill}_{n,t-1})^{(1-\gamma)}}{q^{s,i}_{nt-1}} \right)^{(\sigma-1)} ((1+\lambda^s_n)^{\sigma-1} - 1) \times \\
& \left(\frac{q^{s,i}_{nt-1}}{(1-s_{nt}) w^{\nu}_{nt} p^{1-\nu}_{nt}} \right)^{\sigma-1} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \frac{1}{\sigma-1} \left(\frac{(p^s_{rt})^{\sigma}}{\tau^{\sigma-1}_{rn}} Y^s_{rt} + \frac{(p^s_{ct})^{\sigma}}{\tau^{\sigma-1}_{cn}} Y^s_{ct} \right)
\end{aligned}
$$

Scientists are paid their outside option, which is the expected marginal profits of working in the other sector:

$$
\begin{aligned}
w^{R_s}_{nt} &= (1-\kappa_n) \eta^d_n (R^{d,i}_{nt})^{-\kappa_n} (A^{d,spill}_{n,t-1})^{(\sigma-1)\gamma} (A^{e,spill}_{n,t-1})^{(\sigma-1)(1-\gamma)} ((1+\lambda^d_n)^{\sigma-1} - 1) \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \frac{1}{\sigma-1} \left(\frac{1}{w^{\nu}_{nt} p^{1-\nu}_{nt}} \right)^{\sigma-1} (p \\
w^{R_d}_{nt} &= (1-\kappa_n) \eta^s_n (R^{s,i}_{nt})^{-\kappa_n} (Q^{s,spill}_{n,t-1})^{(\sigma-1)\gamma} (A^{e,spill}_{n,t-1})^{(\sigma-1)(1-\gamma)} ((1+\lambda^s_n)^{\sigma-1} - 1) \\
& \quad \times \left(\frac{1}{(1-s_{nt}) w^{\nu}_{nt} p^{1-\nu}_{nt}} \right)^{\sigma-1} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \frac{1}{\sigma-1} \left(\frac{(p^s_{rt})^{\sigma}}{\tau^{\sigma-1}_{rn}} Y^s_{rt} + \frac{(p^s_{ct})^{\sigma}}{\tau^{\sigma-1}_{cn}} Y^s_{ct} \right)
\end{aligned}
$$

Therefore, the firm's scientists hiring decision is characterized by comparing the expected marginal profits in the two sectors. This gives the following optimal choice

$$\frac{R_{nt}^{s,i}}{R_{nt}^{d,i}} = \frac{R_{nt}^{s}}{R_{nt}^{d}} = \Big[\frac{\eta_n^s((1+\lambda_n^s)^{\sigma-1}-1)}{(1-s_{nt}^{RD})\eta_n^d((1+\lambda_n^d)^{\sigma-1}-1)}\Big(\frac{Q_{n,t-1}^{s,pill}}{A_{n,t-1}^{s,spill}}\Big)^{\gamma(\sigma-1)}\frac{(p_{ct}^s)^{\sigma}Y_{ct}^s(\tau_{nc})^{1-\sigma}+(p_{rt}^s)^{\sigma}Y_{rt}^s(\tau_{nr})^{1-\sigma}}{(1-s_{nt})^{\sigma-1}(p_{nt}^d)^{\sigma}Y_{nt}^d}\Big]^{\frac{1}{\kappa_n}}$$

B.4 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:

$$\frac{dlog p_{nt}}{dlog p_{nt}^e} = \alpha(B_n^e)^{\psi-1}(\frac{p_{nt}}{p_{nt}^e})^{\psi-1} = \frac{p_{nt}^e Y_{nt}^e}{p_{nt}Y_{nt}} > 0$$

$$\frac{dlog p_{nt}^e}{dlog p_{nt}^s} = \alpha_s(\frac{p_{nt}^e}{p_{nt}^s})^{\xi-1} = \frac{p_{nt}^s Y_{nt}^s}{p_{nt}^e Y_{nt}^e} > 0$$

$$\frac{dlog p_{nt}^s}{dlog s_{ct}} = -(p_{nt}^s)^{\sigma-1}\left(\frac{\tau_{nc}(1-s_{ct})A_{ct}^p}{Q_{ct}^s}\right)^{1-\sigma}\frac{s_{ct}}{1-s_{ct}} = \underbrace{-\frac{s_{ct}}{1-s_{ct}}\frac{\int_0^{M_c} p_{nct}^i x_{nct}^i di}{p_{nt}^s Y_{nt}^s}}_{<0}$$

$$\frac{dlog p_{nt}^d}{dlog s_{ct}} = 0$$

B.4.1 Static effects

We first consider the static effects, taking the technologies level as given. The elasticities above show that the price of solar energy generation decreases in both regions, while the price of non-solar energy is unaffected.

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

$$\frac{dlog p_{rt}^s}{dlog s_{ct}} - \frac{dlog p_{ct}^s}{dlog s_{ct}} = \left(\frac{(1-s_{ct})A_{ct}^p}{Q_{ct}^s}\right)^{1-\sigma}\frac{s}{1-s}\left((p_{ct}^s)^{\sigma-1} - \tau_{rc}^{1-\sigma}(p_{rt}^s)^{\sigma-1}\right)$$

We can show that $(p_{ct}^s)^{\sigma-1} - \tau_{rc}^{1-\sigma}(p_{rt}^s)^{\sigma-1} > 0$. Indeed,

$$\begin{aligned}
&(p_{ct}^s)^{\sigma-1} - \tau_{rc}^{1-\sigma}(p_{rt}^s)^{\sigma-1} > 0\\
\Rightarrow\ &(p_{rt}^s)^{1-\sigma} > \tau_{rc}^{1-\sigma}(p_{ct}^s)^{1-\sigma}\\
\Rightarrow\ &\Big(\frac{\tau_{rc}(1-s_{ct})A_{ct}^p}{Q_{ct}^s}\Big)^{1-\sigma} + \Big(\frac{A_{rt}^p}{Q_{rt}^s}\Big)^{1-\sigma} > \Big(\frac{\tau_{rc}(1-s_{ct})A_{ct}^p}{Q_{ct}^s}\Big)^{1-\sigma} + \Big(\frac{\tau_{cr}\tau_{rc}A_{rt}^p}{Q_{rt}^s}\Big)^{1-\sigma}\\
\Rightarrow\ &1 > \frac{1}{(\tau_{cr}\tau_{rc})^{(\sigma-1)}}
\end{aligned}$$

Which holds, since $\sigma > 1$ and $\tau_{nf} > 1$.

Chinese terms of trade deteriorate. The terms of trade of region n are

$$TOT_{nt} = \frac{\left(\int_{M_n} (p^i_{fnt})^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}}{\left(\int_{M_f} (p^i_{nft})^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}} = \frac{\tau_{fn}(1-s_{nt}) A^p_{nt} Q^s_{ft}}{\tau_{nf}(1-s_{ft}) A^p_{ft} Q^s_{nt}}$$

For $n = c$, $s_{ct} > 0$. Therefore, TOT_{ct} decreases at a given technology level, because Chinese exports become relatively cheaper.

For a small subsidy and sufficiently large ν, aggregate output increases in the RoW and decreases in China. Total output, which determines the scale effect on solar and non-solar output, is determined by the budget constraint, since households are hand-to-mouth. Total output will vary following the change in total price, as well as through the reallocation of inputs subject to different tax distortions:

$$\begin{aligned}
p_{nt} Y_{nt} &= \frac{\sigma}{\sigma-1}\frac{1}{\nu} w_{nt} L_{nt} - s_{nt} \frac{\sigma}{\sigma-1}\frac{1}{\nu} w_{nt} L^s_{nt} - s^{p_s}_{nt} p^s_{nt} Y^s_{nt} \\
\Rightarrow Y_{nt} &= \frac{\sigma}{\sigma-1}\frac{1}{\nu}\left(\frac{\sigma-1}{\sigma}\frac{A^p_{nt}}{p_{nt}}\right)^{\frac{1}{\nu}} L_{nt} - s_{nt}\frac{\sigma}{\sigma-1}\frac{1}{\nu}\frac{w_{nt} L^s_{nt}}{p_{nt}} - s^{p_s}_{nt}\frac{p^s_{nt} Y^s_{nt}}{p_{nt}}
\end{aligned}$$

Therefore,

$$\begin{aligned}
\frac{\partial Y_{nt}}{\partial s_{ct}} = &- \frac{\sigma}{\sigma-1}\frac{1}{\nu}\left(\frac{\sigma-1}{\sigma}\frac{A^p_{nt}}{p_{nt}}\right)^{\frac{1}{\nu}} L_{nt}\frac{1}{\nu}\frac{\partial log p_{nt}}{\partial s_{ct}} \\
&- \frac{\sigma}{\sigma-1}\frac{1}{\nu}\frac{w_{nt} L^s_{nt}}{p_{nt}}\left(1 \times \mathbf{1}\{n=c\} + s_{nt}\frac{\partial log(w_{nt} L^s_{nt})}{\partial s_{ct}} - s_{nt}\frac{\partial log p_{nt}}{\partial s_{ct}}\right) \\
&- s^{p_s}_{nt}\frac{p^s_{nt} Y^s_{nt}}{p_{nt}}\left(\frac{\partial log(p^s_{nt} Y^s_{nt})}{\partial s_{ct}} - \frac{\partial log p_{nt}}{\partial s_{ct}}\right)
\end{aligned}$$

For small subsidies ($s_{nt} \approx 0, s^{p_s}_{nt} \approx 0$),[44] this simplifies to

$$\begin{aligned}
\frac{\partial Y_{nt}}{\partial s_{ct}}_{|s\approx 0} &= -\frac{\sigma}{\sigma-1}\frac{1}{\nu}\left(\frac{\sigma-1}{\sigma}\frac{A^p_{nt}}{p_{nt}}\right)^{\frac{1}{\nu}} L_{nt}\frac{1}{\nu}\frac{\partial log p_{nt}}{\partial s_{ct}} - \frac{\sigma}{\sigma-1}\frac{1}{\nu}\frac{w_{nt} L^s_{nt}}{p_{nt}} \times \mathbf{1}\{n=c\} \\
&= \underbrace{\frac{\sigma}{\sigma-1}\frac{1}{\nu}\frac{w_{nt}}{p_{nt}} L_{nt}}_{=Y_{nt} \text{ if } s\approx 0}\left(-\frac{1}{\nu}\frac{\partial log p_{nt}}{\partial s_{ct}} - \frac{L^s_{nt}}{L_{nt}} \times \mathbf{1}\{n=c\}\right) \\
\Rightarrow \frac{\partial log Y_{nt}}{\partial log s_{ct}}_{|s\approx 0} &= -\frac{1}{\nu}\frac{\partial log p_{nt}}{\partial log s_{ct}} - s_{nt}\frac{L^s_{nt}}{L_{nt}} \times \mathbf{1}\{n=c\}
\end{aligned}$$

[44] Formally, this is equivalent to log-linearizing around a steady-state value with no subsidy ($\bar{s}_{nt} = 0, \bar{s}^{p_s}_{nt} = 0$, and $\hat{x} = \frac{x_{nt} - \bar{x}_{nt}}{\bar{x}_{nt}}$), which yields: $\hat{Y}_{nt} = \frac{1}{\nu}\hat{p}_{nt} + \hat{s}_{nt}\frac{\sigma}{\sigma-1}\frac{1}{\nu}\frac{\bar{w}_{nt}\bar{L}^s_{nt}}{\bar{p}_{nt}\bar{Y}_{nt}}$

Since $\frac{\partial logp_{nt}}{\partial s_{ct}} = \frac{dlogp_{nt}}{dlogp^e_{nt}} \frac{dlogp^e_{nt}}{dlogp^s_{nt}} \frac{dlogp^s_{nt}}{dlogs_{ct}} < 0$,

$$\frac{\partial Y_{rt}}{\partial s_{ct}} > 0$$

In the RoW: total output increases with the subsidy.

In China, the distortion decreases total output. If ν is not too small, we can show that the scale effect is negative. Indeed, as $\nu \to 1$, there is no initial distortion, meaning that introducing a subsidy harms global output. Since RoW output increases, Chinese output must decrease by more. Formally, evaluating the derivative at $(s_{nt} = 0, s^{p_s}_{nt} = 0)$, which implies that $P_{nt}Y_{nt} = \frac{\sigma}{\sigma-1}\frac{1}{\nu}w_{nt}L_{nt}$:

$$\begin{aligned}
-\frac{1}{\nu}\frac{\partial logp_{nt}}{\partial s_{ct}} - \frac{L^s_{nt}}{L_{nt}} &= -\frac{1}{\nu}\frac{\partial logp_{nt}}{\partial s_{ct}} - \frac{w_{nt}L^s_{nt}}{w_{nt}L_{nt}} = \frac{1}{\nu}\frac{1}{1-s_{ct}}\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p_{ct}Y_{ct}} - \nu\frac{\sigma-1}{\sigma}\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di + \int_0^{M_c} p^i_{rct}x^i_{rct}di}{(1-s_{ct})wL_{nt}} \\
&= \frac{1}{1-s_{ct}}\left(\frac{1}{\nu}\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p_{ct}Y_{ct}} - \frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di + \int_0^{M_c} p^i_{rct}x^i_{rct}di}{P_{ct}Y_{ct}}\right) < 0 \quad \text{for } \nu \text{ not too small}
\end{aligned}$$

In China: total output decreases with the subsidy if ν us not too small[45].

For a small subsidy, solar production increases with the subsidy in both regions. Recall that

$$\begin{aligned}
Y^s_{nt} = \alpha_s\left(\frac{p^e_{nt}}{(1-s^{p^s}_{nt})p^s_{nt}}\right)^{\xi} Y^e_{nt} &= \alpha_s\left(\frac{p^e_{nt}}{(1-s^{p^s}_{nt})p^s_{nt}}\right)^{\xi}\alpha(B^e_n)^{\psi-1}\left(\frac{p_{nt}}{p^e_{nt}}\right)^{\psi} Y_{nt} \\
&= \alpha^s\alpha(B^e_n)^{\psi-1}(1-s^{p^s}_{nt})^{-\xi}(p^s_{nt})^{-\xi}(p^e_{nt})^{\xi-\psi}(p_{nt})^{\psi}Y_{nt}
\end{aligned}$$

[45] ν amplifies the price effect on total output, through roundabout production. Therefore, if ν is small, the multiplier effect is larger as production relies more on the final good. If solar constitutes a large share of production, which implies that the effect on total price is large, the subsidy could increase total output. Intuitively, this channel arises because the monopoly distortions imply that the economies are producing too little, meaning that they are using too little final good in production. The subsidy partially corrects for that distortion by boosting production. However, since it is only applied to the solar sector, it creates inter-sectoral distortions. The larger the solar sector, the closer to the efficient correction, which would cover all producing sectors, the subsidy will be.

Therefore,

$$\frac{dlogY^s_{nt}}{dlogs_{ct}} =$$

$$\underbrace{-\xi\frac{dlogp^s_{nt}}{dlogs_{ct}} + (\xi-\psi)\left(\frac{dlogp^e_{nt}}{dlogp^s_{nt}}\frac{dlogp^s_{nt}}{dlogs_{ct}} + \frac{dlogp^e_{nt}}{dlogp^d_{nt}}\underbrace{\frac{dlogp^d_{nt}}{dlogs_{ct}}}_{=0}\right) + \psi\frac{dlogp_{nt}}{dlogp^e_{nt}}\left(\frac{dlogp^e_{nt}}{dlogp^s_{nt}}\frac{dlogp^s_{nt}}{dlogs_{ct}} + \frac{dlogp^e_{nt}}{dlogp^d_{nt}}\underbrace{\frac{dlogp^d_{nt}}{dlogs_{ct}}}_{=0}\right)}_{\text{Substitution effects}}$$

$$+ \underbrace{\frac{dlogY_{nt}}{dlogs_{ct}}}_{\text{Scale effects}}$$

We consider small subsidies, such that we can approximate the scale effect by

$$\frac{\partial logY_{nt}}{\partial logs_{ct}}_{|s\approx 0} = -\frac{1}{\nu}\frac{\partial logp_{nt}}{\partial logs_{ct}} - s_{nt}\frac{L^s_{nt}}{L_{nt}} \times \mathbf{1}\{n=c\}$$

In that case,

$$\frac{dlogY^s_{nt}}{dlogs_{ct}} = -\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\left[\xi - \frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}}\left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}}\right)\right] - s_{nt}\frac{L^s_{nt}}{L_{nt}} \times \mathbf{1}\{n=c\}$$

Expenditure shares are weakly smaller than 1 and weakly positive and $\nu < 1$. Suppose that $\sigma > \xi > 1 > \psi > 0$. Then $\frac{1}{\nu} - \psi > 0$. Since $\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}} \geq 0$, $\xi - \psi \geq \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\underbrace{\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}}}_{\leq 1}\right)$.
Therefore, it is straightforward to show that solar output increases in the RoW:

$$\frac{dlogY^s_{rt}}{dlogs_{ct}} \geq -\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\psi > 0$$

In China, the substitution effect and the scale effect go in opposite direction:

$$\frac{dlogY^s_{ct}}{dlogs_{ct}} = \frac{s_{ct}}{1-s_{ct}}\left(\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p^s_{ct}Y^s_{ct}}\left[\xi - \frac{p^s_{ct}Y^s_{ct}}{p^e_{ct}Y^e_{ct}}\left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{ct}Y^e_{ct}}{p_{ct}Y_{ct}}\right)\right] - \frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di + \int_0^{M_c} p^i_{rct}x^i_{rct}di}{P_{ct}Y_{ct}}\right)$$

The scale effect is the most negative in the limit where $\nu \to 1$. Thus, this case is a lower bound for the effect on solar output. With $\nu \to 1$, we get

$$
\begin{aligned}
\frac{dlogY^s_{ct}}{dlogs_{ct}} &= \frac{s_{ct}}{1-s_{ct}}\left(\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p^s_{ct}Y^s_{ct}}\left[\xi-\frac{p^s_{ct}Y^s_{ct}}{p^e_{ct}Y^e_{ct}}\left((\xi-\psi)+\psi\frac{p^e_{ct}Y^e_{ct}}{p_{ct}Y_{ct}}\right)\right]-\frac{\int_0^{M_c} p^i_{rct}x^i_{rct}di}{P_{ct}Y_{ct}}\right)\\
&\geq \frac{s_{ct}}{1-s_{ct}}\left(\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p^s_{ct}Y^s_{ct}}\left[\xi-\frac{p^s_{ct}Y^s_{ct}}{p^e_{ct}Y^e_{ct}}(\xi-\psi)\right]-\frac{\int_0^{M_c} p^i_{rct}x^i_{rct}di}{P_{ct}Y_{ct}}\right)\\
&\geq \frac{s_{ct}}{1-s_{ct}}\left(\xi\frac{\int_0^{M_c} p^i_{cct}x^i_{cct}di}{p^s_{ct}Y^s_{ct}}-\frac{\int_0^{M_c} p^i_{rct}x^i_{rct}di}{P_{ct}Y_{ct}}\right)\\
&= \frac{s_{ct}}{1-s_{ct}}\left(\xi\frac{(p^s_{ct})^\sigma Y^s_{ct}}{p^s_{ct}Y^s_{ct}}-\frac{(p^s_{rt})^\sigma Y^s_{rt}\tau_{rc}^{1-\sigma}}{P_{ct}Y_{ct}}\right)\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}\\
&= \frac{s_{ct}}{1-s_{ct}}\left(\xi(p^s_{ct})^{\sigma-1}-\frac{(p^s_{rt})^{\sigma-1}p^s_{rt}Y^s_{rt}\tau_{rc}^{1-\sigma}}{P_{ct}Y_{ct}}\right)\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}\\
&= \frac{s_{ct}}{1-s_{ct}}\left(\xi(p^s_{ct})^{\sigma-1}-\left(\frac{p^s_{rt}}{\tau_{rc}}\right)^{\sigma-1}\frac{p^s_{rt}Y^s_{rt}}{P_{ct}Y_{ct}}\right)\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}\\
&= \frac{s_{ct}}{1-s_{ct}}\left(\xi\left[\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}+\left(\frac{Q^s_{rt}}{(1-s_{ct})A^p_{rt}}\tau_{rc}\right)^{\sigma-1}\right]^{-1}\right.\\
&\left.-\left[\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}+\left(\frac{Q^s_{rt}\tau_{cr}}{(1-s_{ct})A^p_{rt}}\right)^{\sigma-1}\right]^{-1}\frac{p^s_{rt}Y^s_{rt}}{P_{ct}Y_{ct}}\right)\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}
\end{aligned}
$$

$\xi > 1$ and $\left[\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}+\left(\frac{Q^s_{rt}}{(1-s_{ct})A^p_{rt}}\tau_{rc}\right)^{\sigma-1}\right]^{-1} > \left[\left(\frac{Q^s_{ct}}{(1-s_{ct})A^p_{ct}}\right)^{\sigma-1}+\left(\frac{Q^s_{rt}\tau_{cr}}{(1-s_{ct})A^p_{rt}}\right)^{\sigma-1}\right]^{-1}$ due to the trade costs. Therefore, as long as $\frac{\int_{M_r}^1 p^i_{rrt}x^i_{rrt}di}{P_{ct}Y_{ct}}$ is not too large,[46] the lower bound of the effect of the subsidy on Chinese solar energy generation is positive. Therefore,

$$
\frac{dlogY^s_{ct}}{dlogs_{ct}} \geq 0
$$

Solar output increases in China.

For a small subsidy, fossil fuel production decreases with the subsidy in both regions. Recall that

$$
\begin{aligned}
Y^d_{nt} = \alpha_d\left(\frac{p^e_{nt}}{p^d_{nt}}\right)^\xi Y^e_{nt} &= \alpha_d\left(\frac{p^e_{nt}}{p^d_{nt}}\right)^\xi \alpha(B^e_n)^{\psi-1}\left(\frac{p_{nt}}{p^e_{nt}}\right)^\psi Y_{nt}\\
&= \alpha_d\alpha(B^e_n)^{\psi-1}(p^d_{nt})^{-\xi}(p^e_{nt})^{\xi-\psi}(p_{nt})^\psi Y_{nt}
\end{aligned}
$$

[46] Indeed, $\frac{p^s_{rt}Y^s_{rt}}{p_{ct}Y_{ct}} = \frac{\int_{M_r}^1 p^i_{rrt}x^i_{rrt}di}{P_{ct}Y_{ct}} + \underbrace{\frac{\int_{M_r}^1 p^i_{rrt}x^i_{rrt}di}{P_{ct}Y_{ct}}}_{<1}$.

Therefore,

$$\frac{dlogY^d_{nt}}{dlogs_{ct}} =$$

$$\underbrace{-\xi \underbrace{\frac{dlogp^d_{nt}}{dlogs_{ct}}}_{=0} +(\xi-\psi)\left(\frac{dlogp^e_{nt}}{dlogp^s_{nt}}\frac{dlogp^s_{nt}}{dlogs_{ct}}+\frac{dlogp^e_{nt}}{dlogp^d_{nt}}\underbrace{\frac{dlogp^d_{nt}}{dlogs_{ct}}}_{=0}\right)+\psi\frac{dlogp_{nt}}{dlogp^e_{nt}}\left(\frac{dlogp^e_{nt}}{dlogp^s_{nt}}\frac{dlogp^s_{nt}}{dlogs_{ct}}+\frac{dlogp^e_{nt}}{dlogp^d_{nt}}\underbrace{\frac{dlogp^d_{nt}}{dlogs_{ct}}}_{=0}\right)}_{\text{substitution effects}}$$

$$+\underbrace{\frac{dlogY_{nt}}{dlogs_{ct}}}_{\text{scale effect}}$$

We again focus on small subsidies. In that case,

$$\frac{dlogY^d_{nt}}{dlogs_{ct}} = \underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}}\left((\xi-\psi)-(\frac{1}{\nu}-\psi)\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}}\right)-s_{nt}\frac{L^s_{nt}}{L_{nt}}\times \mathbf{1}\{n=c\}$$

Suppose that $\sigma > \xi > 1 > \psi > 0$. As before, this means that $\left((\xi-\psi)-(\frac{1}{\nu}-\psi)\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}}\right)$ is bounded from above by $\xi-\psi$, while it is bounded from below by $\xi-\frac{1}{\nu}$. For ν not too small, the latter is positive. Therefore,

$$\frac{dlogY^d_{nt}}{dlogs_{ct}} \leq \underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}(\xi-\frac{1}{\nu}) \leq 0$$

The subsidy distortion $s_{nt}\frac{L^s_{nt}}{L_{nt}}\times \mathbf{1}\{n=c\}$ only reinforces the negative effect on the Chinese non-solar sector by decreasing the scale effect.

B.4.2 Dynamic effects

The firms' innovation decision can be written as

$$(\frac{R^s_{nt}}{R^d_{nt}})^{\kappa_n} = \frac{\eta^s_n((1+\lambda_s)^{\sigma-1}-1)}{\sigma-1(1-s^{RD}_{nt})\eta^d_n((1+\lambda_d)^{\sigma-1}-1)}\left(\frac{Q^{s,spill}_{n,t-1}}{A^{d,spill}_{n,t-1}}\right)^{\gamma(\sigma-1)}\frac{(p^s_{ct})^\sigma Y^s_{ct}(\tau_{nc})^{1-\sigma}+(p^s_{rt})^\sigma Y^s_{rt}(\tau_{nr})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}}$$

For a given level of technology:

$$
\frac{dlog((\frac{R^s_{nt}}{R^d_{nt}})^{\kappa_n})}{dlog(s_{nt})} = \underbrace{(\sigma-1)\frac{s_{nt}}{1-s_{nt}}}_{\text{=0 in the RoW ; mc effect}} + \frac{1}{\frac{(p^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt} + \frac{(p^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct}}
$$

$$
\times \left[\frac{(p^s_{rt})^\sigma}{\tau_{rn}^{\sigma-1}}Y^s_{rt} \left(\underbrace{\frac{dlogp^s_{rt}}{dlogs_{ct}}}_{<0} \left[(\sigma-\xi) + \frac{p^s_{rt}Y^s_{rt}}{p^e_{rt}Y^e_{ct}} \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{rt}Y^e_{rt}}{p_{rt}Y_{rt}} \right) \right] \right) + \right.
$$

$$
\left. \frac{(p^s_{ct})^\sigma}{\tau_{cn}^{\sigma-1}}Y^s_{ct} \left(\underbrace{\frac{dlogp^s_{ct}}{dlogs_{ct}}}_{<0} \left[(\sigma-\xi) + \frac{p^s_{ct}Y^s_{ct}}{p^e_{ct}Y^e_{ct}} \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{ct}Y^e_{ct}}{p_{ct}Y_{ct}} \right) \right] - s_{ct}\frac{L^s_c}{L_{ct}} \right) \right]
$$

$$
- \left(\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0} \frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}} \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}} \right) - s_{nt}\frac{L^s_{nt}}{L_{nt}} \times \mathbf{1}\{n=c\} \right)
$$

We can summarize the different effects as follows. The first term is the marginal cost effect: intermediate input producers that benefit from the subsidy see their marginal cost decrease. In the RoW, the marginal cost effect is null, since intermediate input producers don't benefit from the subsidy. $(\sigma-\xi)$ is the direct negative effect on solar price. Finally, $(\xi-\psi)-(\frac{1}{\nu}-\psi)\frac{p^e_{nt}Y^e_{nt}}{p_{nt}Y_{nt}}$ reflects the energy and total output price decrease. The decrease in energy price increases the demand, hence the revenue, of both solar and non-solar inputs. Because the production input and energy are complementary, the energy price decreases *decreases* the revenue of the energy input (ψ). However, the final good price increases energy, hence solar, demand through the scale effect ($\frac{1}{\nu}$).

We've already shown that the non-solar output Y^d_{nt} decreases unambiguously with the subsidy (for ν not too small), while its price is left unaffected. Therefore, the last line contributes to increasing solar innovation for both regions.

We focus on the solar terms:

$$
\left[(\sigma-\xi) + \frac{p^s_{rt}Y^s_{rt}}{p^e_{rt}Y^e_{ct}} \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{rt}Y^e_{rt}}{p_{rt}Y_{rt}} \right) \right]
$$

Suppose that $\sigma > \xi > 1 > \psi > 0$. Because expenditures share are weakly positive and weakly lower than one, and because $\nu \leq 1$, then if ν is not too small:

$$
\left[(\sigma-\xi) + \frac{p^s_{rt}Y^s_{rt}}{p^e_{rt}Y^e_{ct}} \left((\xi-\psi) - (\frac{1}{\nu}-\psi)\frac{p^e_{rt}Y^e_{rt}}{p_{rt}Y_{rt}} \right) \right] \geq \min\{\sigma-\xi, \sigma-\frac{1}{\nu}\} \geq 0
$$

Therefore, in the RoW, the expected marginal profits from solar unambiguously decrease. The overall effect on solar innovation effort depends on how this decrease compares to the decrease in the expected marginal profits from non-solar. Since the latter doesn't suffer from a direct price effect ($(\sigma-\xi)$), it is likely dominated. To get more intuitions, we can rewrite:

$$(\frac{R^s_{nt}}{R^d_{nt}})^{\kappa_n} = \frac{\eta^s_n((1+\lambda_s)^{\sigma-1}-1)}{(1-s_{nt})^{\sigma-1}(1-s^{RD}_{nt})\eta^d_n((1+\lambda_d)^{\sigma-1}-1)}\Big(\frac{Q^{s,spill}_{n,t-1}}{A^{d,spill}_{n,t-1}}\Big)^{\gamma(\sigma-1)}$$
$$\times \frac{1}{(1-s_{nt})^{\sigma-1}}\left(\frac{(p^s_{ft})^\sigma Y^s_{ft}(\tau_{nf})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}} + \frac{\alpha_s(1-s^{p_s}_{nt})}{\alpha_d}\left(\frac{p^s_{nt}}{p^d_{nt}}\right)^{\sigma-\xi}\right)$$

Therefore,

$$\frac{dlog((\frac{R^s_{nt}}{R^d_{nt}})^{\kappa_n})}{dlog(s_{nt})} = \underbrace{(\sigma-1)\frac{s_{nt}}{1-s_{nt}}}_{\text{=0 in the RoW ; mc effect}} + \left(\frac{(p^s_{ft})^\sigma Y^s_{ft}(\tau_{nf})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}} + \frac{\alpha_s(1-s^{p_s}_{nt})}{\alpha_d}\left(\frac{p^s_{nt}}{p^d_{nt}}\right)^{\sigma-\xi}\right)^{-1}$$
$$\times\Bigg[\frac{(p^s_{ft})^\sigma Y^s_{ft}(\tau_{nf})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}}\Bigg((\sigma-\xi)\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} + (\xi-\psi)\left(\frac{p^s_{ft}Y^s_{ft}}{p^e_{ft}Y^e_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right)$$
$$-(\frac{1}{\nu}-\psi)\left(\frac{p^s_{ft}Y^s_{ft}}{p_{ft}Y_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p_{nt}Y_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right) - s_{ft}\frac{L^s_{ft}}{L_{ft}}\times\mathbf{1}\{f=c\} + s_{nt}\frac{L^s_{nt}}{L_{nt}}\times\mathbf{1}\{n=c\}\Bigg)$$
$$\frac{\alpha_s(1-s^{p_s}_{nt})}{\alpha_d}\left(\frac{p^s_{nt}}{p^d_{nt}}\right)^{\sigma-\xi}(\sigma-\xi)\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\Bigg]$$
$$= \underbrace{(\sigma-1)\frac{s_{nt}}{1-s_{nt}}}_{\text{=0 in the RoW ; mc effect}} -(\sigma-\xi)\frac{s_{ct}}{1-s_{ct}}\frac{\int_0^{M_c}p^i_{nct}x^i_{nct}di}{p^s_{nt}Y^s_{nt}} + \left(\frac{(p^s_{ft})^\sigma Y^s_{ft}(\tau_{nf})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}} + \frac{\alpha_s(1-s^{p_s}_{nt})}{\alpha_d}\left(\frac{p^s_{nt}}{p^d_{nt}}\right)^{\sigma-\xi}\right)^{-1}$$
$$\times\Bigg[\frac{(p^s_{ft})^\sigma Y^s_{ft}(\tau_{nf})^{1-\sigma}}{(p^d_{nt})^\sigma Y^d_{nt}}\Bigg((\xi-\psi)\left(\frac{p^s_{ft}Y^s_{ft}}{p^e_{ft}Y^e_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right)$$
$$-(\frac{1}{\nu}-\psi)\left(\frac{p^s_{ft}Y^s_{ft}}{p_{ft}Y_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p_{nt}Y_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right) - s_{ft}\frac{L^s_{ft}}{L_{ft}}\times\mathbf{1}\{f=c\} + s_{nt}\frac{L^s_{nt}}{L_{nt}}\times\mathbf{1}\{n=c\}\Bigg)\Bigg]$$

As $\sigma > \xi$, the first line (direct price and marginal cost effects) is always positive (negative) in China (the RoW). Intuitively, as Chinese (RoW) solar intermediate input producers gain (lose) market shares[47], their expected profits increase (decrease) which redirect innovation toward the solar (non-solar) sector.

Because solar intermediate inputs are traded, there are terms-of-trade effects: if f as a comparative advantage in solar intermediate input production, the solar shares are relatively larger in magnitude in country f, relative to country n. Therefore, $\left(\frac{p^s_{ft}Y^s_{ft}}{p_{ft}Y_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p_{nt}Y_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right) < 0$ and $\left(\frac{p^s_{ft}Y^s_{ft}}{p^e_{ft}Y^e_{ft}}\underbrace{\frac{dlogp^s_{ft}}{dlogs_{ct}}}_{<0} - \frac{p^s_{nt}Y^s_{nt}}{p^e_{nt}Y^e_{nt}}\underbrace{\frac{dlogp^s_{nt}}{dlogs_{ct}}}_{<0}\right) < 0$. Intuitively, this is because domestic non-solar is relatively less affected than foreign solar, which, in turn, affects domestic solar demand. Reasonably, solar expenditures are only a small share of the economy total revenue. In that case, the latter is likely smaller in magnitude, and the relative foreign effect will disincentive solar innovation (abstracting from the subsidy distortion).

Therefore, if China has a comparative advantage in solar, the price effect and the term-of-trade effect go in the same direction in the RoW: RoW innovation effort decreases. Correspondingly, the marginal cost effect (which dominates the price effect) and the (small) term-of-trade effect go in the same direction and Chinese innovation effort increases. If the RoW has a comparative advantage in solar, the effect is ambiguous, but the price effect is likely to dominate since the weight on the foreign effect will be tiny, while the weights on the domestic relative price effects will be large.

[47]Because $\sigma > \xi$, RoW solar intermediate input producers are more affected by the competition from the Chinese solar intermediate than the non-solar sector. Therefore, they lose relatively more market share.