Ray of Hope? China and the Rise of Solar Energy

Ignacio Banares-Sanchez, Robin Burgess, David Laszlo,
Pol Simpson, John Van Reenen, and Yifan Wang*

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Abstract

Do industrial policies that promote clean energy offer a "ray of hope", increasing a country's growth and welfare, whilst simultaneously reducing carbon emissions? We study the impact of Chinese solar subsidies whose implementation by city-regions went alongside massive expansion of the sector and a dramatic fall in solar prices. We construct new city and firm panel data on solar policies, patenting and output. Using synthetic-difference-in-differences 2004-2020, we find production and innovation subsidies were more effective than demand-side (installation) subsidies in generating large and persistent increases in local innovation, net entry, output and exports. Demand policies did, however, reduce local pollution. To examine aggregate effects, we build and structurally estimate a quantitative spatial model with endogenous innovation and heterogeneous productivity across firms and cities, which accounts for business stealing and knowledge spillovers. Counterfactual analysis shows that: (i) local effects remain substantial at the macro level explaining 40%-50% of the aggregate changes in solar innovation, prices and revenues; (ii) social benefits to Chinese citizens exceed subsidy costs by 65% (and double this when environmental benefits are included); and (iii) although all subsidy types increase welfare, innovation subsidies are the most cost-effective.

JEL classification: L5, L52, O31, H25, L25, N5
Keywords: Solar, Innovation, China, Industrial Policy, Renewable Subsidies, Climate Change

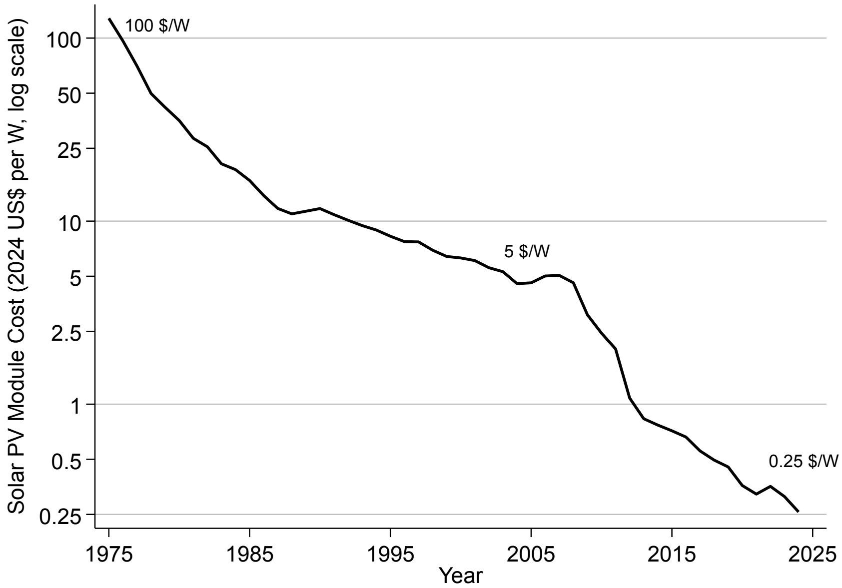
*Banares-Sanchez: LSE, i.banares-sanchez@lse.ac.uk, Burgess: LSE, r.burgess@lse.ac.uk, Laszlo: LSE, d.laszlo@lse.ac.uk, Simpson: LSE, p.simpson1@lse.ac.uk, Van Reenen: LSE and MIT, j.vanreenen@lse.ac.uk, Wang: LSE y.wang390@lse.ac.uk. We would like to thank participants in the Berkeley Energy Camp, Bank of Italy, Bocconi, Brussels NBB, Chicago EEE and IO seminars, Columbia, EIEF, HBS, LSE, Munich, NY Fed, Northwestern, Oslo, Oxford, Singapore, Stanford SITE, UCLA, USC, Yale and Zurich for comments on the paper. Particular thanks are due to Max Auffhammer, Fiona Burlig, Ken Gillingham, Michael Greenstone, Koichiro Ito, Kelsey Jack, Ravi Jagannathan, Bo Li, Jiahua Liu, Runhong Ma, Rob Metcalfe, Emily Nix, Nick Ryan, Joe Shapiro, Nico Voigtlander, Eric Verhoogen, Reed Walker and Zixian Zhong have given both great comments and generous help with data. Frederic Denker has provided superb research assistance. We would also like to thank the IGC, STICERD and the ESRC/UKRI through POID for helping to fund this work.

1 Introduction

What can one country achieve in the fight against climate change? Given the global externality from carbon emissions, addressing climate change is often seen as requiring coordinated international action. Such cooperation remains politically difficult, raising the question of whether unilateral efforts can meaningfully contribute to global decarbonisation. Industrial policy supporting clean technology offers a "ray of hope". It has the potential not only to reduce emissions without compromising economic growth, but also to deliver global benefits even when implemented by a single country.

This paper studies an important case, namely, the explosive rise of China's solar industry. Between 2004 and 2013, the annual production of Chinese solar firms grew by 76% per year, and by 2019, Chinese firms accounted for 89% of global solar patent filings, 63% of the production of PV 44% of exports. In 2023, China installed 217 GW of solar capacity, about the same as the rest of the world combined. This meteoric rise was accompanied by a wave of place-based subsidies implemented by local Chinese governments which are the main locus of industrial policy in China (Bai et al., 2020). Their implementation went hand in hand with a sharp decline in global solar panel prices (91% fall between 2004 and 2019) and a surge in solar adoption worldwide (173-fold increase in installed capacity over the same period). We ask whether this sequence reflects a causal link from local policy, to innovation and production, to falling global prices (see Figure 1).[1]

Figure 1: **Global average price of solar PV modules (in 2024 US$) per Watt**



Source: IRENA (2024a), Way et al. (2022), Farmer & Lafond (2016), & Nemet (2009) with processing by Our World in Data

[1]Statistics in this paragraph are based on the following sources: ENF production data, PATSTAT patenting data, IEA (2020) PV module shipment data, IRENA (2024b) global solar installation data, and PV module price data from IRENA (2024a), Farmer & Lafond (2016), and Nemet (2009) with processing from Our World in Data. See Section 2 and Appendix B for details on the first two sources.

Our analysis proceeds in two parts. First, we estimate the causal impact of local subsidies on solar industry outcomes - patenting, firm numbers, revenues, production and exports - by exploiting variation in whether and when local governments chose to adopt subsidies. In China, local governments use subsidies to boost economic activity in their jurisdictions. Since policy adoption may be correlated with other local shocks, we use a Synthetic Difference-In-Differences (SDID) approach, comparing treated cities to controls with similar pre-trends that never adopt solar subsidies (Arkhangelsky et al., 2021).

Second, to estimate the aggregate impact of these policies within China, we develop a quantitative spatial general equilibrium model with multiple city-regions with different productivity levels and trade costs. Each city is home to a grid planner reflecting consumer energy demand and heterogeneous firms (component manufacturers such as solar panel producers). Grid planners choose between clean and dirty plants (solar vs. coal) to generate power, sourcing intermediate inputs from across the country. Firms make entry, production, innovation and trade decisions in a setting with monopolistic competition. We analyse the impact of the three types of local industrial policy - demand, production and innovation subsidies at the city and aggregate national level. We allow for negative spillovers to other cities from business stealing (as might occur from production subsidies), as well as positive spillovers from demand policies (as firms in other cities may supply solar components), and - importantly - knowledge spillovers as we allow past innovation by other firms to spread across cities.

To undertake this analysis, we compile new city level panel data from 2004 to 2020, tracking solar policies and industry outcomes across all Chinese city-regions. Using the PKULaw database, which records all national and subnational regulations in China since 1949, we identify the universe of solar-related policy interventions. Using text analysis, we identify 78 solar subsidies and classify them by target - demand (installation), production and innovation - following Chen & Xie 2019 and Wang & Yang 2025. We analyse multiple solar industry outcomes using firm-level data drawn from supplier directories, administrative records, and financial databases. Our dataset spans 358 cities, 18 years and covers 1,718 solar firms. The first solar policy was in 2007 and by the end of our time period in 2020, 12% of cities had adopted at least one solar subsidy policy.

Using the SDID approach, we find that local subsidies triggered substantial and sustained growth in the local solar industry. Cities that adopted solar policies experienced a 64% average increase in patenting, equivalent to 8.4 additional patents per year for the average city-year in our sample. These local Average Treatement on the Treated (ATT) effects are robust to adjustments for patent quality and are mirrored by gains in productivity. Solar revenues, production capacity, exports and firm numbers all rose sharply following policy adoption. We also find declines in local air pollution, suggestive of broader global and local environmental benefits. Importantly, these effects seem to be persistent after the introduction of the subsidy consistent with what we would expect from effective industrial policies.

To examine the extent to which these local effects also bring benefits at the aggregate level, we quantify key parameters of the macro model in the pre-policy period using moments from the existing literature and our own new micro data. We then structurally estimate the magnitude of each of the three subsidy types using our reduced form ATT moments through minimum distance. Armed with the quantified model, we simulate the aggregate impact of subsidies, calculate welfare and evaluate counterfactual policy scenarios.

We find that local industrial policy drove aggregate growth in China's solar industry, rather than merely shifting activity across cities. Compared to a non-subsidy counterfactual, we estimate that these policies accounted for 45% of the increase in solar, 38% of the revenue increase and 50% of the fall in solar prices. Chinese consumer welfare from energy consumption rose by 12%. When we incorporate subsidy costs, we find that $1.65 of social benefit per $1 of subsidy cost, and that these benefits double when accounting for the social cost of carbon. A key finding from our counterfactuals is that although production and demand subsidies increase welfare, focusing resources on innovation subsidies is much more cost effective. This suggests that policies to support innovation should lie at the heart of industrial policies.

The structure of the paper is as follows. After a literature review, Section 2 describes a short background on China's solar industrial policy and our data. Section 3 describes the econometric strategy and the empirical results. Section 4 outlines the model with its quantification in Section 5. The results from the quantified model are in Section 6 and Section 7 concludes. Online Appendices provide further details on institutions (A), data (B), the theory and its quantification (C), econometrics (D) and results (E).

Related Literature. China's case pushes us to reconsider the set of tools available to address climate change. A large literature has focused on global co-ordination problems, emphasising free-riding and the need for treaties, coalitions, or trade-based enforcement (e.g. Nordhaus 2015, Hsiao 2025, Farrokhi & Lashkaripour 2025). Yet over the past two decades, China has pursued an unusually aggressive and decentralised clean industrial policy - especially in solar (e.g., Lin & Luan 2020, Zhi et al. 2014), but also in wind and electric vehicles - as part of a broader industrial strategy which has been the subject of existing research (Aghion et al. 2015; Li & Branstetter 2024; Song et al. 2011; König et al. 2022; Wei et al. 2023; Barwick et al. 2021; Wang & Yang 2025). We show that these policies were beneficial to Chinese citizens: they increased innovation, firm revenues, and exports, and their fiscal costs were outweighed by domestic benefits. The global benefits of lower prices and reduced emissions come on top of this. This suggests that under some conditions, industrial policy can be a rational form of unilateral climate action. It can not only drive innovation and growth in an industry, but also help with domestic and global decarbonization efforts.

Our findings relate to a broader literature that evaluates industrial policy. Early theoretical focused on Terms of Trade effects and infant industry protection. More recent work has emphasised the potential for productivity gains through coordination, scale effects, and/or learning (e.g. Murphy et al. 1989; Harrison & Rodríguez-Clare 2010; Rodrik 2004; Rodrik 2014; Buera et al. 2013; Itskhoki & Moll 2019; Bartelme et al. 2025; Liu 2019; Garg 2024). A smaller but growing empirical literature has used quasi-experimental methods to estimate firm-level impacts of national programmes (e.g. Criscuolo et al. 2019; Kalouptsidi 2018; Lane 2025; Lane 2020; Juhász et al. 2022; Goldberg et al. 2024). We contribute to this work by using China as a laboratory where the large number of local industrial policies aid empirical identification. Hence, we are connected to work on place-based industrial policy interventions (e.g., Greenstone et al. 2010; Kline & Moretti 2014).

Our paper makes methodological contributions, through the development of a rich quantitative macro model that captures multiple cross firm and cross city spillover effects and allows the integration of various reduced-form moments to enable a calculation of equilibrium impacts. This allows us to quantify aggregate impacts and welfare from the actual policies as well as many alternative policy counterfactuals. See Garg & Saxena (2025) for an example of a structural approach to the Indian solar industry. Our evidence on learning-by-doing mechanisms in patent data and from the impact of standalone production subsidies (even without R&D subsidies) is consistent with learning-by-doing mechanisms identified in prior work (e.g., Levitt et al. 2013; Bradt 2024; Manelici & Pantea 2021; Choi & Shim 2023; Goldberg et al. 2024).

We also speak to the literature on directed technical change. Green technologies have been a focus of the empirical literature in this area, looking at the role of oil price shocks as a proxy for carbon pricing (e.g. Acemoglu et al. 2012; Aghion et al. 2016; Acemoglu et al. 2016; Dugoua & Gerarden 2025; Popp 2002; Popp 2019), as well as more recent work on direct support through R&D subsidies, regulation, and procurement (e.g. Howell 2017; Myers & Lanahan 2022; Shapiro & Walker 2018; Arkolakis & Walsh 2023; Dechezleprêtre & Hémous 2023; Acemoglu et al. 2023). We show that production-oriented policies can also play a central role, driving innovation, scale-up, and global price declines in solar (see also Gao & Rai 2019).

More broadly, we contribute to the literature on innovation policy - e.g., Bloom et al. (2019); Goolsbee & Jones (2022); Liu & Ma (2022). We show how demand and production subsidy polices influence innovation, but demonstrate that direct R&D subsidies have the largest aggregate effects both on innovation and welfare. Hence, innovation seems key to successful industrial strategy.

Finally, and most obviously, we contribute to papers on the economics of solar power. For a recent survey see Gerarden et al. (2025) and earlier work by Borenstein (2012), Borenstein (2017) and Baker et al. (2013) for an overview of the economic issues. Hahn et al. (2024) compares a range of climate tax policies in a Marginal Value of Public Funds framework, concluding that renewable energy subsidies have highest taxpayer return, similar to Borenstein & Kellogg (2023). Other leading contributions include Gillingham & Bollinger (2021); De Groote & Verboven (2019); Gonzales et al. (2023); Van Benthem et al. (2008); Gillingham & Tsvetanov (2019); Gerarden (2023).

2 Background and Data

We gather data on the Chinese solar industry during this period of extensive policy support, resulting in essentially the population of local solar industrial policies and solar outcomes aggregated to the city-level. Full data details are in Appendix B.

2.1 Institutional Setting: Local Industrial Policy in China

Our analysis focuses on the central contribution of city-level industrial policies to the development of the solar industry in China. More institutional details are in Appendix A. China has a five-tier administrative framework: Central, Provincial, City, County and Township governments. Subnational governments have strong administrative capacities and are responsible for most of the state's public service delivery, partly due to the country's size and complexity (Wingender, 2018). For example, in 2013 in the middle of our data period, the OECD scored China as the most fiscally decentralized country in terms of public expenditure in their sample (OECD, 2016). Local governments also have effective control over regional labor and land inputs, as well as state-owned enterprises operating in their jurisdictions, which offers them a wide toolkit of policy instruments.

While the central government is responsible for guiding national policies,[2] local governments implement these policies with a great degree of autonomy (Xu, 2011; Bai et al., 2020). Beyond economic benefits, career incentives contingent on regional performance measures, like GDP growth, facilitate fierce competition among local policymakers to build and grow strategic industries. (Jia et al., 2015; Li & Zhou, 2005) The resulting close cooperation between regional policy-makers and private firms, termed "special deals" by Bai et al. (2020), have been argued to be central to China's industrial development. The importance of bottom-up, autonomous policy-making is also reflected in Fang et al. (2025)'s recent study, which utilises large language models to identify and analyze over 770,000 Chinese industrial policy documents. They find that 84% of policies originate from subnational governments. They further find systematic variation in the content of policies depending on the level of government, with fiscal subsidies, labor policies, land supply policies, and infrastructural investments being increasingly more common at lower levels, and a substantial degree of variation in policy content within higher-level jurisdictions at all levels.

These broad patterns are also reflected in the history of the solar industry. City governments have been at the forefront of initiating manufacturing policies, utilizing subsidies, tax incentives, land discounts, and cash investments from 2007 onwards, to build, support and attract solar firms in this initially export-oriented sector (Ball et al., 2017).[3] Following the designation of the solar industry as a strategic sector in the Tenth Five-Year Plan, central

[2]The most famous component of Chinese industrial strategy are the 'Five-Year Plans', which reflect national priorities and provide guidance for policy-makers at all levels of government.

[3]Examples of close cooperation between firms and cities include LDK Solar based in Xinyu and Suntech based in Wuxi (Corwin & Johnson, 2019).

and provincial governments have focused mostly on developing the domestic market by subsidising installations, especially after the industry-threatening weakening of international demand in the wake of the global financial crisis (Chen, 2016).

2.2 Measuring industrial policy

Measuring industrial policy is challenging, particularly when it is decentralised. Our approach is to combine direct textual analysis of policy documents with model-based approaches to detect subsidies.[4] Turning to the direct approach first, our starting point is PKULaw's Laws & Regulations database (henceforth "PKULaw"), a comprehensive source of Chinese legal information since 1949, although the first subnational solar policy appears in 2007. From this dataset, we extract and classify all policies/regulations related to solar photovoltaics, focusing on subsidies policies that provide direct financial support. The dataset has the title of the policy, its administrative level, department, and implementation dates. We scrape the text of each regulation, manually read through each one, then classify policies into key types. The key ones are demand (solar installation), production, and/or innovation.[5] Table 1 shows our classification criteria and key examples and Appendix Table B.1 offers some further examples. Subsidies include tax breaks, price reductions, cheap loans and land, etc.

We identify 78 city (equivalent to "admin 2 region" or "municipality") level subsidy policies in total, with demand subsidies being the most common (61 policies).There are 27 production subsidies, 12 of which also include innovation subsidies. Notably, no city implemented innovation subsidies without production subsidies, meaning our empirical analysis can study the impact of standalone demand or production policies, but only the bundle of innovation and production policies. As detailed below, we will unbundle the independent impact of standalone innovation policies using more of the structure of the model.

The PKULaw dataset does not allow us to always reliably identify the end date of policies.[6] We therefore treat policy adoption as an absorbing state, relying on the first adoption date in each city. The vast majority of cities who introduce a policy also report keeping a policy in place at the end of our sample.

Figure 2 shows the cumulative number of cities that have implemented a solar policy. Policy adoption grew steadily from 2007 onwards, reaching 43 out of 358 cities by 2020. Most early policies were production subsidies (often bundled with innovation subsidies), while demand subsidies became more common after 2010. By 2020, 19 cities had production subsidies (10 with innovation subsidies), and 30 had demand subsidies.

[4] Juhász et al. (2022) use an automated classification algorithm to directly classify subsidies, whereas we manually classify all solar policies. Kalouptsidi (2018) is a leading example of a model based approach to detect "hidden" Chinese shipbuilding subsidies).

[5] We found large numbers of solar policies without financial subsidies such as exhortation, announcements and information. We also looked at these but found no effects on any outcomes.

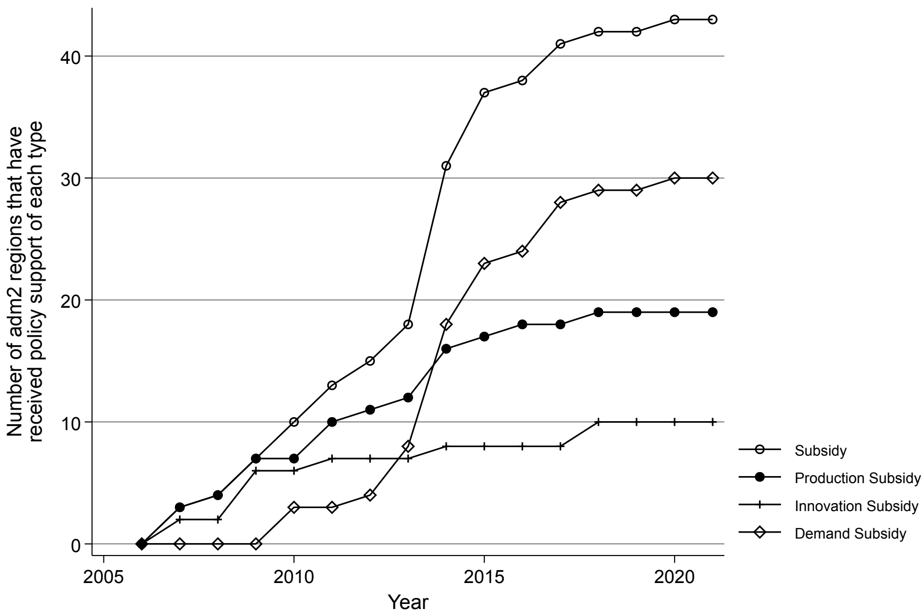
[6] Testing for permanent effects after policy removal, as in Kline & Moretti (2014), would require better end-date data as well as a longer post-policy period.

Table 1: **City-level solar policies**

Type of policy	*Number*	*key feature*	*Example*
Subsidy	78	Policy text contains precise information on the size of the subsidy	
1. Production subsidy	27	Subsidises solar production	*"A new solar production line built in Hefei will be subsidized by 12% (2018)"*
2. Innovation subsidy	12	Subsidises solar innovation	*"Firms will be awarded 10,000 RMB if they earn provincial level R&D center certification (Guilin, 2011)"*
3. Demand subsidy	61	Subsidises the installation of solar panels	*"1 RMB per watt for the electricity generated by solar projects installed in Beijing (2010)"*

Note: All policies are at the city ("admin 2 region") level over the 2006-2020 period. There are 358 cities. 43 cities are treated by some subsidy by the end of our sample. Sometimes a policy is a bundle of demand and supply subsidy policies which is why the sum of the disaggregated policy numbers exceeds 78. Table B1 contains additional example policies.

Figure 2: **Number of cities receiving solar subsidy**



Note: All policies are at the "admin 2 region" level. There are 358 of these in China (we remove Taiwan, Hong Kong and Macao from the analysis). The time series for 'Subsidy' includes any demand, production, or innovation subsidy.

Our approach builds on recent efforts to quantify industrial policy in China. Like Chen & Xie 2019, we use the PKULaw to measure city-level policies, extending their approach by analysing all solar-related laws, classifying policies by type and geographic variation and manually reading the documents in order to carefully distinguish financial subsidies from other policies (see also Gerarden et al. (2025)).

We found no examples of sub-city level solar subsidy policies (i.e., at the county or township level). There were a few examples of national policies that had subnational variation and province-level policies and we examine these in subsection 3.3.

2.3 Measuring solar industrial activity

We take a bottom-up approach to measuring solar industry activity - identifying a set of solar firms, gathering information on their performance and then aggregating these to the city-level for the main longitudinal analysis, as this is where the policy variation lives. We use the firm level panel for some auxiliary analysis to discipline the aggregate model such as innovation effects on productivity (see **??**).

Identifying solar firms: We identify all solar manufacturers operating in China at any point between 2004 and 2021 using data from ENF solar, a market research company and global directory of photovoltaic firms. Between 2004-2013, we draw on ENF's Chinese Cell & Panel Manufacturers Report (*ENF Production dataset*), which compiles market research based on firm surveys. From 2010 onwards, we can also use the ENF Solar Industry Directory (*ENF Register dataset*), an online platform designed to connect suppliers and buyers. As the leading global solar directory, companies have strong incentives to self-register, while ENF supplements this by identifying missing firms through industry news, trade fairs, government sources, and automated web searches. Firm exits are detected via automated scanning and expert verification.[7]

Combining these two datasets gives us 1,718 Chinese solar panel manufacturers operating at some point between 2004 and 2021, which detailed location data, allowing us to assign firms to their respective cities. We validate ENF entry and exit information using Chinese administrative data on firm registration. We access this data through Qichacha (https://www.qcc.com/) a platform that compiles and periodically updates firm-level information from official government sources.[8] We compared the aggregated values from our dataset (e.g., total revenues by year) with government reports and confirmed that we capture the entire industry.

Measuring production capacity, revenues and inputs: The ENF Production dataset is very detailed - containing firm-level solar PV production and capacity (measured in MWh) from 2004-2013. To extend beyond 2013, we match the identified sample of Chinese all solar panel manufacturers to Bureau Van Dijk's (BVD) Orbis dataset, which provides firm-level financial data (e.g., revenue, capital and employees, etc.) between 2004 and 2020. We execute this match with Orbis using standardised names and firm contact details identified in the Qichacha firm registry.[9] We confirm the accuracy of Orbis by also matching with ASIE

[7]The 2010-13 overlap in the two datasets allowed us to confirm the consistency of the two sources.

[8]These include the National Enterprise Credit Information Publicity System, the China Court Judgment Documents Network, and the China Enforcement Information Disclosure Network.

[9]We adjust revenue to capture only solar-related activity as some solar firms are multi-product. This

administrative data which covers larger firms through 2013. We draw on ASIE for other exercises. For example, ASIE also has some limited information on the value of subsidies, which we use to cross-validate the estimates from the structural model.

Export value: To gather data on firms' yearly exports, we use a similar strategy of matching Chinese solar panel manufacturers to the transaction-level Chinese Customs Dataset, available between 2000 and 2016. This allows us to derive firms' yearly total exports. Since some of our firms may sell non-solar products, we use identify solar exports using Harmonised System (HS) product code 854140, which includes solar panels and cells.[10]

Innovation: We measure innovative activity using patent filings. We match firms to their patents using data from the former State Intellectual Property Office (SIPO) accessed through Qichacha. For each firm, we know the name, patent ID, type, application date, publication date, and assignee, of all filed patents. For additional information (e.g., citations, IPC codes, patent abstracts and texts) we match with PATSTAT based on the SIPO patent ID.

It is much less costly to obtain a Chinese patent as the standards of novelty are lower than in the US or Europe. This is actually an advantage in our context, because it means we have a "paper trail" for some of the more incremental process innovations that we would not have from the USPTO. These may be much more important for the kind of learning-by-doing (LBD) productivity increases highlighted in the industrial policy literature. In some specifications, we distinguish between solar and non-solar patents using IPC codes following Shubbak (2019) and use machine-learning on patent texts to identify learning-by-doing (LBD) patents using the manual classification developed in Liu (2023) as our training dataset. Examples of process innovations are given in the Appendix Figure B.2 and show cost reduction, minimized production errors, and suitability for mass production. Other patents typically involve new product invention or fundamental research in chemistry and materials science.

Nonetheless, it would be a concern if policy-induced patents were all of little or no value. To address this issue, we considered other patent quality measures. First, we can use the SIPO classification that splits patents into invention, utility model, and design patents. Invention patents have the longest protection period, higher filing costs, and a more complex administrative process than the others, indicating higher quality. Second, we use the conventional approach of weighting patents by future citations using patent families from offices all over the world via PATSTAT.

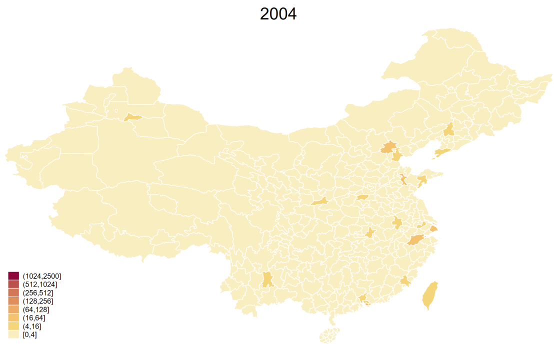
Aggregation: We aggregate our outcome data to the city-level by summing outcomes for all firms located in that city. The maps in Figure 3 illustrate the spatial variation in solar patents and subsidies across Chinese cities, which we exploit in our empirical analysis.

adjustment uses firm-level export data that does split out solar vs. non-solar products. The results are essentially unchanged if we use the raw revenue figures (see Appendix B.7).

[10]In addition to solar products, the 854140 HS6 code includes some non-solar-related semi-conductor devices as well, such as LED. Our results are similar if we use the more detailed 85414020 HS8 code, but we focus on the HS6 code as HS8 codes were introduced only in 2009.

What is striking is that we capture the whole of the development of the solar industry in China from beginning to the present. In 2004 (map on the left), the starting year of our analysis, there was very little innovation in solar and no policy support. On the other hand, by 2019 (map on the right), we observe a total of 43 cities whose solar industry has been subsidised, and crucially, innovative activity skyrocketed across the country. For example, 82 of the 358 city-regions in China had some patenting by solar firms in 2019, compared to only 25 in 2004.

Figure 3: **Number of solar patents in each city and subsidy policy**

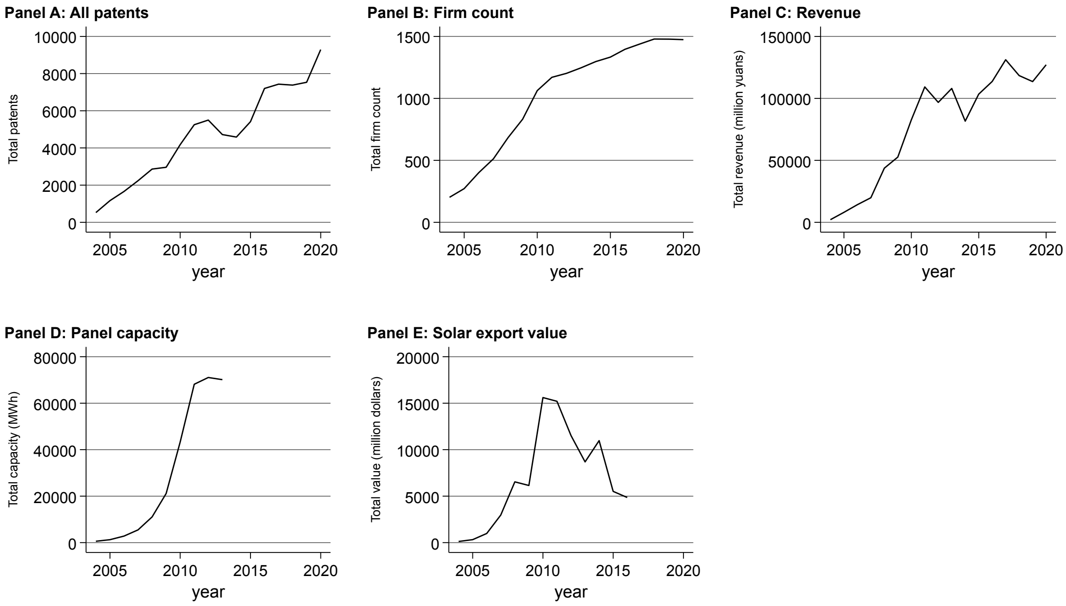


Note: Each white-bordered region represents an admn2 level city region. Black circled cities are treated by any subsidy policy. We use a heat map scale, where cities colored in a stronger red are filing more solar patents (patent counts in parentheses).

With our final dataset we see that during the 2000s and 2010s, the solar industry in China experienced rapid growth: patents increased from a few hundred in 2004 to over 10,000 by 2020, production capacity reached 70,000 MWh by 2013, and firm revenues exceeded 100 billion yuan by 2019 (Figure 4).[11]

[11] Although there were slowdowns in all outcomes after the global financial crisis, solar exports exhibit a particularly substantial fall. We have confirmed this is a real feature of exports data from many sources (note that there is some recovery in the macro export data post 2016, after our micro data runs out). There are several reasons for the downturn. First, there were big falls in foreign demand following the financial crisis, especially in Europe when many solar subsidies were scaled down (e.g., Gerarden et al. (2025) and Nemet (2019)). Second, the EU and US increased tariffs on Chinese solar producers (e.g., Houde & Wang (2022)). Third, as shown in Figure 1, there was a big drop in unit prices that led to much greater falls in the value of exports than in their volume. See Carvalho et al. (2017) for more details on these global trends.

Figure 4: **Chinese solar manufacturers activity over time**



Notes: Time series for total number of patents filed by solar firms at the SIPO; firm count obtained from the Chinese firm registration platform; revenue obtained from Orbis, panel capacity obtained from ENF Market Research reports, and solar export value obtained from the Chinese Customs Dataset. The sample is the universe of solar panel manufacturers in China, obtained from ENF's register. The revenue numbers are adjusted to account for multi-product firms following the approach described in Appendix B.7.

3 Method and Results

3.1 Econometric Strategy

Our objective is to study whether solar industrial policy was effective in increasing innovation and output in the Chinese solar industry. We study this question using a Synthetic Difference-In-Differences (SDID) design (Arkhangelsky et al. (2021)) exploiting variation in policy implementation across time and space.

Our choice of empirical approach reflects two challenges that arise when evaluating causal effects of solar industrial policies. First, implementation of policies is not wholly random. Cities with nascent solar industries may have been more likely to implement subsidies than those specialising in other areas. Alternatively, areas in which the solar industry was lagging behind may have used subsidies to catch up. Second, the impact of policies may vary over time. R&D expenditure may take time to lead to new innovations (Juhász 2018, Choi & Levchenko 2021) or may be effective in the short run but not have persistent impacts (Ball et al., 2017). In light of the recent work on two-way fixed effects with differential treatment timing (Callaway & Sant'Anna 2021, Sun & Abraham 2021), our approach should also be robust to these potential dynamic effects of policy intervention and their staggered implementation.

The SDID approach combines a familiar difference in differences approach, with a synthetic control approach to construct a counterfactual group for treated units from the sample of never-treated cities (i.e., cities that never implement a solar industrial policy in our study period). Synthetic control groups, specifically, are constructed for each outcome and cohort of treated cities separately by making the pre-treatment path of the outcome variable as similar as possible for average treated and weighted control cities.[12] This allows us to relax the assumption that treated and (unweighted) untreated cities would have evolved in parallel in the absence of policy support.[13]

Treatment effects can differ across units and over time. To summarize, our estimates succinctly, we first derive ATT estimates for each policy cohort (i.e., policies enacted in a given year), which we then aggregate into a single statistic – as proposed in Arkhangelsky et al. (2021) - by weighting the cohort-level estimates with the number of treated units present in each cohort. These "overall" ATTs are reported in Table 2. We also aggregate cohort- and time-specific ATTs into event studies using an analogous weighted aggregation method discussed in Callaway & Sant'Anna (2021), as shown in Figures 5-9 below.[14] In both cases, standard errors are estimated with bootstrapping clustered at the city level. Further technical details of the estimation can be found in Appendix D.

3.2 Main Results

Table 2 contains our core results estimating how local solar subsidies shaped the development of China's solar industry. Column (1) shows the SDID ATT of any subsidy with the following columns breaking this down into our three subsidy types - demand, production and innovation (the latter being the bundle of innovation and production subsidies. Each panel has our different solar outcomes. Patents in panel A, the number of firms (B), revenues (C), production capacity (D) and exports (E). We find large and sustained impacts on all these local outcomes as well as suggestive evidence of positive spillovers.

3.2.1 Innovation

Our most striking finding is that solar subsidies led to a large increase in patenting by solar firms. The first column of Panel A Table 2 shows a positive and significant ATT effect of

[12]Note that for our earliest policy, introduced in 2007, weights are constructed using data from 2004-2006. As discussed in Section 2, whilst the 2006-2010 period saw the fastest growth in the industry and decline in the price of solar modules, there was some initial growth during 2001-2005. We therefore are able to compare outcome trends for this cohort across cities where the solar industry existed even if it was at a nascent stage.

[13]When we conduct SDID estimations for several outcome variables, weights are allowed to vary across estimations. In Section E.8, we show that we can also construct unit weights using multiple outcomes, which ensures balance in the pre-trend region across this broader set of variables. Our results are qualitatively similar using these weights.

[14]The trends visible in these event studies may driven by both dynamic effects (i.e. variation in effect size across different time horizons) and compositional effects (i.e. changes in the composition of cohorts contributing to different years' estimates). In Section E.9, we explore the contribution of these effects in more detail and find that composition is not driving the results.

Table 2: **SDID Estimates by Outcome and Subsidy Type**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel A: All patents (2004-2020)				
Subsidy policy ATT	0.496**	0.236	0.871***	1.060***
	(0.200)	(0.275)	(0.227)	(0.367)
Panel B: Number of solar firms (2004-2020)				
Subsidy policy ATT	0.212**	0.031	0.377**	0.412***
	(0.096)	(0.038)	(0.155)	(0.148)
Panel C: Revenue (2004-2020)				
Subsidy policy ATT	0.994**	0.060	1.772***	2.502***
	(0.448)	(0.278)	(0.615)	(0.819)
Panel D: Panel production capacity (2004-2013)				
Subsidy policy ATT	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Panel E: Solar export value (2004-2016)				
Subsidy policy ATT	3.192***	1.153	4.298***	6.092**
	(1.231)	(1.145)	(1.498)	(2.366)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables are IHS-transformed. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms. All regressions are based on a balanced panel of admin 2 regions covering the period where the outcome variable is available. Patents, firm count, and revenue outcomes are based on a sample of 6,086 observations covering 2004–2020, solar export value is based on 4,654 observations covering 2004–2016, panel production capacity is based on 3,580 observations covering 2004–2013.

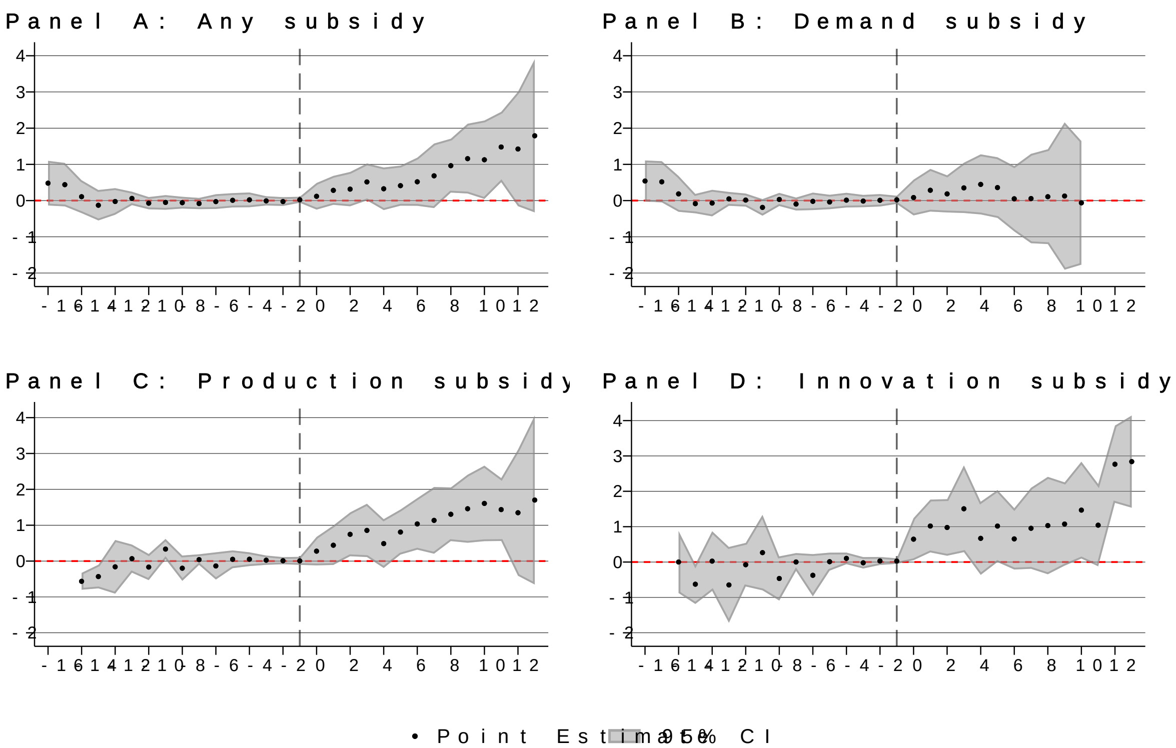
0.496. This is about 64% which corresponds to a rise of 8.4 patents annually (from 13.1 to 21.5) for the average city-year in our sample. This is estimated using the inverse hyperbolic sine (IHS) transformation which handles zeros while closely approximating the log for large values. This makes it particularly suitable for count variables with many zero observations.[15]

To examine the dynamics of this response, Panel A of Figure 5 presents the event study estimates. We observe a clear and sustained increase in patenting following policy adoption, with effects that grow gradually and persist for at least 13 years. This persistence suggests

[15] While coefficients from IHS regressions are not directly interpretable as elasticities, we use $e^{\beta} - 1$ as a rough approximation of percentage changes. There has been extensive recent discussion about the interpretation of IHS models (e.g. Aihounton & Henningsen 2021; Chen & Roth 2024; Mullahy & Norton 2024), particularly regarding their sensitivity to outcome scaling. We find similar magnitudes when using alternative transformations, such as untransformed levels of patents or log(1 + Y). These results are shown in Appendix Tables E.3 and E.4.

that firms were not simply bringing forward activity that would have occurred anyway. Importantly, we see no evidence of pre-trends in the years leading up to treatment.

Figure 5: **All Patents by Solar Firms**



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is total patents of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Disaggregating by subsidy type, we find that innovation and production subsidies drove large and persistent increases in patenting, while demand-side subsidies have a positive but statistically insignificant effect. As shown in the final column of Table 2 (Panel A), the ATT for innovation subsidies is 1.060 - more than twice the average effect in column (1). Production subsidies also have a strong impact (0.871) in column (3), whereas the effect of demand subsidies is small (0.236) in column (2). Event study estimates by subsidy type (Panels B–D of Figure 5) confirm this dynamic pattern.

Note that the low ATT of demand subsidies do note mean they have no aggregate effect. The SDID identifies the relative impact of policy between treated and untreated cities, so will underestimate the aggregate effect if increased demand for solar in one city can be met by panel production in another Chinese city. In that case, any additional innovative activity resulting from these subsidies may not necessarily occur in the treated regions. This intuition is investigated in later in the paper through the lens of our formal model.

Table 3: **Citation weighted Patent Counts**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent citations	0.676***	0.388	0.854***	1.076**
	(0.218)	(0.328)	(0.300)	(0.482)
Observations	5,370	5,370	5,370	5,370

Notes: *0.1 ** 0.05 *** 0.01. SDID on 358 cities. Time: 2004-2018 (to allow extra two years for citations). Each column is one SDID regression. Without controls. Outcome is IHS of forward citations of patents by solar firms in a city-year pair. Citations are measured as the number of patent families citing a patent's patent family globally. SE cluster bootstrapped by city.

Does this increase in patenting reflect genuine creation of new knowledge and increases in productivity? Other studies of innovation policy in China (e.g. Wei et al. 2023) have raised concerns that patenting increases reflect very low-quality filings. In Table 3, we show that our results are similar in magnitude and significance if we weight the patent counts by future citations (based on global patent family data across international offices using PATSTAT). As a further test, we show that policy effects are large and significant only for "invention/utility" (high value) patents and not for design patents (which are of low value).[16]

As an alternative approach, we considered more direct ways of measuring productivity. First, using our firm-level panel data (see Appendix Section E.3), we find that firm level output, exports and productivity are positively and significantly associated with a firm's lagged solar patenting (Appendix Table E.19). This relationship supports the idea that patenting captures economically meaningful innovation. We also found evidence of spillovers (e.g., Appendix Table E.20) - a firm's output was higher when innovation rose in other solar firms within the city or in other cities (in the same province), even conditional on a firm's own patenting and inputs. We use these findings both to motivate our theory and discipline the structural quantification of its parameters in Section 5 (see Table 4).

As a second direct approach, we implemented our standard SDID approach at the city-level using productivity as an outcome. The results in Appendix Tables E.14 and E.15 are consistent with productivity gains from subsidies with the same ranking of impacts across policy types (i.e., lowest for demand and highest for innovation).

The large impact of production subsidies on innovation in Table 2 raises questions about the underlying mechanism. To test learning-by-doing, we classify patent abstracts based on whether they describe process innovations rather than new products or basic science.[17] We find large and significant effects of production and innovation subsidies on the number of

[16]As noted in the data section, we draw on a classification system used by the Chinese patent office (SIPO), which distinguishes between design, utility model, and invention patents. Design patents are generally considered low value and would not receive protection in the US or EU. As reported in the second and third rows of Appendix Table E.5, policy effects are small and statistically insignificant for design patents, but large and significant for invention and utility model patents.

[17]We build on the work of Liu (2023), who manually labelled 3,299 Chinese solar patents, and train a random forest algorithm on 85% of this data. The model achieves over 90% accuracy on a holdout set and is applied to all patents filed by ENF-listed solar firms during our study period.

learning-by-doing patents, consistent with this mechanism (see Appendix Table E.13).

How tightly is the observed increase in innovation linked to solar technology itself or spread more broadly across non-solar fields? As shown in Appendix Table E.5, the ATT for solar patents is roughly twice as large as for non-solar patents, and only the solar category is statistically significant. Hence, the policy appears to have induced a targeted innovation response that aligns closely with its industrial aims.

3.2.2 Industry Scale: Number of Firms, Revenue, Production and Exports

Having shown an increase in innovation and productivity, we now turn to examine the role of policy on the scale of the industry. We start with the extensive margin (firm counts) and then move to the intensive margin (revenues, production and exports). Panel B of Table 2 reports ATTs for the number of solar firms. For the average city-year, the estimated treatment effect is 21%,an increase of approximately 0.6 firms per year. As with patenting in Panel A, demand policies have the weakest effects (0.031 and insignificant), then production subsidies (0.377) and with innovation subsidies (0.412) the strongest impacts. Figure 6 plots event study estimates. As with innovation, we observe parallel trends in the pre-treatment period and a sustained, statistically significant increase after treatment. Effects continue to grow over time and persist at least 13 years post-intervention.

Are these firms producing more? As discussed in Section 2, we track production for 2004–2013 (when ENF data is available) and use revenue data for the entire period, 2004-2020. Panels C and D of Table 2 present ATTs for revenue and production capacity, respectively. The ATT for production capacity is 2.098[18] and for revenue is 0.994. These correspond to an increase of approximately 590MWh in panel capacity and 371 million RMB in firm revenues per city-year.

The event studies in Figures 7 and 8 show that both revenue and production have sustained post-treatment increases for treated cities relative to controls. Effects emerge gradually and remain statistically significant over a decade after policy introduction. Disaggregating results by subsidy type, we see a consistent pattern: production and innovation subsidies drive large and significant increases in both revenue and production.

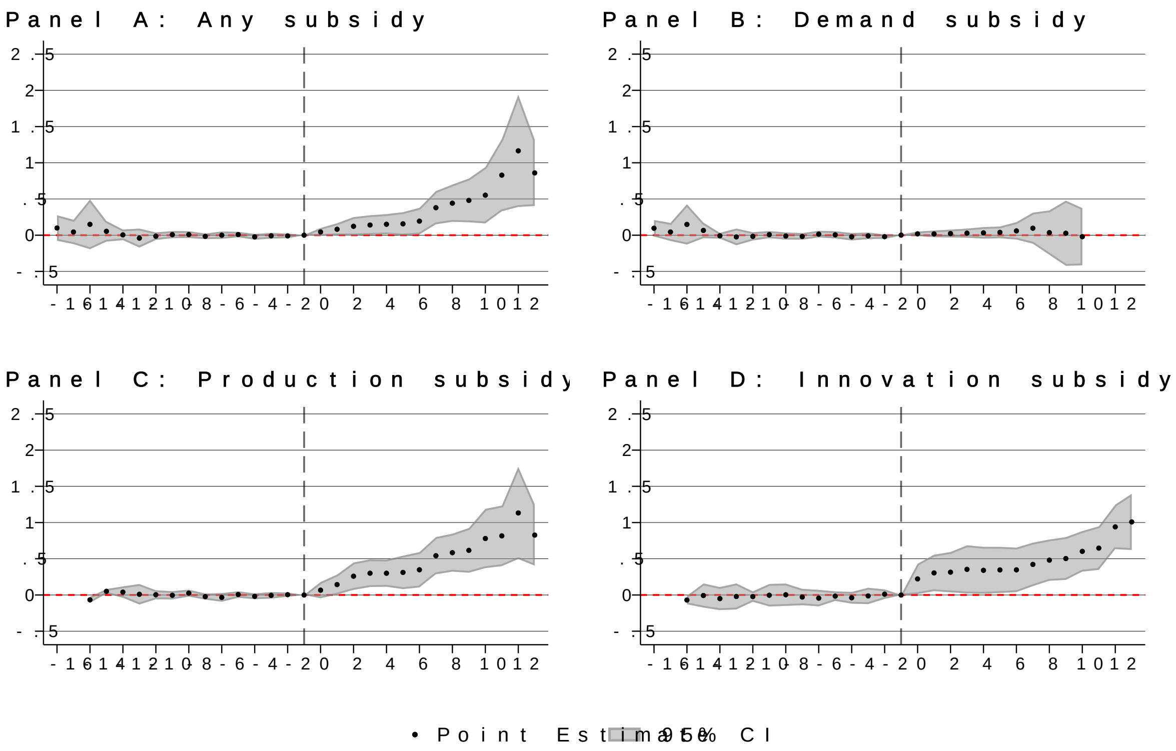
The impact on revenue is about five times larger than the effect on firm counts, implying that not only are there more solar firms, but they have grown substantially in size.[19]

We also find large and sustained increases in the value of exports from solar firms in

[18] Appendix Figure E.6 shows that we find very similar results if we use PV module production (an adjusted measure based on expected orders), solar cell production, or solar cell production capacity as outcomes.

[19] The ATT for production capacity is roughly twice as large as that for revenue, suggesting large falls in average prices consistent with our model. Note that some of this is driven by the different time periods for which data is available. Restricting the revenue analysis to 2004–2013 (to match the ENF production data window) brings the ATT for revenue closer to that of production (see Appendix Table E.14). The fact that the ATT falls over time is not inconsistent with the event studies showing growing impacts for a city since it introduces a treatment. Rather, it suggests that later policy cohorts experienced smaller effects — probably due to increased competition and lower markups.

Figure 6: **Firm Count**



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is the number of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

treated cities (Figure 9 and Table 2 Panel E), suggesting that a substantial share of the newly produced solar panels entered international markets.[20] These patterns are consistent with the idea that local subsidies contributed to international diffusion.

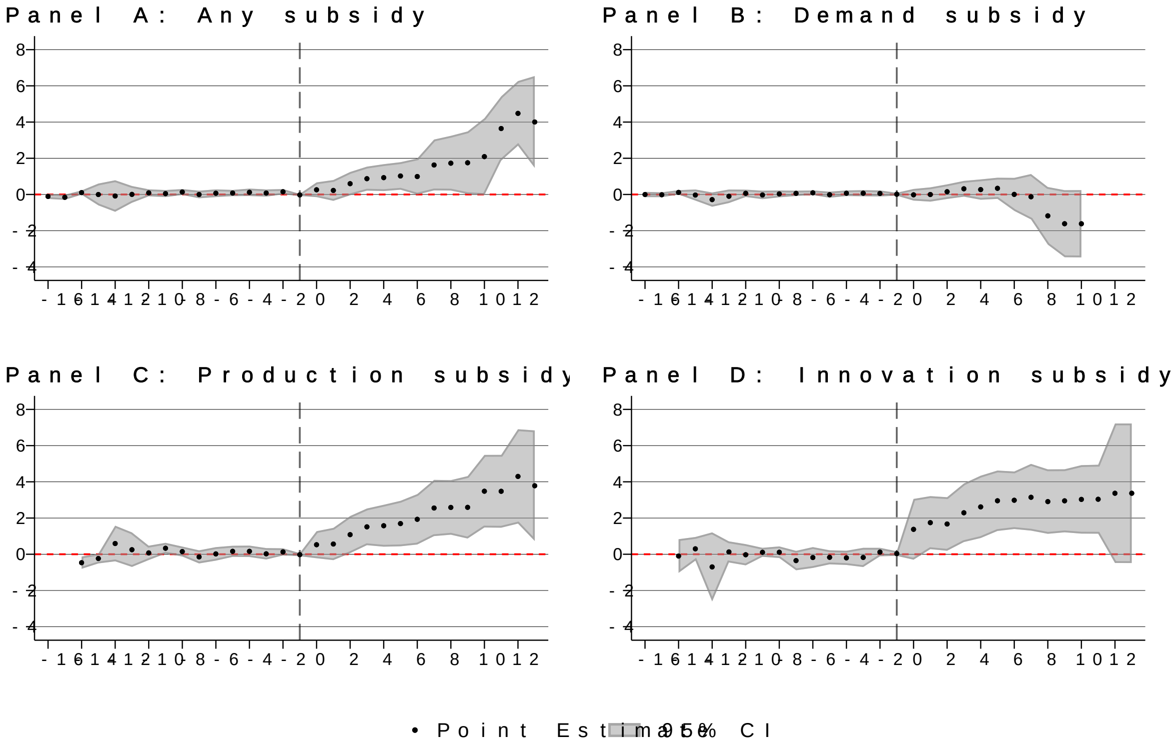
3.2.3 Broader impacts: Pollution and Knowledge Spillovers

This final set of results examines broader effects that extend beyond the innovation and production results documented above. These findings are more exploratory, but they point to potential wider local and global benefits from city-based industrial policy in China.

Pollution: Subsidies that shift energy production toward solar may also reduce pollution, with important local health benefits. We examined $PM_{2.5}$ concentrations as an outcome and found that policies do reduce local pollution. The ATTs are small and statistically insignificant, however, with the notable exception of demand subsidies. A simple back-of-the-envelope calculation using this estimate suggests that China would have faced 277,170 more PM2.5-related deaths (5.1% more than the attributed number) 2004-2020 if

[20] Appendix Table E.8 shows that the effects are much larger for these solar exports compared to non-solar exports and the number of exporting firms also rose (extensive margin).

Figure 7: **Revenue**

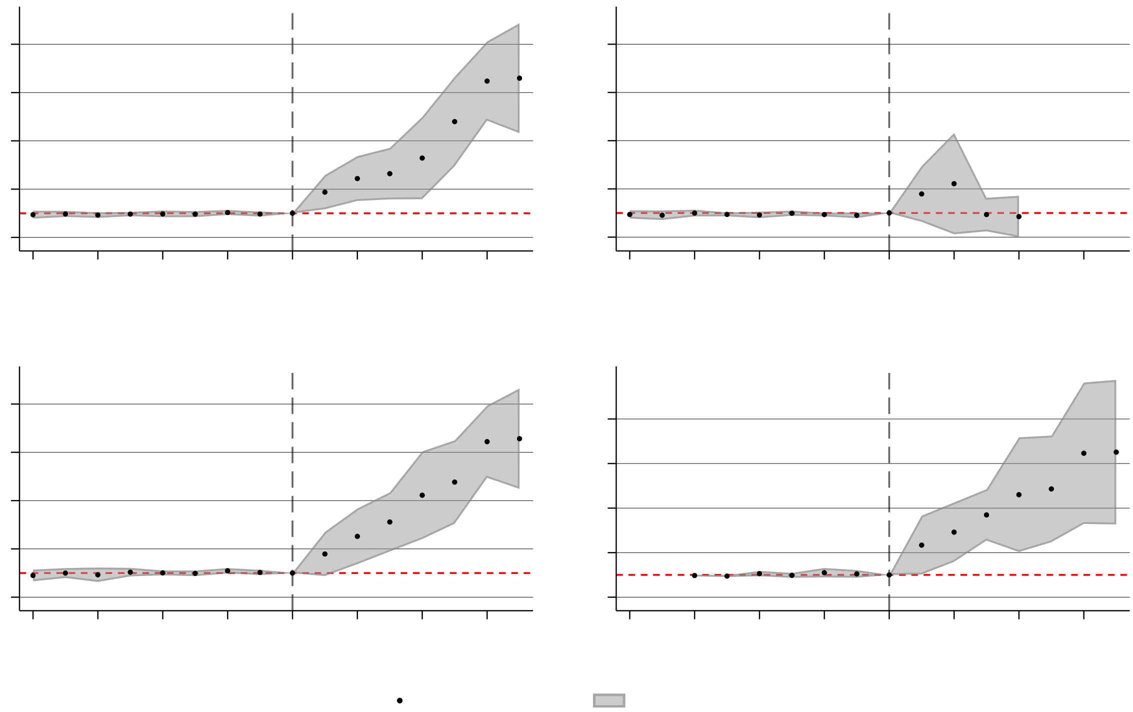


Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is the total revenue of solar firms (with IHS transformation and adjustment leveraging export data). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

demand policies not been introduced (see Appendix Table E.11 and Appendix B.10). The effectiveness of demand policies contrasts with our economic outcomes, where supply-side policies dominated, but aligns with the logic that demand subsidies alter local energy sourcing directly. Results for CO_2 emissions are qualitatively similar but smaller (Appendix Table E.12). While only suggestive, these findings highlight the potential for industrial policy to deliver social benefits through the energy transition.

Spillovers and aggregate effects: Do our observed effects reflect local reallocation or net national gains? Our SDID framework estimates relative impacts, so may understate aggregate effects if nearby cities also benefit from policies or overstate them if activity is simply reallocated across cities. To explore this, we identify cities most exposed to potential spillovers - those contiguous to treated cities - and estimate SDID models treating them as the "treated" group, using synthetic controls drawn from non-contiguous, never-treated cities. Appendix Table E.9 suggests that these neighbouring cities experience net positive spillovers - the ATT is positive across outcomes and subsidy types, although smaller than for directly treated cities. Accordingly, when we exclude contiguous cities from the donor

Figure 8: **Panel Production Capacity**



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is the total panel capacity MWh of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates

pool (Appendix Table E.10), the estimated effects rise in magnitude.[21] Overall then, we find evidence of positive spatial spillovers, suggesting that local subsidies may yield even larger gains at the national level.

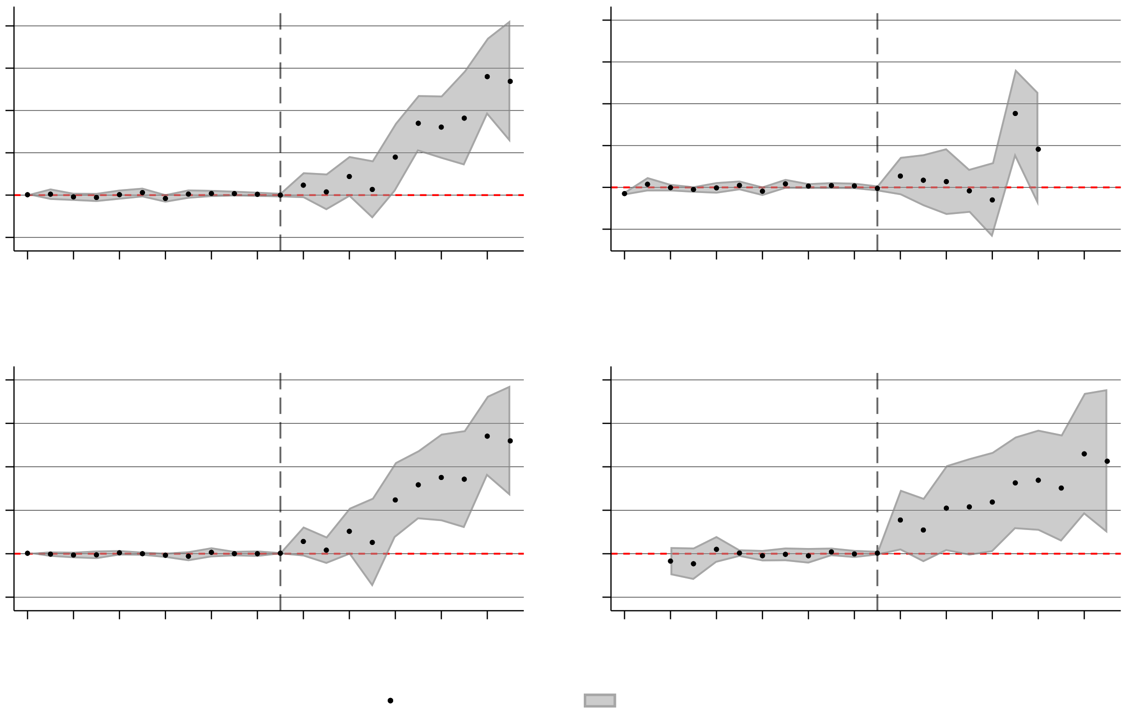
We return to this question directly in the next section, where we explicitly model the aggregate impact of China's solar industrial policy.

3.3 Robustness

We have run a large battery of robustness tests on our results and discuss a few of these here. One important concern is that policies are introduced in cities that would have done well regardless of the intervention, or maybe there were coincident non-solar policies driving the results. To address this issue, we conduct placebo tests with other outcomes. For example, looking at SDID ATT effects on GDP per capita and non-solar patenting we

[21] Demand subsidies are likely to create these positive spillovers, but it may appear more surprising that we also see them for production subsidies. This is likely because positive between-city innovation spillovers are larger than business stealing effects (consistent with Bloom et al. (2013)). Some firm-level evidence for this is provided in Appendix Section E.3. We formalise these different spillover effects in Section 4.

Figure 9: **Solar Export Value**



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is the total value of solar exports from solar firms (with IHS transformation, million dollars). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

found statistically and economically insignificant effects, suggesting that our results are not driven by confounding shocks (see also Appendix Tables E.16 and E.17). A related approach is to show that the results are stable when including controls such as GDP and population (see Appendix E.7).

Second, we have focused on city-regions as our primary level, but as discussed in Section 2, there are also some solar policies at higher levels (provincial and national) that could potentially confound our results. We show this is not the case in Appendix E.6. National policies should largely be absorbed by the time effects. However, we identified in PKULaw Feed In Tariff demand policies that divided China into zones with different levels of generosity. To tackle this, we re-estimated our models solely in the largest zone where all cities were affected in the same way and generated very similar results (Appendix Table E.23). Additionally, we also found 17 province-level subsidies demand subsidies and one innovation subsidy. We re-estimated our models on the set of cities that were outside the places with province-level subsidies. Again, as shown in Appendix Table E.26, the results changed in only minor (and predictable) ways.

Third, recall that our innovation measure is based on aggregating the patents of solar firms listed in the ENF register. This has the problem that it excludes patenting by entities such as universities, government labs and non-solar producing firms.[22] To tackle this, we identified all "solar-related" patents filed in a city, regardless of whether the filer is a solar producing firm. Appendix E.4 shows that our results are qualitatively unchanged when using this alternative, content-based definition of city solar innovation.

Fourth, we have assigned firms to cities based on their headquarters. Appendix E.5 shows that adjusting for the small share (7.3%) of firms operating in multiple cities does not affect our results.

Finally, we also confirmed that the event study patterns are not driven by compositional changes in which treated cohorts contribute over time (Appendix E.9), and that using a common set of synthetic control weights across outcomes leaves our results qualitatively unchanged (Appendix E.8).

4 An Aggregate Model: Theory

The results in the previous section show strong effects on city solar innovation and scale of industrial policies. Since there are various spillover effects, however, it is not straightforward to deduce the aggregate effects of such policies. Consequently, to analyse the equilibrium impact of solar policy we develop a quantitative spatial model. Full details and proofs are in Appendix C, but we sketch the set-up here.[23] The model features multiple city-regions with different productivities and bilateral transport costs, firms (energy component manufacturers) and a grid planner. Consumers derive utility from locally produced electricity. Grid planners choose between solar ("clean") and coal ("dirty") plants to generate power, sourcing intermediate inputs from manufacturers across the country. Heterogeneous firms make entry, production, and innovation decisions in a setting with monopolistic competition. Paying a fixed cost to innovate means a firm will enjoy lower marginal production costs, but (with a lag), this innovative knowledge spills over to other firms. We also include an export market as an overseas city-region that Chinese firms can sell into.

The model allows us to move from our empirical estimates of relative impacts across treated and untreated cities to aggregate effects at the national level. We also use it to back-out the magnitude of local subsidies.[24] We estimate the total effect of these policies

[22]It also has the issue that some of the patents of our solar producing firms may be non-solar patents. Above, in subsection 3.2.1 we showed our results are driven by the solar-specific patents of solar producing firms, as one would expect.

[23]Appendix C is split into four parts. Subsection C.1 presents a simplified version of the model in order to gain intuition and derive analytic closed form solutions. The simplified model considers only the solar industry and two symmetric regions. We derive comparative statics for the local city impact of our three types of subsidies on a range of solar outcomes in four propositions. Subsection C.2 has technical derivations for the full model including proofs of equilibrium uniqueness. Subsection C.3 gives the details of how we quantify the full model and subsection C.4 gives the welfare and cost-benefit calculations.

[24]This is in the spirit of using models to detect "hidden subsidies" (e.g., Kalouptsidi 2018), but we go beyond this as in addition to the timing of policy introduction, we also have information on the variation of policy incidence across different cities within China.

on China's solar industry compared to a simulated no-policy counterfactual. Moving from a positive to normative analysis, we then examine the welfare effects of the actual policy roll out compared to alternative policy strategies. Looking ahead, Section 5 describes how we quantify the model, and Section 6 presents results.

4.1 Geography

Each city-region is indexed as a destination d when referring to where electricity is generated and consumed, and as an origin o when referring to where power plant components are manufactured. Intermediate inputs for power generation can be traded across cities, subject to iceberg trade costs τ_{od}, that vary by origin-destination pair. Trade costs are normalised such that $\tau_{od} = 1$ if and only if $o = d$. We simplify the international trade aspect by having a 'rest of world' region d, with its own trade cost like other locations. We assume that China does not import solar components, just exports them (broadly consistent with the data).[25]

4.2 Demand for electricity and power plant components

In each region d, a representative consumer derives utility $U_d = u(e_d)$ from electricity services e. We assume all energy is from electricity for simplicity and abstract from consumption of other goods, since our focus is on how demand for electricity drives demand for power plant components (we relax this in subsection 6.2.5 below). The representative consumer provides L_d effective units of labour used to produce electricity. Labour supply is exogenous, and we abstract from migration or labour reallocation in response to electricity price changes.

Electricity services e_d are generated by a local grid-planner, who builds and operates power plants. Electricity services are not traded across regions.[26] Plants of energy sector k belong to one of two categories: solar (s) or non-solar (s', e.g. coal). These are imperfect substitutes due to differences in the timing and flexibility of electricity generation. We model final electricity output as a CES aggregator: $e_d = \left(e_{d,s'}^{\frac{\sigma-1}{\sigma}} + e_{d,s}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$, where final electricity services e_d depend on solar $e_{d,s}$ and non-solar $e_{d,s'}$ generation.

In practice, power plants are assembled from a range of components, such as solar cells, inverters, charge controllers and racking systems. In the model, the grid planner purchases differentiated, energy sector-specific intermediate inputs from firms across China and combines them to generate electricity. The 'power plant' (e.g. solar farm) is modelled as a second-tier CES aggregator:

[25] We also considered a fixed trade cost in addition to iceberg trade costs. The key intuitions of the model did not change at the cost of much additional complexity, so we keep with the simplified version here.

[26] Cross-provincial exchange was rare and largely governed by administrative planning rather than market mechanisms in the early 2000s (Guo et al. 2020; Li et al. 2025) Even after two rounds of reform in 2002 and 2015, most electricity continued to be traded within provinces through rigid long-term contracts, with spot markets and real-time interregional trade still underdeveloped. That said, our results would remain largely similar even if electricity trade with trade costs were allowed.

$$e_{d,k} = \left(\sum_o \int_{\omega \in \Omega_{o,k}} q_{od,k}(\omega)^{\frac{\sigma_k - 1}{\sigma_k}} d\omega \right)^{\frac{\sigma_k}{\sigma_k - 1}} \tag{1}$$

Here, $q_{od,k}(\omega)$ denotes the quantity of variety ω of sector k input from region o used by the grid-planner in region d. Each variety is uniquely produced by a single firm. The elasticity of substitution across varieties is σ_k.

The grid planner chooses total electricity output, the mix between solar and non-solar generation, and the input mix for each energy sector, subject to an exogenously given expenditure budget E_d.[27] Solving the nested CES problem in the usual way yields the following demand for each intermediate input variety

$$q_{od,k}(\omega) = \left(\frac{p_{od,k}(\omega)}{P_{d,k}} \right)^{-\sigma_k} \left(\frac{1}{P_{d,k}} \right)^{\sigma} \frac{E_d}{P_{d,s'}^{1-\sigma} + P_{d,s}^{1-\sigma}} \tag{2}$$

where $p_{od,k}$ is the price of a particular variety, and $P_{d,k} = \left(\sum_o \int_{\omega \in \Omega_{od,k}} p_{od,k}(\omega)^{1-\sigma_k} d\omega \right)^{\frac{1}{1-\sigma_k}}$ is the price index which captures the cost of producing a single unit of electricity in energy sector s when using a cost minimising mix of intermediate inputs.

4.2.1 Demand-Side Solar Policy

We define *demand* subsidies as policies that reward the grid-planner for each unit of electricity from a specific energy source. A real-world example are feed-in tariffs, which guarantees above-market per-unit prices for electricity generated from solar sources and sold to the grid. These subsidies effectively reduce $P_{d,s}$, the cost of generating a unit of solar electricity, regardless of the mix of intermediate inputs chosen by the grid planner. We model this as a reduction in the effective price by a scaling factor $\chi_{d,s} < 1$, which pre-multiplies $P_{d,s}e_{d,s}$ in the grid planner's cost function.

A solar demand subsidy in location d shifts electricity production towards solar, increasing demand for solar intermediate inputs. In partial equilibrium, when prices are fixed, this results in a proportionate rise in demand for all solar intermediate varieties in d and (subject to trade costs) in other cities. Because these components are sourced from firms across the country, subsidies in one city-region will generally affect firm choices elsewhere.

4.3 Manufacturing of power plant components

Intermediate inputs for each energy sector are produced by heterogeneous firms located in different city-regions. Each origin city o has a continuum of potential manufacturing firms

[27] We assume that power plants are not durable: all generation capacity is chosen anew in each period. This simplifies the model and is less restrictive in a setting like ours, where electricity demand is growing rapidly, allowing frequent adjustments to the energy mix. We assume the electricity expenditure budget E_d is proportional only to the local population and is not determined by any other factors.

i in each energy sector k. Each firm produces a differentiated variety ω of a sector-specific intermediate good. The resulting market structure is one of monopolistic competition.

Consider a firm deciding whether to produce an intermediate good for energy sector k. Entry requires paying a sunk cost $w_o f_k^e$, expressed in effective labour units (e.g. for initial product development). After entry, the firm draws an initial productivity level φ, from a Pareto productivity distribution with a mean that varies by sector and city-region. Firms can equivalently be indexed by their productivity φ or the variety they produce ω.

A firm's marginal cost depends on two factors: its own productivity and the state of knowledge in the wider economy. Higher productivity φ reduces the effective labour required to produce each unit of output. Marginal costs also fall when a greater number of solar firms are innovators — we refer to this as knowledge spillovers. This mechanism captures how industrial policy in one city-region can raise productivity elsewhere. We summarise spillovers with the parameter $\kappa_s \geq 1$, which increases in the share of innovating firms.[28]

After observing their productivity draw φ, firms decide whether to pay a fixed cost $f_{o,k}^i$ to innovate. We follow Bustos (2011) in modelling innovation as a discrete decision that lowers marginal costs to $\frac{1}{\kappa_k \xi_{o,k} \varphi}$, with $\xi_{o,k} > 1$. While stylised, this formulation captures a range of mechanisms through which firms improve productivity, including process upgrading, adoption of new technologies, or learning by doing.

4.3.1 Supply-Side Solar Policy: Production and Innovation subsidies

Firms are impacted by two types of supply-side subsidies set by local governments. We model solar *production* subsidies as a reduction in input costs, lowering the marginal cost to $\frac{a_{o,s}}{\kappa_s \xi_{o,s} \varphi}$ where $a_{o,s} < 1$. This captures the sort of production subsidy shown in Table 1, where the cost of the entire production run is proportionately reduced. We model solar *innovation* subsidies as a reduction in the fixed cost of technological upgrading to $\phi_{o,s} w_o f_s^i$, where $\phi_{o,s} < 1$. This corresponds to the example innovation subsidy in Table 1, where firms are given a fixed payment for establishing an R&D center.

Although we observe whether a city introduced a specific policy in a particular year, we do not have a consistent way of defining the exact magnitude of the subsidy for every policy. Consequently, we assume that each of the three policy types has an unobserved level, and we back this average level out using the model and the data as described in Section **??**.

4.3.2 Firm optimal choices

After paying the entry cost, firm profits are the maximum of three alternatives: the profits from exiting, from producing without innovating, and from producing and innovating. Firms

[28] We define knowledge spillover to be linear in the mass of innovators from the previous period. Therefore $\kappa_{s,t} = 1 + \delta \times \frac{\sum M_{d,s,t-1}^i}{\sum (M_{d,s,t-1} + M_{d,s',t-1})}$. The time subscript is omitted in the main text for simplicity, as this is the only place where it is needed. δ captures the strength of knowledge spillovers.

make four sequential choices: (i) whether to enter, (ii) whether to innovate, (iii) what price to charge and how much to produce and (iv) and whether to exit.

4.3.3 Solution

We solve this problem in stages (see Appendix C for full details). Given the firm's innovation decision, solving for the optimal price gives the usual result: manufacturers charge a constant markup, $\frac{\sigma_k}{\sigma_k - 1}$, over marginal cost. Substituting optimal pricing and demand functions into the expression for firm profits yields the potential value functions for each choice. Given their productivity draw, firms choose whichever strategy yields the highest profits - exit, produce and do not innovate or produce and innovate. The solution can be characterised as a set of productivity cut-offs that determine firm behaviour. Finally, with knowledge of their optimal profits and the distribution of productivity, firms choose whether to pay the sunk entry cost needed to draw a productivity and enter the market. [29]

To obtain analytical solutions that can be used to generate a series of qualitative predictions for comparison with our empirical results, we begin by simplifying our full model to first consider a one sector version (solar industry only) and only two symmetric Chinese city-regions. We find that the model's predictions are consistent with the empirical results at the city level (see Appendix C.1). In particular, all three types of subsidies increase innovation (Proposition 3). Innovation subsidies increase patenting by lowering the cost of R&D, which raises the share of firms that choose to innovate. Production subsidies increase innovation indirectly by reducing marginal cost and growing the equilibrium scale of production, increasing the likelihood that firms pay the fixed cost of upgrading technology. Demand subsidies increase local production (especially when transport costs are high), increasing incentives to pay the fixed cost of innovation. As expected, all subsidies increase the number of firms (Proposition 2), and revenues, while also reducing prices (Proposition 4). Higher revenues and lower prices implies an increase in output and exports. Production-side policies have larger local effects than demand-side policies (Propositions 2–4) essentially because production subsidies increase local output through a business stealing effect (i.e. a negative spillover on other cities), whereas demand subsidies increase production in other cities (a positive spillover effect). Innovation subsidies have some of the business stealing effects of production subsidies, conveying a negative spillover, but because of knowledge spillovers there is also a positive productivity spillover.

5 Model Quantification

We now explain how to quantify the full model outlined in Section 4 for the period 2004–2020, where 2004-2006 serves as the pre-policy baseline. Table 4 gives the the parameter values

[29] Because the model does not have external economies of scale (Allen & Arkolakis 2014; Redding 2016; Garg 2024), we can prove there is only one unique equilibrium (see Appendix C.2 for full details).

and we detail how they are derived in this section. We treat each period in the model as one calendar year and solve for the static equilibrium. We use census data to assign yearly population to every city-region in China.[30] We consider the two energy sectors to be solar and coal. We construct the solar sector from our dataset of solar manufacturers, and measure the non-solar sector using firms in the Coal/Coking industry from the ASIE dataset. We calibrate the ratio of solar energy consumption in the rest of the world to that of China using Orbis data on solar revenues in China and customs data on solar exports. We measure total coal revenue in China using ASIE.

Both energy sectors are tradable and can exhibit innovation, but we assume that coal-based inputs are not traded internationally. We also assume that knowledge spillovers operate only in the solar sector as it is a much younger, growing industry than coal. Solar subsidies follow the empirically observed policies.

We next proceed in three steps. First, we externally calibrate structural parameters such as elasticities of substitution, iceberg trade costs, and the dispersion of firm productivity from both the existing literature and our data. Second, building on the first step, we use pre-policy data (2004–2006) to recover fixed costs of production and innovation, the sunk cost of entry and city-specific productivities. Third, assuming fixed costs and fundamental productivities remain constant over time, we use post-subsidy data 2007-2020 to back out the implied magnitudes of demand, production, and innovation subsidies using the reduced form ATT effects in Section 3.2.

5.1 Step 1: Calibration

We obtain five sets of parameters using a mixture of the extant literature and estimated moments from our data: substitution elasticities, productivity dispersion, trade costs, innovation productivity gains and knowledge spillovers.

Elasticity of substitution across and within energy sectors: We set the elasticity of substitution across energy sectors to $\sigma = 3$, following Jo (2025) and Papageorgiou et al. (2017). To assign values for sector-specific elasticities of substitution within solar and non-solar industries (σ_s and $\sigma_{s'}$), we follow Shapiro & Walker (2018), who infer these values from observed markups. We use their estimate, 8.18, for Coke, Refined Petroleum and Fuel as our non-solar elasticity ($\sigma_{s'}$), and a value of 5 for solar, averaging relevant manufacturing sectors such as fabricated metals and electrical equipment.

Shape parameter of firm productivity distribution: We calibrate the shape of the firm productivity distribution in each sector using the approach of Hsieh & Ossa (2016), Antras et al. (2017), and Shapiro & Walker (2018). Since firm productivities follow a Pareto distribution with shape parameter θ_s, the resulting distribution of firm revenues is also Pareto, with shape parameter $\theta_s/(\sigma_s - 1)$. This implies a linear relationship between the logarithm of revenues of firm i ($R_{i,s}$) and the logarithm of the probability of revenues

[30] Census data is available every 5 years. We linearly interpolate for years without population data.

exceeding that level ($\Pr\{x > R_{i,s}\}$). This gives us the following expression which we can estimate in our firm-level data:

$$\ln\left(\Pr\{x > R_{i,s}\}\right) = \zeta_{0,s} + \zeta_{1,s}\ln\left(R_{i,s}\right) + \epsilon_{i,s} \tag{3}$$

We recover the slopes in equation (3) by running separate log-linear regressions for the solar (s) and non-solar (coal/coking, s') sectors using ASIE data.[31] We obtain slope coefficients $\zeta_{1,s'} = -1.62$ and $\zeta_{1,s} = -0.875$. Using the relationship $\theta_s = \zeta_{1,s} \cdot (1 - \sigma_s)$, and our calibrated elasticities ($\sigma_s = 5$, $\sigma_{s'} = 8.18$), we recover $\theta_s = 5.3$ and $\theta_{s'} = 11.66$. We can recover the industry average scale parameters b_s and $b_{s'}$ using the relationship $b_s = exp(\zeta_{0,s} \cdot (\sigma_s - 1)/\theta_s)$. Given our estimates we find $b_s = 0.267$ and $b_{s'} = 0.256$.[32]

Iceberg trade cost: We use bilateral trade cost estimates between Chinese cities from Egger et al. (2023), who estimate a gravity model using inter-city trade flows from the Investment Climate Survey (ICS) and travel times derived from China's road and rail networks. Travel times tt_{od} reflect the fastest available route between cities, based on typical speeds and shortest-path routing. Trade costs take the iceberg form $\tau_{od} = \exp(\phi tt_{od})$, with $\phi = 0.032$ as the estimated elasticity. We use their ϕ and tt_{od} values directly to construct the bilateral trade cost matrix in our model.

Productivity gain from innovating and knowledge spillovers: We estimate the productivity gains from innovation and knowledge spillovers using our firm-level panel data. As discussed above in subsection 3.2.1, we do this through regressions estimating the "knowledge production function" relating current output to lagged patent activity by the firm itself and those of other firms, controlling for the firm's other productive inputs as well as firm fixed effects.[33]

5.2 Step 2: Model Inversion

Using pre-policy data (2004-2006): We use data from before the introduction of subsidies (as well as the structure of the model) to calibrate the sunk cost of entry (2 parameters), the fixed costs of production (2 parameters), the fixed cost of innovation (2 parameters), and city productivities across both types of energy (two parameter values for each of the 358 Chinese cities).

[31] We use observed revenue data to derive the empirical probability distribution function of revenue. We restrict to firms above the 90th percentile in the revenue distribution, although nothing hinges on the exact cut-off point.

[32] Appendix C.3 shows that our results are robust to allowing for city-specific heterogeneity in the parameters.

[33] Details are in Appendix Section E.3. Our estimates imply that a new solar patent increases output by just under 6% in future years. Moreover, past patenting by other firms increase a firm's revenue by 8.4%. The spillover coefficient is larger than the own effect because the relationships are in logs. A doubling of patents by all other firms in the province is a much larger "treatment" than a doubling of patents by the firm itself.

Table 4: **Model Quantification Strategy**

Parameters		Values	Identification/Moments	
Preference Parameters				
σ	Elasticity of substitution across energy sectors (solar vs non-solar)	3	Jo (2023), Papageorgiou et al. (2017)	External
$\sigma_s, \sigma_{s'}$	Elasticity of substitution across power plant input varieties (e.g. solar panel models)	5, 8.18	Shapiro and Walker (2018)	External
Trade Parameters				
τ_{od}	Iceberg trade costs (intra-China)	$e^{0.032\, tt_{od}}$	Egger et al. (2023)	External
Production Technology Parameters				
$\xi_s, \xi_{s'}$	Productivity gain from innovating	1.058	Estimated (Appendix Table E.19 column 3)	External
δ	Knowledge spillover parameter	1.084	Estimated (Appendix Table E.20 column 2)	External
$\theta_s, \theta_{s'}$	Shape parameter (of Pareto distribution)	5.3, 11.7	Sales revenue (ENF, ASIE)	External
$b_s, b_{s'}$	Industry average scale parameter (of Pareto distribution)	0.267, 0.256	Sales revenue (ENF, ASIE)	External
$b_{o,s}, b_{o,s'}$	Location specific scale parameter (of Pareto distribution)	2 values for each of 358 cities	Local solar and coal revenue 2004-2006	Model inversion
$f_s^e, f_{s'}^e$	Sunk entry cost	24.05, 0.0016	Average productivity of solar and coal	Model inversion
$f_s, f_{s'}$	Production fixed cost	0.05607, 0.0462	Solar and coal average revenue	Model inversion
$f_s^i, f_{s'}^i$	Innovation fixed cost	0.05610, 0.2784	Share of solar and coal innovators	Model inversion
Policy Parameters				
a_s	Production subsidy	16%	Revenue and Innovation empirical ATTs	Minimum distance
χ_s	Demand subsidy	8%	Revenue and Innovation empirical ATTs	Minimum distance
ϕ_s	Innovation subsidy	12%	Revenue and Innovation empirical ATTs	Minimum distance

Note: Details given in text and Appendix subsection C.3. In Step 1, *External* calibrated parameters are taken from the literature or estimated using our own data. In Step 2, we use *Model inversion* to estimate fixed and sunk costs and the location parameters of the Pareto distribution (city productivities). In Step 3, *Minimum distance* estimation is used to estimate the subsidy parameters by matching model-generated average treatment effects (ATT) to empirical ATTs from the data. First two steps on pre-policy (2004-6) data.

5.2.1 Step 2.1: Fixed production and innovation costs

Given the externally calibrated parameters from Step 1, we can pin down the fixed costs of production and innovation in each sector using data on average firm revenues and the share of innovating firms. Intuitively, (i) the larger the share of innovators, the lower the fixed cost of innovation relative to the fixed cost of production; and (ii) when firms are big (as measured by average firm revenues), the larger are likely to be the fixed cost of production. More precisely, we solve a system of four equations in four unknowns - the fixed costs of entry (f_s, $f_{s'}$) and innovation (f_s^i, $f_{s'}^i$) in the solar and non-solar sectors (see equation (5) in Appendix C.3).

5.2.2 Step 2.2: Sunk entry costs and city productivity

Next, we estimate productivity in each city for both forms of energy, as well as the two sunk entry costs. The key data here are differences across cities in the size of their solar and coal sectors. Higher productivity increases city revenues, whilst higher sunk entry costs reduce them, all else equal. First, we derive the equations that link productivities in each city and sunk entry costs in both sectors to the observed city-level revenues from ASIE (coking/coal sector firms) and Orbis (ENF solar manufacturers), as well as the previously calibrated parameters (fixed costs, elasticities, etc.). Second, recall from subsection 5.1 we calculated the average productivity across China in each of the two energy sectors from the estimated scale parameter of the Pareto productivity distribution, finding $b_s = 0.267$ and $b_s' = 0.256$. We use these two additional moment conditions to (just) identify all city productivity levels and the sunk costs.[34]

5.3 Step 3: Matching the Reduced Form Treatment Effects

Conditional on the parameters in steps 1 and 2, we recover the values for demand, production, and innovation subsidies (χ_s, a_s and ϕ_s respectively), by matching model-implied treatment effects to their empirical counterparts.

We target the estimated average treatment effects (ATT) from our regression specifications for revenue and patenting. We guess a value for subsidies, solve for the equilibrium of the model and simulate outcomes, running regressions on this simulated data using the actual policy roll-out, then iterate this process to minimise the quadratic distance (l_2) between the model and empirical ATTs.[35]

We do this exercise separately for each of the three subsidy types. Since innovation subsidies are never observed in isolation (they are always bundled with production subsidies), we first calibrate demand and production subsidies separately using cities that receive these policies. Then, we fix the production subsidy and calibrate the innovation subsidy using treatment effects from cities receiving both production and innovation support.

Our estimated subsidy sizes are 16% for production, 8% for demand, and 12% for innovation. Table 5 shows that ATT moments for the estimated subsidy costs match reasonably with the empirical treatment effects and lie within the 95% confidence intervals. The model's demand subsidy parameter has the weakest fit with the data, which is a function of the larger standard errors around the ATT effects.

[34] For details see Appendix C.3 and in particular, equation (8)

[35] Our baseline regressions on the simulated data using Two-Way Fixed Effects regressions matched to the SDID ATTs. We also ran SDID on the model-simulated data, which produced very similar results at much greater computational cost.

Table 5: **Model fit in the estimation of subsidy costs**

	Moments			
	Innovation ATT		Revenue ATT	
Subsidy	Model	Data / 95% CI	Model	Data / 95% CI
Production $[1 - a_s]$ (16%)	0.689	0.871	1.973	1.772
		[0.426, 1.316]		[0.567, 2.977]
Demand $[1 - \chi_s]$ (8%)	0.067	0.236	0.120	0.060
		[-0.303, 0.775]		[-0.485, 0.605]
Production $[1 - a_s]$ (16%)	1.182	1.060	2.486	2.502
& Innovation $[1 - \phi_s]$ (12%)		[0.341,1.779]		[0.897, 4.107]

Note: We estimate production, demand, and innovation subsidies by minimizing the quadratic difference between model-generated average treatment effects (mass of patenting firms and revenue) and empirical average treatment effects (patenting and revenue from Table 2), using data from 2007 onward while holding pre-subsidy parameters fixed. Since innovation subsidies were always implemented alongside production subsidies, we first calibrate production and demand subsidies, then estimate innovation subsidies with production subsidies fixed. 95% confidence intervals in square brackets.

6 Quantitative Results

We now turn to the results from our quantitative model. Our key finding is that local industrial policies significantly expanded aggregate solar industry output and innovation in China and reduced solar prices (subsection 6.1). In other words, the relative impacts estimated in Section 3.2 are not solely driven by cross-city reallocation of activity. We attribute a material share of the industry's transformation to these policy interventions. In subsection 6.2 we show that overall Chinese welfare rose because of these policies (especially when accounting for the social cost of carbon) and use counterfactual experiments to show how (i) an alternative subsidy designs focused on innovation would have raised welfare by even more and (ii) that a common policy across all Chinese cities is no more effective than the actual pattern of city specific subsidies.

6.1 Contribution of policy to the aggregate transformation of the Chinese solar industry

To estimate the impact of local industrial policies on solar industry outcomes, we use our estimated model to show the predicted change in key aggregate solar outcomes: innovation, revenues and prices. We then simulate a counterfactual scenario without these subsidies to gauge the policy impact.

Figure 10 shows the model's predicted evolution of aggregate innovation, revenue, and price (panels (a), (b) and (c) respectively) under the actual subsidy policies (the solid teal line entitled "Real Subsidy") compared to a counterfactual without these policies (orange dashed line entitled "No Subsidy"). We index all values relative to 2006, the year before the first local solar policy was introduced. In our reconstruction of the no-policy counterfactual, we find that innovation and revenues would both have increased by about 270% between 2006 and 2020 and price fallen by 25%. This is primarily because of increases in energy demand coming from China and the rest of the world, boosting market size and therefore production and innovation.

The impact of policies is the vertical distance between the two lines in Figure 10 and implies that by the end of the period, China's industrial policies increased solar innovation by about 300%, revenues by 230%, and prices further fell by a quarter. This suggests substantial benefits of the policy for the growth of the solar industry in China. Importantly, the city level partial equilibrium effects identified in the empirical section do not wash out at the aggregate level. Comparing real subsidy with no subsidy, it implies that local industrial policy explains almost half (300% / 670 % = 45%) of the aggregate growth in innovation, almost two-fifths (230% / 600 % = 38%) of revenue growth and around one-half (25% / 50%) of the fall in price. Unsurprisingly, industrial policy cannot explain all the growth in the Chinese solar sector, but it plays an important quantitative role of around 40% to 50%.

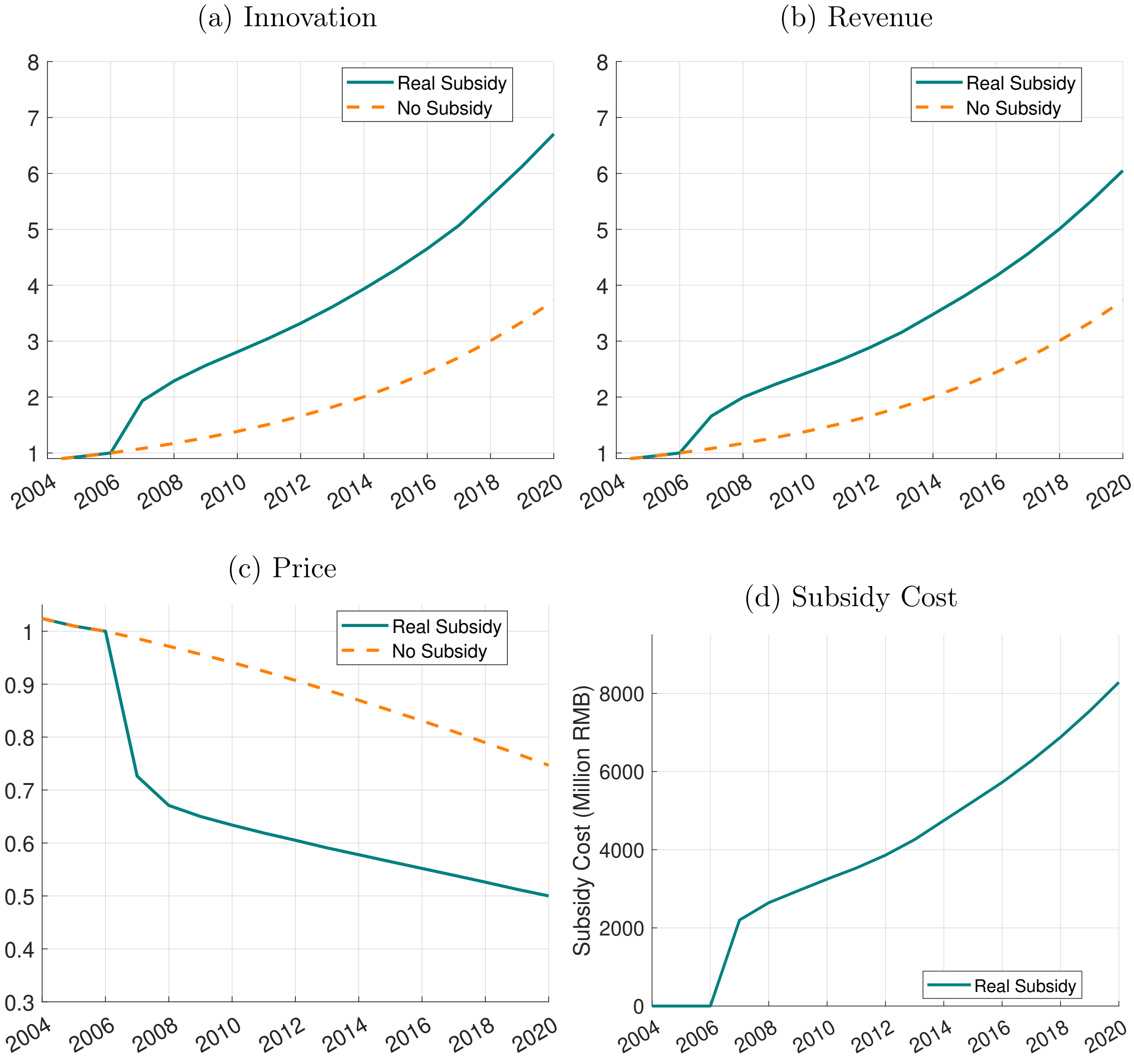
Panel (d) of Figure 10 reminds us that there was also a substantial subsidy cost of this growth, which we take into account in the welfare calculations in the next section. There are explicit firm subsidy data from the ASIE dataset in some years, that we can compare these model generated estimates (more details in Appendix subsection E.2). First, the time series profile is comparable, especially the jump in 2007 when policies turn on. Second, SDID estimates using subsidies as an outcome mirrors what we would expect (e.g, no effect of demand subsidies but strong effects of producton subsidies). Third, our levels somewhat higher, however. For example, our model predicts that solar subsidies amounted to RMB 3 billion in 2010, while the ASIE data suggest RMB 2 billion. This likely reflects that formal declarations of subsidies in the ASIE data underestimate the full degree of "hidden" policy interventions as revealed by our model.

In Figure 11, we consider similar counterfactual simulations to Figure 10, but now disaggregate into the contributions of each type of subsidy. We consider introducing each of three types of subsidy independently, continuing to follow the timing of implementation in the data (so the impacts are a combination of the policy itself and the number and identity of cities introducing the policy). We look at the path of aggregate innovation, revenue, price and subsidies in panels (a), (b), (c) and (d) respectively. The dotted orange line reproduces the no subsidy baseline from Figure 10, so as before, the vertical distance between this baseline and each line shows the impact of the specific policy type.

We see a broadly consistent pattern on the three main performance outcomes in panels (a)-(c). There is a positive, but quantitatively small effect of demand policies. By contrast, production subsidies lead to substantially larger increases in revenue and innovation and earlier reductions in solar prices. Again, consistent with the city-level empirical results, combined production and innovation subsidies have the largest effects.

The subsidy costs in panel (d) of Figure 11 are informative. Demand subsidies may have relatively low impacts, but they are also much less expensive. Recall that the "pure"

Figure 10: **Overall impact of solar subsidies**

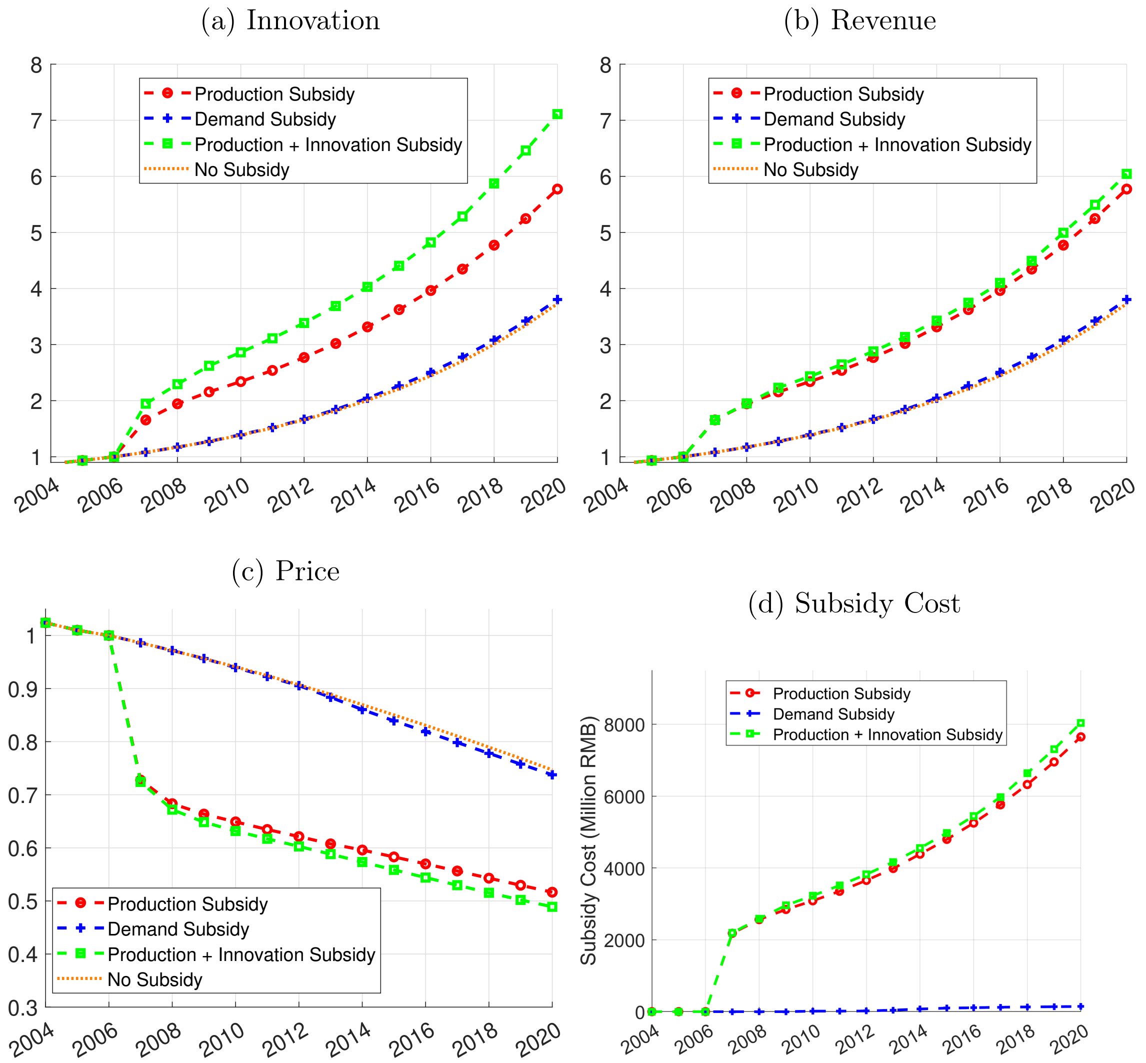


Note: The Figure presents the aggregate change across China: (a) Innovation (number of patenting firms), (b) Revenue, (c) Price and (d) Subsidy Cost. In panels (a) through (c) levels are normalised to 1 in 2006 (so a value of 2 indicates a doubling). Absolute values are given in panel (d).The orange dashed line is the no-policy counterfactual. The solid teal line represents the combined effect of the actual roll-out following the timing of the real subsidies across cities as in Figure 2. We use the calibrated subsidy sizes from Table 5.

innovation policy effect is the vertical distance between the green line (squares) and the red line (circles). These innovation policies are not much more costly than demand policies, but have a larger impact (especially on patenting in panel (a)). Innovation policies are also less common than the other two policies (recall Figure 2), which makes their impact even more impressive because Figures 10 and 11 reflect the number of policies as well as their impacts.

We have shown that local industrial policies led to large increases in aggregate solar industry activity, but also at substantial cost. To move from positive analysis to normative statements, we now turn to an explicit welfare analysis of the overall impact of different industrial policies.

Figure 11: **Subsidy impacts by policy type**



Note: The Figure presents the aggregate change across China in: (a) Innovation (number of patenting firms), (b) Revenue, (c) Price and (d) Subsidy Cost. In panels (a) through (c) levels are normalised to 1 in 2006 (so a value of 2 indicates a doubling). The difference in the two lines is the impact of the policy. Absolute values are given in panel (d). The orange dotted line is the no-policy counterfactual. The blue crossed line considers just demand subsidies; the red circled line just production subsidies and the green squared line the combination of production and innovation subsidies. We use the calibrated subsidy sizes from Table 5.

6.2 Welfare: Main Results

We assess the aggregate welfare implications of solar subsidies in two steps. We first focus on consumer welfare changes from energy consumption. We then consider total social benefits (and costs) which means taking into account of the revenue gains for solar manufacturers from exporting.

6.2.1 Consumer Welfare: Energy consumption

Solar subsidies raise welfare from energy consumption by making the overall mix both cheaper and cleaner. Recall that the utility of the representative consumer of electricity services e in region d takes the form $U_d = u(e_d) = \left(e_{d,s'}^{\frac{\sigma-1}{\sigma}} + e_{d,s}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$. After substituting the equilibrium solutions and reintroducing the time subscript, this naturally yields $W_{d,t} = U_{d,t} = \frac{E_{d,t}}{P_{d,t}}$. We compute discounted aggregate consumer welfare by aggregating across all locations and across years:[36]

$$W = \sum_{t=\tau} \beta^{t-\tau} \sum_{d} W_{d,t} \tag{4}$$

Where β is the discount factor (which we set to 0.98).

Solar subsidies first increase welfare from energy consumption through their effect on lowering the price index for electricity consumption paid across regions in China. This takes place via the reduction in the price of solar panels and via increasing the share of solar installation in the energy mix. Solar subsidies bring an additional social benefit by reducing the environmental costs of electricity consumption. We translate coal expenditures in each scenario into coal usage by dividing expenditure over the average coal price between 2004 and 2006. Using emissions data from IEA, we convert coal usage into additional carbon emissions, and apply the social cost of carbon (SCC) estimates in Carleton et al. (2022), translating emissions into monetary damages. We first report welfare gains from electricity consumption in the presence of solar subsidies without accounting for the reduction in environmental externalities. We then add these additional social gains from avoided emissions in our estimates of the net monetary gains from the policies.

6.2.2 Social Cost-Benefit analysis

We now consider whether the benefits of solar industrial policy we have identified for Chinese citizens outweigh the subsidy costs. To do this, we need to go beyond the consumer welfare from lower prices considered in the previous subsection. As the industry expands, even if firm profits remain constant, revenues and costs increase. These costs are paid in units of labour, machinery, and materials, which are incurred mostly within China.[37] To capture these benefits from the solar industry's expansion, we examine aggregate solar and coal manufacturers' revenue. Intuitively, solar subsidies increased solar firms' revenues and decreased coal manufacturing revenues. We assess how this change in energy manufacturing

[36] Note that the summation is across all Chinese city-regions, i.e., we ignore the welfare enjoyed in the region representing the rest of the world.

[37] In a model setup where other sectors are explicitly defined and labour markets clear, all revenues would be reflected in a representative consumer's income and thus captured by consumer welfare. In our framework, however, since we model only the energy sector, consumer welfare and producer surplus remain distinct objects.

revenue compares to our estimated subsidy costs.[38]

6.2.3 Counterfactual exercises

We start by evaluating the consumer welfare implications of the actual subsidies implemented, a natural baseline. We then examine two counterfactual policy strategies that maintain the same total policy cost as the baseline. The first applies all three policy types uniformly across every Chinese city, starting from 2007 (the "Equal" scenario). This is an interesting counterfactual, as it resembles a national policy where the national government applied subsidies uniformly instead of allowing decentralized choices by cities. This could result in better outcomes if, for example, places with low comparative advantage in solar were those that introduced particularly generous production subsidies (a common critique of industrial policy). On the other hand, a nationally equal policy could produce worse outcomes if city policy-makers are better informed as to what works best in their local areas.

The second counterfactual policy explores whether placing greater emphasis on innovation policies within the policy bundle would have increased welfare, as suggested by our earlier results. We investigated this in various ways, but our leading implementation is to consider an "Equal + Innovation" scenario. Here, all cities again have identical policies starting from 2007, but we set the level of the innovation subsidy at 75% as this is the minimum level required to induce all solar firms to innovate (i.e., the maximum possible rate of innovation in our model). Since we still have some budget left over (based on what local governments actually spent on all subsidies), we allocate this residual to demand and production subsidies, which are also applied uniformly across cities. This way, we prioritise innovation targeting but keep total policy costs the same across experiments.

These counterfactual policies are summarized in Table 6. The "Real" column (1) reproduces our estimated levels of subsidies in Table 5. The final row shows the numbers of cities affected by each policy. The "Equal" column (2) shows that for the same budget we can have a 9.4% subsidy on all three policies in all cities. Column (3) shows that once we induce innovation by all solar firms, the fiscal budget constraint can still allow a 4.2% subsidy on demand and production policies in all cities.

6.2.4 Welfare: Main Results

Figure 12 shows the main consumer welfare results. We contrast the "Real" path of subsidies to three counterfactuals discussed above: "No Subsidy", "Equal" subsidies across all cities and "Equal + Innovation" (i.e., equally distributed, but tilted towards innovation subsidies). Panel (a) displays the path of flow annual consumer welfare under the alternative policy

[38] The total revenue in China is defined as $R = \sum_t \sum_d R_{o,t}$, and the total subsidy cost as $C = \sum_t \sum_o C_{o,t}$. These summations are taken solely over the city-regions in China, i.e., we do not include the rest of world region.

Table 6: **Counterfactual Policy Designs**

Subsidy	Real	Equal	Equal + Innovation
	(1)	(2)	(3)
$1-\alpha_s$	16%	9.4%	4.2%
$1-\chi_s$	8%	9.4%	4.2%
$1-\phi_s$	12%	9.4%	74.7%
Regions	(18, 30, 10)	358	358

Note: The last row presents the number of treated regions under production, demand, and innovation subsidies. The "Real" subsidy column shows the calibrated subsidy sizes from Table 5, with different regions receiving subsidies in different years, following Figure 2. In the "Equal" subsidy column, every 358 region receives the same level of subsidy across all subsidy types starting in 2007, while keeping the total cost the same as in column (1). Column (3) applies a full innovation subsidy, ensuring that all firms in all 358 regions choose to innovate, while also providing the same level of demand and production subsidies across all regions from 2007. The total cost remains the same as in column (1).

rollouts (where the pre-policy year of 2006 is normalised to 1). Panel (b) includes the present value of the welfare gain relative to the no-subsidy baseline, from the perspective of 2007.[39] Panel (c) shows the total social benefit (summarized by revenue changes) vs. social cost ratio. Values above the horizontal line at one indicate benefits exceed costs. The yellow bars exclude the social cost of carbon, whereas the green bars include them. Each pair of bars corresponds to the three counterfactuals.

Turning first to the actual policies implemented (the teal bar in panel (b) of Figure 12, "Real" subsidy), we estimate that these subsidies increased consumer welfare by 12 percent relative to a no-policy counterfactual. Next, we examine a counterfactual in which subsidies are uniform across all Chinese cities (the purple bar labelled "Equal" in panel (b)). The results are nearly identical to the baseline "Real" subsidy. This indicates that adopting a simple, national subsidy scheme would have yielded no better outcomes than the actual local policies. The main reason is that the geographical distribution of subsidy policies was already roughly balanced once both productivity and market access are taken into account (see Appendix E.1).[40]

A clearer contrast emerges in the "Equal + Full Innovation" scenario given by the blue bars in panel (b) of Figure 12. Here, an innovation-oriented policy delivers much larger welfare gains: consumer welfare rises by 52%, more than four times the gain under the real policy. In other words, a strategy focused solely on innovation, without additional demand or production subsidies, could have achieved the same overall consumer welfare benefits at a much lower fiscal cost. This is illustrated by the horizontal red line in panel (b), showing that innovation policy alone still yields higher welfare than the first two policy designs.

[39] We assume that after 2020 the world remains unchanged, and we compute the infinite sum using a 2% discount factor.

[40] A fully optimal spatial subsidy schedule would be difficult to derive given the model's complexity. Our analysis suggests that what matters most is not the spatial allocation of subsidies, but rather the type of policy, hence the focus on innovation-heavy counterfactuals below.

Why is innovation policy so much more effective? The key lies in knowledge spillovers: when solar innovators experiment and learn, other firms benefit as well. This knowledge externality appears to be the dominant market failure that industrial policy addresses in our setting.

Finally, we turn to the full social cost-benefit analysis in panel (c) of Figure 12. This analysis reinforces the patterns we have already seen for consumer welfare. Under the "Real" subsidy policy, the yellow bar indicates that each $1 of subsidy increases total revenue by $1.65. This partly reflects Chinese firms becoming more competitive internationally and expanding exports. If we consider the deadweight loss from government taxation, it means that the policy would only fail a cost-benefit test if the deadweight was over 65%, which is much higher than standard estimates. Thus, even without accounting for emission externalities, solar subsidies generated net welfare gains for Chinese citizens. This is a key result for the paper.

The green bars in panel (c) of Figure 12 show what happens when we include the social cost of carbon. they indicate that total benefit roughly doubles, rising to over $3.24 for every $1 of subsidy. The "Equal" policy of the middle two bars show similar qualitative patterns to Figure 12, namely that welfare is similar to the actual policy roll-out. In contrast, the "Equal + Innovation" subsidy policy delivers the largest gains: each $1 spent raises revenue by $5.24, rising to $9.47 when climate benefits are included.

6.2.5 Welfare Results: Robustness and Extensions

We explored several alternative policy counterfactuals (see Appendix E.1). For example, concentrating the entire budget on production-only subsidies produces a consumer welfare gain of 9.2%, and a benefit to cost ratio of 1.69. Focusing solely on demand-side subsidies yields a 11.3% increase in consumer welfare and a benefit to cost ratio of 1.04. Overall, both subsidy implementations improve welfare, but a pure production subsidy has a larger net benefit mainly because Chinese firms are earning export revenue. However, it yields lower consumer welfare gains since many solar panels are exported rather than consumed locally.

We have performed a number of robustness tests on the welfare findings and discuss some of them here. In each case, we vary one key parameter, re-calibrate the model to ensure consistency in subsidy magnitudes and fiscal costs, and recompute welfare gains relative to a new no-subsidy counterfactual.

Reducing trade-related travel times for goods by 15%, consistent with the estimated improvement in transport infrastructure between 2000 and 2013 reported by Egger et al. (2023), leaves the consumer welfare gain almost unchanged: a small increase from 12% to 13% under the "Real" subsidy, and to 55% under the "Equal + Innovation". Increasing the fixed cost of innovation by 50% increases the consumer welfare gain to 18% under "Real" subsidy and to 61% under "Equal + Innovation". Finally, halving the knowledge spillover parameter changes welfare to 13% and 27% for the two policies respectively. The large drop in the welfare gain for the innovation-heavy policy is intuitive: as the underlying spillover externality shrinks, the market failure that innovation policy seeks to address becomes less severe, dampening the welfare benefits.

Overall, while the magnitudes shift modestly, the qualitative ranking of policies is preserved. The "Equal + Innovation" strategy consistently delivers the largest welfare gains, reinforcing our main conclusion that innovation support dominates demand or production subsidies.

Note that the consumer welfare effects reflect utility derived from energy consumption. Although this does not affect the social benefit cost ratio, we should rescale the consumer welfare impacts to approximate aggregate, economy-wide changes. Consider a Cobb-Douglas utility function combining energy (Y) and all other goods and services (X):

$$U = X^{1-\alpha}Y^{\alpha}.$$

If industrial policy reduces the price of energy (P_y), real energy consumption (Y) increases - by about 12% in our baseline - while the expenditure share of energy (α) remains constant. Holding non-energy prices (P_x) fixed, total utility rises by approximately $\alpha \times 12\%$.

Using China's 2007 input-output table, we estimate α to be around 0.12.[41] This implies an overall consumer welfare increase of about 1.4%. This is economically meaningful. For comparison, China's WTO accession, one of the most significant policy shifts in recent history, has been estimated to raise national welfare by roughly 1.5 to 3%.[42] Moreover, our estimate likely understates the full effect, since lower energy prices would reduce production costs (and hence P_x) throughout the economy.[43]

6.2.6 Summary on Welfare

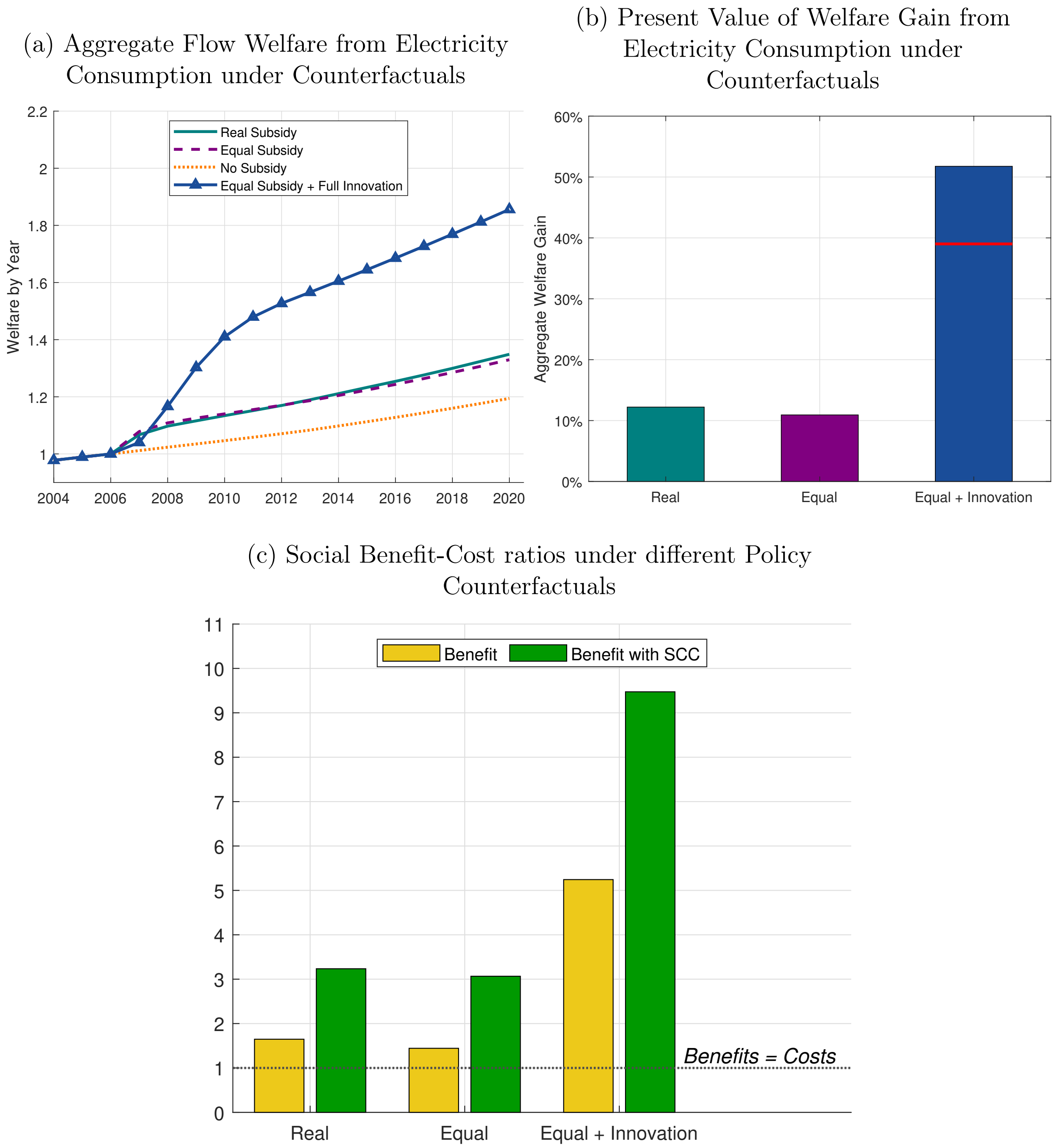
Taken together, these results underscore that China's solar industrial policies generated substantial and robust net welfare gains for Chinese citizens, even before accounting for environmental externalities. Nevertheless, the bundle of policies could have been improved if they were more heavily tilted to innovation subsidies.

[41] We approximate the energy expenditure share by dividing the sum of intermediate and final electricity consumption by total GDP. As a robustness check, we also construct the share from *China Statistical Yearbook* data on coal, oil, gas, and electricity consumption multiplied by respective unit prices. Both methods yield similar results.

[42] Fan et al. (2021) estimate welfare gains of 2.7%; Chen & Ravallion (2004) report 1.5%; Ianchovichina & Martin (2004) 2.2%; and Tombe & Zhu (2019) attribute a 2.9% gain to reductions in external trade costs between 2000 and 2005.

[43] Lower electricity costs could also spur innovation in electricity-using technologies and strengthen China's comparative advantage in electricity-intensive goods, amplifying trade and specialization effects.

Figure 12: **Welfare and Cost and Benefit**



Note: Welfare calculated as in equation (9). Aggregate welfare is calculated based on the utility of the representative consumer, aggregated across cities. Panel (a) has the flow level of welfare ($\sum_d W_{d,t}$) in each year. The solid teal line ("Real Subsidy") is flow welfare from the actual policy roll out. The dotted bottom orange line is the baseline alternative counterfactual of "No Subsidy". The other lines look at counterfactuals discussed in the main text. In panel (b), we calculate the present value of discounted welfare (W) from the perspective of 2006 (just prior to first solar subsidy in 2007). Each bar is the percentage welfare gain relative to the "No Subsidy" baseline. The first (teal) bar corresponds to the real policy roll-out, showing an additional welfare gain of 12%. This requires a policy implementation cost, which we keep constant when considering two other scenarios. "Equal" has a uniform set of demand, production and innovation policies in all cities. "Equal + Innovation" also has the uniform policies across regions, but gives sufficient innovation subsidy so that all Chinese firms innovate (indicated by the horizontal red line). We then allocate the remaining budget to production and demand subsidies. Panel (c) shows the social benefit-cost ratio with subsidy cost normalized to 1, so values greater than 1 are desirable (shown by the dashed black line). The yellow bars represent monetary benefits from increased revenue, whereas the green bars include the social cost of carbon (SCC).

7 Conclusions

In the sphere of climate change, we ultimately care about *global* emissions. This has naturally led to a policy focus on international cooperation in areas such as regulation and taxation. This paper points towards a different path which countries can pursue unilaterally - green industrial policies through demand, production and R&D subsidies. In principle, these policies may promote industrialization whilst simultaneously decarbonising the economy.

Our key contribution has been to demonstrate that city-level solar industrial policies have played a central role both in establishing China as the global leader in solar energy and also in improving the welfare of its citizens.

We compiled new data on city-level policies and performance to show that production and (particularly) innovation subsidies caused large and persistent increases in solar patenting, net entry, output and exports. We observed this both locally through an SDID estimator, and nationally through the lens of a spatial model we quantified using our empirical estimates. The interventions raised the welfare of Chinese citizens, and these benefits almost double when we take into account the social cost of carbon.

A key finding that drops out of both our reduced form and general equilibrium analysis is the outsized effects of innovation subsidies. These, it turns out, are particularly effective in not only driving up solar innovation and production but also in bringing down solar prices. This suggests that investing in R&D in clean energy firms may be a particularly effective means of balancing the decarbonization and growth needs of countries. This makes analysis of green industrial policies pursued in other territories, such as the US Inflation Reduction Act an important direction for future research.

We have focused on China and a natural question is whether its success has come at the expense of other countries. Maybe Chinese production and innovation gains (see Gentile et al. 2025) simply displaced activity that would have occurred in the US, EU, India or Japan? Our model can be extended to allow for these effects, but we leave a full exploration of this for future work. But note the ambiguity of the sign of these international spillover effects effects. First, city-level solar demand subsidies reduced pollution which is significant given that China's is the world largest emitter of particulate pollution and greenhouse gases. Second, Chinese policies can explain almost two-fifths of the decline in the global cost of solar panels. This is a powerful driver of the diffusion of solar electricity across the world. Third, our model captures many of the likely spillovers. The supply side subsidies do create business stealing effects (negative spillovers), but higher innovation (especially from R&D subsidies) creates positive productivity spillovers. Within China, our analysis finds that these are net positive from our analysis, but further work needs to be done to determine whether this remains true from a global perspective.

Another limitation of our work is that we examine a single industry. Using our framework to look at other green technologies like wind and electric vehicles, other sectors such as semiconductors, and other countries, would be a natural extension. Our intuition is that the positive impacts may be weaker for industries that are more technologically mature, like shipbuilding (e.g. Kalouptsidi (2018)), as there is less room for innovation spillovers.

Finally, we have abstracted from other legitimate concerns of China's dominance such as security of supply. These are legitimate concerns, but of less importance for renewables than other forms of supply (like oil), as disruptions of components such as solar panels whether driven by politics or nature are less immediately harmful.

What China has achieved over the past two decades is remarkable. Local industrial policies not only built a domestic industry but also helped make clean energy more affordable in China and around the world.

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ONLINE APPENDICES

A History of China's Solar Industrial Policies

In this Appendix we expand on the main text regarding the history of China's solar policy, borrowing extensively from Ball et al. (2017), Chen (2016) and Nemet (2019). The Chinese national government outlines its vision for industrial policy in its five-year plans. These provide national guidance for stakeholders, leaving the intensity of policy support to local implementation. Although there was some policy interest as early as the 1995 State Planning Commission, solar only became a targeted sector in the 2001-2005 Tenth Five-Year Plan. In these years, policies were mainly in the form of exhortation, but in 2005, a comprehensive legal base for the promotion of renewable energy was provided in the Renewable Energy Law (*zaisheng nengyuan fa*). The law established national Feed-In-Tariffs and legalized the provision of financial incentives (taxes and low interest rates) for renewables. Subsequently, the Chinese government has promoted solar energy in its Eleventh, Twelfth, and Thirteenth Five Year Plans. These Plans first emphasised export-based manufacturing and subsequently emphasised R&D and the wider value chain.

At the start of the Tenth Five-Year Plan for New-and Renewable-Energy-Industry Development, China had no domestic solar photovoltaic industry. Through the State Economic and Trade Commission, the Plan encouraged the production of solar cells and modules through exhortation. The Eleventh Five-Year Plan (2006-2010), emphasised the expansion of factory production and outlined strategies to increase R&D on polysilicon material and cell efficiency. It also encouraged the adoption of solar panels across the country. The solar industry witnessed strong growth during this period - see Figure 4, helped by big increases in demand from the US and EU due in part to policies to boost solar energy (such as Germany's generous feed-in-tariffs). China reacted to the 2008-09 global financial crisis through many stimulus policies including towards solar energy. First, the "Golden Sun" initiative in 2009 provided upfront financial support for solar projects - up to 50% of investment costs for grid-connected and up to 70% for off-grid. This was phased out in 2013. Second, there was investment in domestic power stations through Feed-In-Tariffs. These were introduced in 2011 with a high level of generosity comparable to those in the EU. There was regional variation in this, and section E.6 details how we deal with this.

With the Twelfth Five-Year Plan (2011-2015), R&D goals became more detailed and covered all aspects of the production cycle: raw materials, ingots, wafers, cell, modules, auxiliary systems, and even production methods and tools. WTO complaints against the Chinese solar industry were launched in 2011 by the US and in 2012 by the EU. Due to overcapacity concerns many firms consolidated and exited after 2012, with Suntech and LDK both going bankrupt. China's Thirteenth Five-Year Plan (2016-2020) again mentions solar, targeting capacity and R&D expansion, as well as industry-wide cost-reduction. Within this plan, the China's National Energy Administration issued, in December 2016, a specific

Thirteenth Five Year Plan for Solar Energy Development. In 2021 (outside our sample period), the "Whole Country PV" initiative for rooftop solar was launched.

China's national, provincial, and city governments all provided subsidies to the solar industry. However, the magnitude of this policy remains a disputed issue, which has reached the international courts.[44] Ball et al. (2017)'s qualitative research, based on interviews with government officials, high-level members of the industry, manufacturing firms and academics, provides some clarity on the administrative level and characteristics of policy support. Subsidies to solar manufacturing were managed and allocated by city governments. The timing, size, and targeting of policy support thus varied significantly by city-region as local governments engaged in competition via policy support to build up their solar manufacturing industry.

Solar firms are predominantly privately owned with the strong patronage of local government. As Chen (2016) puts it, "local governments in the solar PV episode have been essentially strategic partners to local enterprises", making investments like Venture Capitalists. Local government bureaucrats are inventivised to grow their local economies (and solar in particular) as it helps their cities "look good" and fosters their career advancement (see Bai et al. in press). Examples include Suntech (PV producer) sponsored by the city of Wuxi and LDK (wafer producer) sponsored by the city of Xinyu.

Subsidies followed a similar structure to that of other sectoral industrial policies in China. At first, they were mostly targeted towards solar manufacturing. Since 2006, cities took advantage of the national legal framework that allowed local policy support for renewable energy such as tax incentives, land discounts, cash investments and other forms of financial aid. Ball et al. (2017) conjecture that this continuous and wide ecosystem of policy support may lay behind the continuous process innovation and improvements in China's solar manufacturing productivity, which is something we investigate directly in our analysis.

China's national vision and ecosystem for R&D involve a variety of governmental, corporate, and academic actors, coordinated by the Five Year Plans' national guidance. At the national level, there are several state entities who contribute.[45] As is the case for manufacturing subsidies, the exact magnitudes are opaque. Ball et al. (2017) use public information and interviews with key actors in the Chinese solar industry to estimate that about a third of solar R&D was government funded.

[44]For example, the US Department of Commerce's investigation in the wake of the SolarWorld trade allegations. The EU and US anti-dumping investigations produced lengthy reports, but unfortunately most of the information is redacted, which is why we have gone to considerable lengths to estimate solar policies.

[45]National Development and Reform Commission (NDRC), the National Energy Administration (NEA), the Ministry of Science and Technology (MOST), the Ministry of Industry and Information Technology (MOIIT), the Ministry of Finance (MOF), and the Ministry of Education (MOE)

B Data

We summarized the rich data set we have compiled in the main text in Section 2. Here, we go into more details on various sources.

B.1 Solar industrial policy

The main data on industrial policy towards solar manufacturing and installation comes from PKULaw's Laws & Regulations dataset. PKULaw is a comprehensive and reliable source of China's legal information, including all laws, regulations, and any related legal information implemented by the central and local governments since 1949. We obtain data disaggregated by industry and gather all regulations and policies pertaining to the solar photovoltaics industry. The dataset contains information on the title, validity, administrative level, department, release date, and implementation date of each policy. It also includes a link to the original policy document, which contains the text of each regulation or announcement. We manually read and inspected the full text of each of the 2,000 or so policy documents and classified them into subsidies, announcements, poverty alleviation and information ("records") policies. We further sub-classify subsidy policies according to whether they target solar installation, production, or innovation. Table 1 and Appendix Table B.1 provide examples for each subsidy type. Financial subsidies include direct grants, tax breaks, cheap loans, sub-market priced land, etc. As noted in the main text, we found no effect of the policies without financial subsidies, so we focus on policies with explicit financial subsidies towards solar.

B.2 Solar panel and cell manufacturers register, production, and capacity data

The ENF Solar Industry Directory is a register of 50,800 worldwide photovoltaic (PV) companies. Because it is the leading solar website, most companies self-register on ENF's platform. ENF reviews daily news regarding the solar industry, as well as available lists of key solar exhibitions, to incorporate new solar companies. Additionally, ENF uses government organizations and a variety of web-scraping techniques to complete the full list of solar companies. It automatically scans to detect company updates, which triggers careful checks from ENF database experts to update manufacturers' information and for signs of companies ceasing their activities. Hence, ENF is able to capture a snapshot of the population of solar panel manufacturers each year. We obtained access to the historical directories of solar panel producers from ENF Solar Industry Directory, available from 2010 until 2021 (henceforth, "ENF Register" dataset). We also accessed ENF's Chinese Cell & Panel Manufacturers Report. This dataset (henceforth, "ENF production" dataset) allows us to measure, for each firm, their production and capacity figures (in MWh) for both solar panels and solar cells across the 2004-2013 period.

The ENF register and ENF production datasets overlap for the 2010-2013 period. We matched the two datasets by firm name and contact details (address, phone, website, fax, and email). We manually inspect the information and addresses of the remainder to match them. We are left with a sample of 1,718 Chinese solar panel manufacturers, operating at some point between 2004 and 2020, which (in addition) includes production and capacity data for each manufacturer during the 2004-2013 period.[46]

B.3 Firm counts, entry and exit

The Qichacha platform (*https://www.qcc.com*) allows us to gather detailed firm-level information, spanning from registration to exit, and updated periodically following government requirements. This includes the type of business, the identity of affiliated enterprises, a variety of judicial and legal details, company news, corporate annual reports, and our main variables of interest, firm entry and exit dates. The Qichacha platform collects this information from multiple data sources, but mostly relies on government's official sources, which include the National Enterprise Credit Information Publicity System, the China Court Judgment Documents Network, and the China Enforcement Information Disclosure Network.

To retrieve the key variables for our sample of ENF solar manufacturers, we manually search in the platform using ENF firms' Chinese names. Some of the firms included in the ENF register are based in Hong Kong or Taiwan and are therefore excluded from the Qichacha platform. Our final sample of manufacturers is restricted to those with an address in mainland China.

Note that ENF solar manufacturing registers only recorded a firm's English name in the 2013 and 2014. For these years we use Google and Baidu to obtain the corresponding Chinese name for these firms to match into the Qichacha platform. There are a few very small firms that entered the sample in 2013 and exited in 2014 that we could not match.

B.4 Patents and their characteristics

The Qichacha platform contains detailed intellectual property information from the State Intellectual Property Office (SIPO). This enables us to obtain, for each ENF manufacturer, the name, patent ID, type, application date, publication date, and assignee, of the patents it has filed. We then use the SIPO patent ID to extract IPC codes and patent abstracts from the PATSTAT database.

[46] The ENF production dataset includes projections of production and capacity in 2014, but we chose not to use this. 2013 is a transition year with actual and a few observations with projected data. We also checked robustness of the results to ending the sample in 2012.

Since patents are of different quality, we consider two approaches. First, we rely on the SIPO classification of patents into Invention, Utility Model and Design patents. Invention patents have longer protection periods, require paying higher filing costs, and involve a more cumbersome administrative process. They are therefore patents of higher quality and a more innovative nature. The firms in our solar manufacturers dataset file mostly invention and utility model patents. Second, using IPC codes from Shubbak (2019), we further classified invention and utility model patents into solar and non-solar patents.

Second, as a further measure of patent quality we also constructed cite-weighted patents. We use the match between SIPO and PATSTAT which contains patents from all the world's patent offices. PATSTAT creates patent families, so each invention is only counted once even if it is filed in multiple jurisdictions. The future cites (from all other patent families) are used to weight each Chinese patent count as a measure of its importance.[47]

We also use text mining techniques to detect "learning-by-doing" (LBD) patents based on the information in the patent abstracts (see next subsection).

Our results, with two exceptions, build on the data set described above. One exception is the city-level solar patent count used in Section E.4 that also takes into account patents from non-solar firms and other entities (like universities). These counts are derived from the Qichacha website through the keyword-based search of patent abstracts rather than IPC codes, which we use for our main results. The reason for this is only that the keyword-based search is easier to carry out on the Qichacha platform. The second exception is the global patent statistic cited in Section 1. This was derived from the PATSTAT data set by collecting all solar applications via solar IPC codes. We then followed De Rassenfosse et al. (2013) to identify worldwide patent counts.

B.5 Text analysis on patent abstracts

To characterize the innovative content of patents filed by our sample of solar manufacturers, we built a supervised learning model using Liu (2023)'s dataset to train our text classification procedure. This dataset contains 3,299 solar patents (according to their IPC code), manually classified by the author into *productivity-improving* or not, after careful analysis of the text of all patent abstracts. These are essentially process innovations as opposed to the product innovations that are more common in patent datasets. The low cost of patenting in the Chinese patent office is an advantage in this respect as we capture many of the more incremental improvements that LBD may foster. Figure B.1 display the most common words contained in the patent abstracts for productivity increasing or learning-by-doing patents.[48]

We follow standard text cleaning procedures and train a random forest algorithm on 85%

[47] We also looked at triadic patents and those filed just in the US or Europe, but this dramatically reduces the information available.

[48] The word 'solar' has been removed to ease visualisation.

of Liu (2023)'s data. The model classifies the remaining patent abstracts in the hold-out sample with an accuracy of 85-90%, which seems a high rate of validation. We then use our model to classify the universe of patents filed by ENF solar manufacturers during the full time period of our analysis.

Figure B.2 illustrates three examples of learning-by-doing process patents. The patent abstracts highlight the benefits for productivity of production processes and industrial development. Figure B.3 is an example of a solar-related new product, i.e., a patent that is not learning-by-doing - it does not refer to productivity improvements.

B.6 ORBIS and ASIE data

For revenues and other accounting variables including capital and labour, we use Bureau Van Dijk's (BVD) Orbis dataset. Unlike the ENF production data Orbis variables are reported throughout the 2004-2020 period. We use the comprehensive firm contact information included in both the Orbis and ENF register datasets to merge the two datasets, and obtain Orbis variables for our sample of solar manufacturers.

We validate the Orbis data making use of the Annual Survey of Industrial Enterprises (ASIE). ASIE, also called the Annual Survey of Industrial Firms), is an administrative dataset covering all large industrial firms in China.[49] ASIE is only available between 1998 and 2013 and the sample of firms included in the survey changes over time.[50] Before 2011, the revenue threshold for inclusion in the ASIE was 5 million RMB. After 2011, this threshold was raised to 20 million RMB. Despite these limitations, given that the Chinese government and other researchers (e.g. Aghion et al. 2015) frequently use this dataset, we also use ASIE for various purposes throughout the paper.

We match our ENF firms with the ASIE through a two-stage process. First, we search ENF firms in the Qichacha platform and retrieve their registration data, which includes the standardised official Chinese name. This name standardisation is also used in the ASIE, so we can conduct exact matching with the ASIE dataset on a second stage. We are therefore able to identify ENF firms on ASIE and Orbis using two different matching procedures based on rich contact information and the standardised naming convention shared by the ASIE and the firm registration dataset. We can then compare the values registered in Orbis and ASIE for the same variable, same ENF firm, and same year. Both Orbis and ASIE include information on the value of total assets. Figure B.4 compares log(assets) in Orbis and in ASIE, with each data point representing a firm-year combination. The fit is exceptionally close to the 45 degree line with a coefficient of 1.01 and an R^2 of 0.97. [51]

[49] "Industrial" includes manufacturing, mining and utilities.

[50] There is some data for three selected provinces after 2013, but with fewer variables and access is highly restricted.

[51] We can discard the possibility that Orbis just used ASIE data for the overlapping years by noting that there was no noticeable break in the time series of ENF firms' total yearly assets as reported in Orbis before

Broadly, there are three types of missing values for revenues in the Orbis dataset. First, we observe revenue data for the same firm in two different non-consecutive years, but there are missing values for in between. In this case, we use linear interpellation to fill in missing values. Second, we observe some values for revenue, but not in the first few years, when the firm enters the market, or the last few years, before the firm exits. In this case, we use the values we observe to replace the missing ones through extrapolation. The third case occurs when we do not observe any information for a firm. In this case, we simply drop the firm from the analysis when revenues are used as an outcome variable. We checked that the results are robust to just using the non-imputed data and alternative ways of imputation.

B.7 Solar exports

The Chinese Customs Dataset contains information on all imports and exports between 2000 and 2016. It records all international trade transactions by Chinese firms, allowing us to observe the name of the importing/exporting firms, the value of the transaction, the HS8 product code, and the country of the trading partner. We obtain export information for our sample of ENF manufacturers following the same two-step procedure used for the ASIE data. First, we search by name in the Qichacha platform and retrieve the standardised official name for all ENF firms. This allows us to match exactly with the customs data and get information on exports by ENF solar manufacturers. Not all exports by ENF manufacturers are solar products. We classify exports as solar-related using the HS6 code "854140". This includes LED products as well as solar, so we also used the HS8 code “85414020" which is solar-only, but was only created in 2009. The results were very similar using the narrow category on the smaller set of years to the broader category thta we use in the baseline analysis.

B.8 Adjustment of revenues to reflect multi-product firms

As noted in the previous subsection, some of the ENF solar producers also sell non-solar products. The solar-specific revenue is not generally available for such multi-product firms. Whereas we are able to split out solar patents, exports and production from the other datasets, we are not generally able to do this for revenue (or other accounting variables from Orbis). To address this, we use the solar exports data. From the customs data we know the value share of solar in total firm exports and use this to adjust downward the revenues for firms where this is under 100%. For non-exporters, we make the following three adjustments. First, if a firm never exports, we use the city-level solar export ratio of the exporting firms. If this is missing, we use the province level and if this is also missing we use the national average. Second, some firms have no exports in their first few years after entry, and this

and after ASIE became available. This is visible in Figure ??

is likely because entrants will sell some solar modules locally in China before starting to export. We account for this "ramping-up" behavior by a linear interpolation between the first year of export and the entry data. Third, we only observe exports data through 2016, so we keep to the adjustment values from 2016 for all years after

We can validate our adjustment by using the ENF data on solar panel production in the years up to 2013. Even though we do not use these data for our adjustment, we find that regressing the adjusted revenue on the panel production at the city level yields a higher R^2 than the non-adjusted revenue (0.62 vs. 0.57). This suggests our export-based adjustment filters most non-solar activity. Figure B.5, shows binscatters of city-level panel production (x-axis) on both adjusted and unadjusted revenue. The adjusted revenue is very close to the 45-degree line, whereas the raw revenue lines lies a long way above. The over-estimation of revenues seems particularly large for cities with small amounts of solar activity, suggesting that a lot of this may be non-solar revenues.

We confirm that our results were robust to various ways of doing these imputations and indeed, even using the unadjusted revenue data (e.g., Figure E.10 and Table E.7). The main difference is in the precision of the estimates which improves when we deal with these various sources of measurement error.

B.9 Pollution and CO_2 emissions data sets

To capture PM2.5 concentrations in Chinese cities between 2004 and 2020, we use the V5. GL.04 data set of Van Donkelaar et al. (2021), which estimates annual average PM2.5 $\mu g/m^3$ concentrations using information from satellite-, simulation- and monitor-based sources. The estimates are stored on a 0.1 x 0.1 (approximately 11 km x 11 km) resolution grid. The data set was validated against ground-based measurements specifically for China from 2014 to 2020 by Ali et al. (2023), and the validation results demonstrated a good agreement between the estimates and ground-based PM2.5. We map information to our cities by calculating, for all cities, the area-weighted average concentration from all 0.1 x 0.1 resolution pixels with which it overlaps. The distribution is much less skewed than our other outcome variables, motivating using levels rather than the IHS transformation.

To capture CO_2 emissions, we use the county-level data set of Chen et al. (2020), which is available until 2017, and provides the most comprehensive coverage of our studied cities and time period. The data set is constructed using provincial estimates of energy-related carbon emissions and nighttime light data which is used to disaggregate these measures to 2,735 Chinese counties. The technique is shown to perform well in validation exercises. We map these to our city-level observations using county names, which allows us to derive annual CO_2 emission for 348 cities from 2004 to 2017. (The data set does not cover cities in the Tibet Autonomous Region.)

B.10 Pollution-related mortality calculation

We derive the impact of demand subsidies on the number of pollution-related deaths through the following calculation.

1. First, for treated city-year observations, we derive counterfactual PM2.5 levels without the introduction of subsidies as:

$$PM2.5'_{ct} = PM2.5_{ct} - (t - T_c + 1) * ATT_d$$

where $PM2.5_{ct}$ is the actual pollution level in city c in year t, $t - T_c - 1$ is the number of years passed in year t since the year of treatment in T_c, and ATT_d is the estimated ATT associated with the PM2.5 outcome. For non-treated city-years, we take $PM2.5'_{ct} = PM2.5_{ct}$.

2. Then, for both actual and counterfactual cases, city-year pollution observations are converted to a risk ratio of the given $PM2.5$ level of the city-year observation with the following formula:

$$RiskRatio_{ct} = 1.055^{\frac{PM2.5_{ct}-5}{10}}$$

here 1.055 is taken to be the risk ratio of all-cause related mortality for 10 $\mu g/m^3$ increase in PM2.5 levels , and 5 $\mu g/m^3$ is the minimum threshold above which exposure to PM2.5 has detrimental health affects, in line with WHO guidelines (Zhang, 2021; Han et al., 2022).

3. These values are converted to the fraction of deaths attributable to PM2.5 as:

$$AttributableFraction_{ct} = \frac{RiskRatio_{ct} - 1}{RiskRatio_{ct}}$$

4. Total pollution-related death for year t in China are then calculated as:

$$AttributableDeaths_t = \sum_c TotalDeaths_t \cdot w_{ct} \cdot AttributableFraction_{ct}$$

where $TotalDeaths_t$ is total yearly deaths in China in year t, w_{ct} is the share of Chinese population in city c in year t, $w_{ct} = \frac{Population_{ct}}{\sum_c Population_{ct}}$, to approximate the number of city-year-level deaths in absence of direct data, and the city-year-level attributable deaths are added up to derive a single country-level statistic for the year.

5. We base the statistics mentioned in the main body of the paper on these actual and counterfactual yearly paths of $AttributableDeaths_t$ values.

B.11 City panel dataset

Our main analytic dataset is a "city" (second administrative level) level panel that exploits the policy variation at the city-level stemming from PKULaw data to examine the impact on economic outcomes.

The ENF production dataset contains detailed address information, which allows us to geolocate all firms through the Google API, and assign them their corresponding city. We aggregate all production and capacity figures from ENF cell and panel manufacturers at the city-level. We identify, for each city, the number of ENF panel and cell manufacturers using the ENF register, ENF production, and firm registration dataset, which provides reliable firm entry and exit data. We aggregate our patent data from SIPO, revenue and assets from Orbis, as well as the total volume and total value of exports from customs data, for the same sample of ENF manufacturers, at the city level. We additionally gather annual GDP, population, number of workers, and government budget from the statistics yearbook, released by the Bureau of Statistics.

Table B.2 reports descriptive statistics for the key variables at the city-level. The panel has 6,086 observations - 17 years for 358 city-regions. The average city produced 13.1 patents by solar firms per year, a total of 79,902 over the period as a whole. About 40% of of 358 cities had at least one solar firm who patented (there were a quarter with patents in 2020, for example). The 42 cities with solar subsidies accounted for about half (48.5%) of all the 9,261 solar patents in 2020. 67% of all patents were in five cities (three of these had solar policies). In 2012, 102 cities had some solar PV capacity, 133 had nonzero revenue and the top 5 cities accounted for 23.2% of all capacity.

Solar market structure was reasonably fragmented. For example, in the middle of our sample period in 2012, the top 5 firms had 20.6% of panel production. These were Suntech (5.9%), Yingli (4.5%), Trina (4.2%), Canada Solar (3.7%) and Renesola (2.1%).

Table B.1: **Further solar policy examples**

Type of policy	*Example 1*	*Example 2*	*Example 3*
1. Demand subsidy	*"Electricity price subsidy: In addition to enjoying the national electricity policy subsidy, a municipal fiscal subsidy of 0.2 RMB/kWh is provided. Construction and installation subsidy: A one-time construction and installation subsidy of 3 RMB/W is given based on the installed capacity. (Jincheng, 2018)"*	*"In addition to enjoying national and provincial electricity subsidies according to policy, from the date of grid-connected power generation, the municipal finance will provide an additional subsidy of 0.1 RMB/kWh based on the actual electricity generation. (Changsha, 2015)"*	*"Huzhou municipal government implements a PV electricity subsidy for urban residential rooftops, subsidizing 0.18 RMB per kilowatt-hour. (2016)"*
2. Production subsidy	*"For local polycrystalline silicon enterprises supplying the Golden Sun Demonstration Project, a special subsidy of 500 RMB per ton will be given from the industrial optimization funds. (Luoyang, 2012)"*	*"A one-time subsidy of 500,000 RMB will be given to photovoltaic enterprises registered in our city that reach 500 megawatts (or megawatt-hours) of domestic sales of solar cells or modules (without double counting), or 1,000 megawatts for the first time in domestic inverter sales. An additional subsidy of 5,000 RMB (2,000 RMB for inverters) will be given for each additional megawatt (or megawatt-hour) sold. The maximum annual subsidy for the same enterprise shall not exceed 1 million RMB. (Xi'an, 2018)"*	*"For projects with fixed asset investments between 10 million RMB and 1 billion RMB, the reward amount is 1% of the fixed asset investment; for projects with investments between 1 billion RMB and 3 billion RMB, the reward amount is 1.2 million RMB; for projects with investments between 3 billion RMB and 5 billion RMB, the reward amount is 1.5 million RMB; for projects with investments over 5 billion RMB, the reward amount is 2 million RMB. (Jinzhou, 2009)"*
3. Innovation subsidy	*"For the city's newly recognized national, provincial, and municipal key laboratories in the photovoltaic industry, provide a one-time special subsidy of 2 million RMB, 500,000 RMB, and 300,000 RMB respectively. (Jiaxing, 2018)"*	*"For photovoltaic industry projects with provincial-level or above recognized high-tech achievements that come to our city for implementation, a one-time entrepreneurial support fund of 1 million RMB will be awarded. (Huai'an, 2009)"*	*"For newly recognized research institutes that have been in operation for more than one year, a funding reward based on 20% of the original value of R&D equipment is given, with a maximum of 1 million RMB. (Huzhou, 2014)"*

Note: All policies are at the city (admin-2) level over 2006–2022. There are 358 cities. 43 cities are treated by some subsidy by the end of our sample.

Table B.2: **City-level summary statistics**

	Mean	Std. Dev.	Sample Size
SIPO, 2004-2020, 358 cities:			
Total patents by solar firms	13.1	111.3	6,086
Design patents	1.2	10.4	6,086
Utility model and invention patents	11.9	102.8	6,086
Orbis and Qichacha, 358 cities:			
Total number of solar firms, 2004-2020	2.9	10.2	6,086
Total revenue of solar firms, RMB, billions, 2004-2020	0.218	1.38	6,086
ENF, 2004-2013, 358 cities:			
Total Solar Panel capacity, MWh	82.4	483.3	3,580
Total Solar Panel production, MWh	40.7	265.5	3,580
Total Solar Cell capacity, MWh	50.8	353.4	3,580
Total Solar Cell production, MWh	31.3	233.0	3,580
Total Number of Solar Panel firms	0.9	3.5	3,580
Total Number of Solar Cell firms	0.2	1.0	3,580
Customs, 358 cities:			
Total export value of solar firms, millions USD, 2004-2016	24.8	186	4,654
Statistics Yearbook, 2004-2020, 284 cities:			
GDP, billion RMB	196.0	307.2	4,828
Population, thousand	4,453	3,176	4,828
GDP per capita, RMB	43,497	46,936	4,828
V5. GL.02 pollution data, 2004-2020, 358 cities:			
Annual PM 2.5 concentration, $\mu g/m^3$	36.6	15.8	6,086
Chen et al. (2020) CO_2 emissions data, 2004-2017, 348 cities:			
Annual CO_2 emissions, Mt	22.6	22.5	4,872

Notes: Each observation is city-year pair. There are up to 358 cities between 2004 and 2020 (6,086 observations), but different datasets may have lower numbers of observations as noted in the table. The revenue numbers are adjusted to account for multi-product firms. See Section B.7 for more detail.

Figure B.1: **Learning-by-doing patents wordcloud**

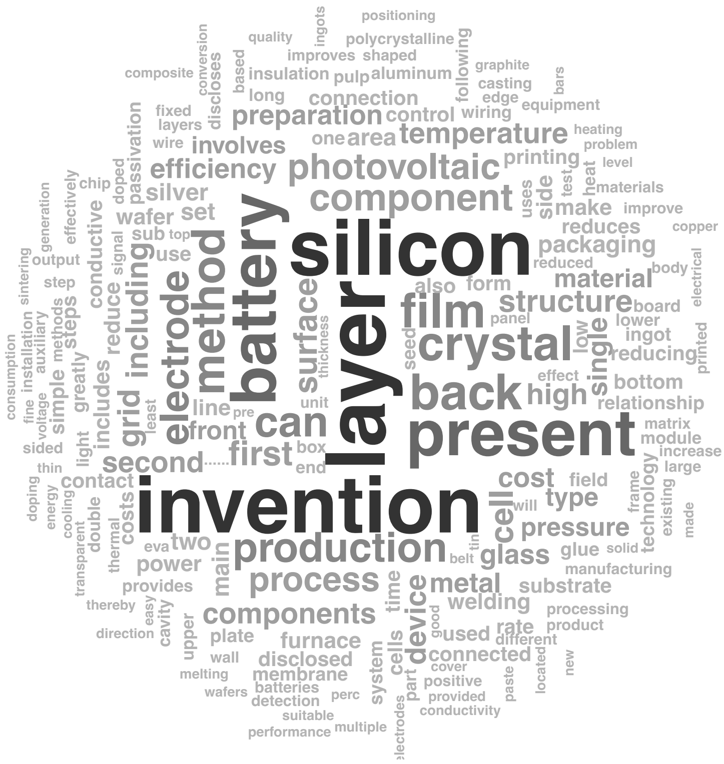
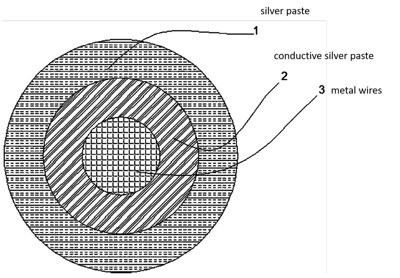
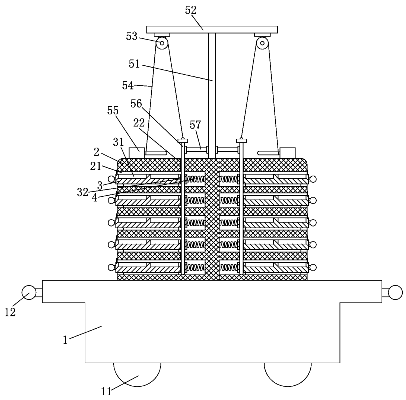


Figure B.2: **Examples of process (learning-by-doing) patents in solar cells**



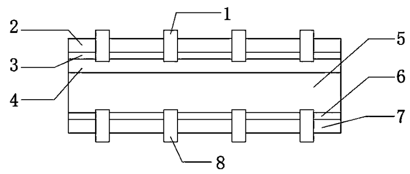
(a) Solar cell grid line structure

Patent Abstract: The present invention discloses a grid line structure for a solar cell, which comprises metal wires, conductive silver paste and silver paste. The grid line is woven from metal wires, with a layer of silver paste applied to the metal wires and then a layer of silver paste, which ensures excellent adhesion between the silver paste and the metal wires and ensures good ohmic contact between the sub-grid line and the silicon wafer. The silver paste used for the main grid line does not contain glass material, which ensures good adhesion between the main grid line and the silicon wafer and reduces the recombination of minority carriers under the main grid line. *Compared with the prior art, the present invention greatly reduces the amount of silver paste used, thus saving more expensive silver paste, effectively reducing production costs, and ensuring excellent aspect ratios of the grid lines, eliminating the possibility of broken lines and false prints, thereby improving the photovoltaic conversion efficiency of the solar cell, and being suitable for large-scale industrial production*



(b) Transfer assembly of solar cell piece

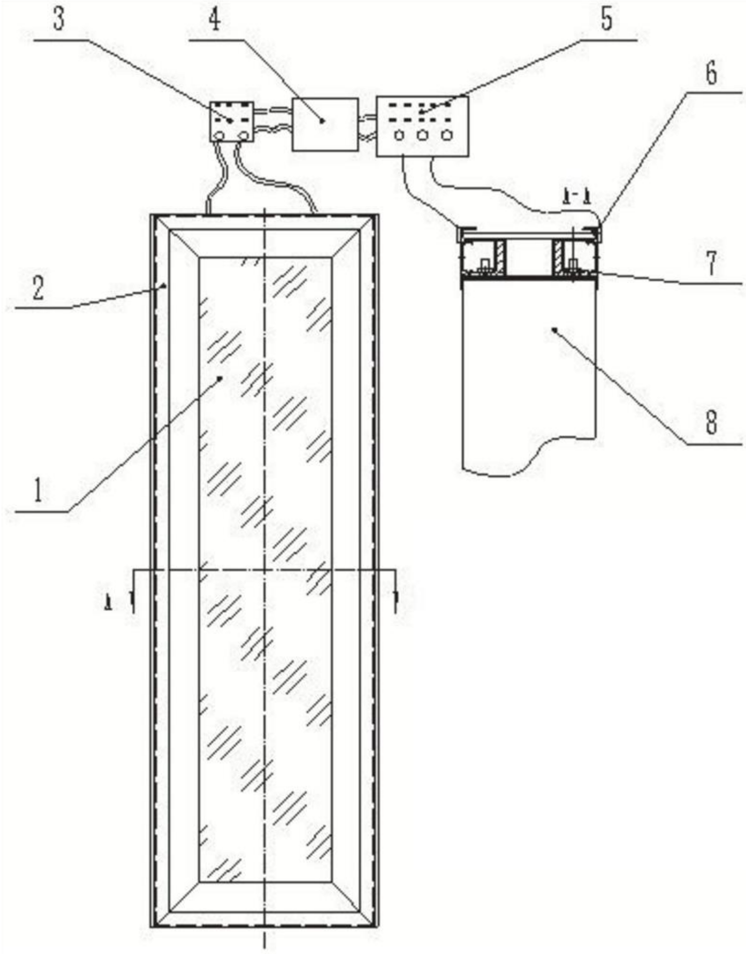
Patent Abstract: The utility model discloses a transfer assembly of a solar cell piece with a metal-stacked electrode. The assembly comprises a trolley body, a storage member arranged on the top of the trolley body, and a positioning component arranged on the storage member. A plurality of slots are opened on the storage member, and a storage plate is slidably connected in each slot. The top of the storage plate is provided with a groove, a spring is provided on the inner wall of each slot, the spring is connected to the storage plate, a first connecting hole is opened on the storage plate, and a second connecting hole penetrating all the slots is opened on the storage member. The positioning component includes a support column, a crossbar, a pulley, a rope, a motor, a limit rod, and a sliding block. *The utility model delivers the solar cell piece through the newly designed transfer assembly. The structure is simple, easy to install and transport, and will not damage the solar cell piece during transportation, reducing the defect rate and ensuring product quality.*



(c) Light-receiving solar cell

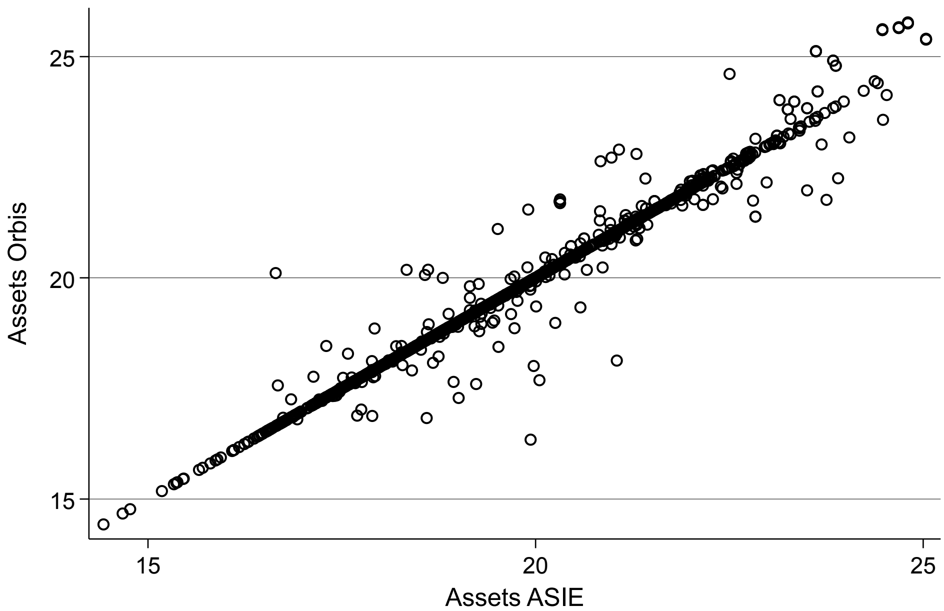
Patent Abstract: The present invention discloses a new type of double-sided light-receiving solar cell, which includes a front electrode, a front anti-reflection layer, a front passivation layer, a PN junction, and a P-type silicon substrate. A back passivation layer, a back anti-reflection layer, and a back electrode are also provided on the back of the P-type silicon substrate. *The present invention reduces the preparation process of existing double-sided cells and is more conducive to industrial development.*

Figure B.3: **Product patent (not learning-by-doing)**



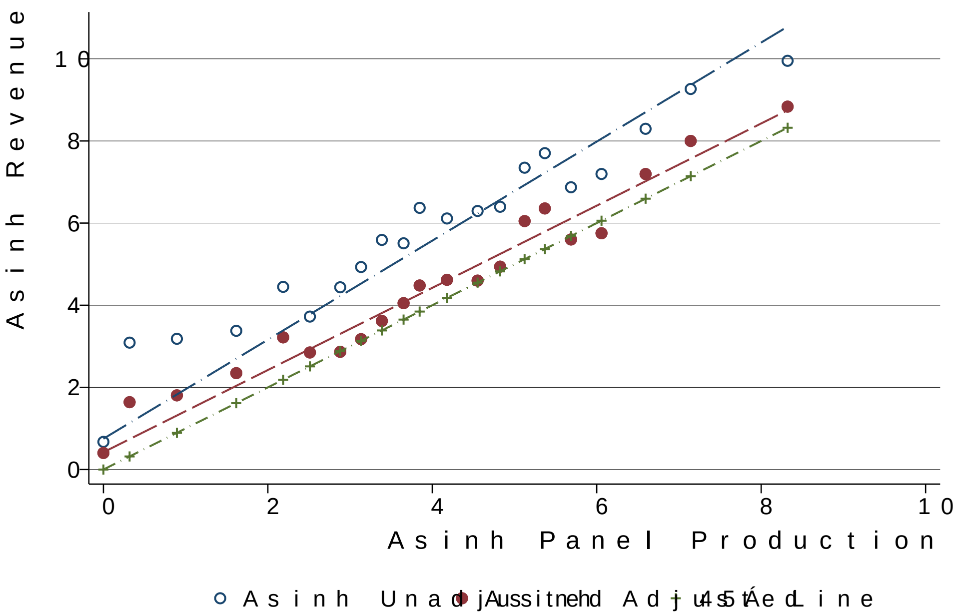
Patent Abstract: This utility model patent relates to a road cliff photovoltaic lighting device, which includes a road cliff stone or road guardrail connected to the outer surface of a photovoltaic component. The photovoltaic component is connected to the inverter and battery through a controller in sequence, and the controller is connected to the light strip. The light strip is located on one side of the road cliff stone or road guardrail facing the center of the road. By combining the photovoltaic power generation system with the road cliff or guardrail lighting, photovoltaic power generation, which serves as green energy, is closely integrated with transportation, solving the power supply and subsequent maintenance problems of traditional road lighting and reducing construction and maintenance costs. It also produces an uninterrupted power supply to indicate the road dividing lines and boundary lines, guiding the passage of vehicles and pedestrians, relieving driving fatigue and beautifying the road.

Figure B.4: **Value of firm assets in Orbis and ASIE**



Notes: The axis is the log(assets) in the ASIE data set, and the y-axis is the log(assets) in the Orbis data set. Each point is one firm in one year. If we fit a linear line, the coefficient is 1.01, p<0.01, and $R^2 = 0.9679$

Figure B.5: **Revenue Adjustment**



Notes: The plot shows the binned city-level relation between revenue and panel production with the Asinh transformation. The dashed green line shows the 45-degree line.

C Further Details on Theory and Quantified Model

Section 4 in the main text introduced the theoretical model that we develop in the paper. In this Appendix, we give some more of the technical details of this model and how we quantify it. To build intuition, we begin with a simplified version in Subsection C.1 where we consider only two Chinese city-regions and one energy sector (solar). This enables us to derive comparative statics analytically. We focus on the impact of the three types of subsidies (demand, production and innovation) on local outcomes in the city that introduced the subsidy. This takes into account solving for the full general equilibrium across all of China. Subsection C.2 then considers the theoretical details of the "full model" which has two sectors and multiple city-regions (including a foreign "rest of the world" region to allow for trade). We quantify this full model for the counterfactual and welfare exercises in Sections 5 and 6 where we are focusing on aggregate China-wide outcomes. More details on the quantification of the full model are in C.3 and more details on the welfare and social cost-benefit analysis are in C.4.

C.1 Simplified version of the Model

C.1.1 Derivations

We first provide some useful derivations to understand the predictions in our simplified model.

Demand for electricity and power plant components. From the problem faced by the local grid-planners:

$$\max_{q_{od,s}(\omega)} U_{d,s} = \left(\sum_{o} \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}}$$

$$\text{s.t.} \quad \left(\sum_{o} \chi_{d,s} \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega) p_{od,s}(\omega) d\omega \right) = E_{d,s}$$

We obtain optimal demand:

$$q_{od,s}(\omega) = \frac{(p_{od,s}(\omega))^{-\sigma_s}}{(P_{d,s})^{1-\sigma_s}} \frac{E_{d,s}}{\chi_{d,s}}$$

Where the price index is:

$$P_{d,s}^{1-\sigma_s} = \sum_{o} \int_{\omega \in \Omega_{o,s}} (p_{od,s}(\omega))^{1-\sigma_s} d\omega$$

Manufacturing of power plant components. Profits are defined by:

$$\pi_{o,s}(\varphi) = \sum_d \left(p_{od,s}(\varphi) q_{od,s}(\varphi) - w_{o,s} \frac{a_{o,s} \tau_{od,s} q_{od,s}(\varphi)}{\xi_{o,s} \varphi} \right) - w_{o,s} f_s - w_{o,s} \phi_{o,s} f_s^i$$

Where the fixed costs of innovating f_s^i and the productivity benefit from doing so $\xi_{o,s}$ are 0 and 1 respectively if the manufacturer chooses not to innovate.

Maximising and substituting optimal demand, yields the following expression for manufacturer's price:

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{w_{o,s} a_{o,s} \tau_{od,s}}{\xi_{o,s} \varphi}$$

The productivity thresholds that characterise the second stage of the solution –choice of exiting, producing with existing technology, or innovating– are the following:

Exit threshold:

$$\varphi_{o,s}^* = \left(\sum_d \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \left(\frac{w_{o,s} a_{o,s} \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \frac{E_{d,s}}{\chi_{d,s} f_s} \right)^{\frac{1}{1-\sigma_s}}$$

Innovation threshold:

$$\varphi_{o,s}^i = \left(\sum_d \frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \left(\frac{w_{o,s} a_{o,s} \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \frac{E_{d,s}}{\chi_{d,s} \phi_{o,s} f_s^i} \right)^{\frac{1}{1-\sigma_s}}$$

We impose the following free entry condition, that states that expected profits from entering the market minus the sunk entry costs are equal to zero:

Free entry:

$$\begin{aligned} w_{o,s} f_s^e &= \left(1 - G\left[\varphi_{o,s}^*\right]\right) \mathbb{E}\left[\pi_s \mid \varphi > \varphi_{o,s}^*\right] \\ &= \left(G\left[\varphi_{o,s}^i\right] - G\left[\varphi_{o,s}^*\right]\right) \mathbb{E}\left[\pi_s \mid \varphi_{o,s}^i > \varphi > \varphi_{o,s}^*\right] + \left(1 - G\left[\varphi_{o,s}^i\right]\right) \mathbb{E}\left[\pi_s \mid \varphi > \varphi_{o,s}^i\right] \end{aligned}$$

Where the distribution of firm productivity is Pareto:

$$G\left(\varphi; b_{o,s}\right) = 1 - \left(\frac{\varphi}{b_{o,s}} \right)^{-\theta_s}$$

Combining the definition of the productivity thresholds and the free entry condition, we can express the productivity thresholds as:

$$\left(\varphi_{o,s}^*\right)^{\theta_s} = b_s^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1-\sigma_s}} \left(\frac{\xi_{o,s}^{1-\sigma_s}}{1 - \xi_{o,s}^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right)$$

$$\varphi_{o,s}^{i} = \varphi_{o,s}^{*}\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\frac{f_s}{\phi_{o,s}f_s^i}\right)^{\frac{1}{1-\sigma_s}}$$

This is useful, as the thresholds become a function of fundamentals and subsidies only. We combine the definition of the price index with our expressions for optimal prices and the exit threshold, which gives:

$$P_{d,s}^{(1-\sigma_s)} = \sum_o \frac{M_{o,s}\theta_s}{\theta_s+1-\sigma_s}\left(w_{o,s}a_{o,s}\tau_{od,s}\frac{\sigma_s}{\sigma_s-1}\right)^{1-\sigma_s}$$
$$\times\left(\left(\frac{\phi_{o,s}f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{o,s}^{1-\sigma_s}}{1-\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1\right)(\varphi_{o,s}^{*})^{\sigma_s-1}.$$

This simplifies to the following expression, which relates price indices with the mass of firms in each region:

$$P_{d,s}^{(1-\sigma_s)} = \sum_o \left(w_{o,s}a_{o,s}\tau_{od,s}\frac{\sigma_s}{\sigma_s-1}\right)^{1-\sigma_s}\frac{f_s^e}{f_s}\frac{M_{o,s}\theta_s}{b_s^{\theta_s}(\sigma_s-1)}(\varphi_{o,s}^{*})^{\sigma_s+\theta_s-1}$$

Expressions for prices and mass of firms in two regions. The price indices and mass of firms for the two regions in our simplified framework are:

$$P_{1,s}^{\sigma_s-1} = \frac{\sigma_s^{\sigma_s}}{(\sigma_s-1)^{\sigma_s-1}}\frac{\chi_{1,s}f_s}{E_{1,s}}\frac{(a_{1,s}\tau)^{\sigma_s-1}\left(\varphi_{1,s}^{*}\right)^{1-\sigma_s}-\left(\varphi_{2,s}^{*}\right)^{1-\sigma_s}}{(\tau)^{\sigma_s-1}-(\tau)^{1-\sigma_s}}$$

$$P_{2,s}^{\sigma_s-1} = \frac{\sigma_s^{\sigma_s}}{(\sigma_s-1)^{\sigma_s-1}}\frac{f_s}{E_{2,s}}\frac{\tau^{\sigma_s-1}\left(\varphi_{2,s}^{*}\right)^{1-\sigma_s}-(a_{1,s})^{\sigma_s-1}\left(\varphi_{1,s}^{*}\right)^{1-\sigma_s}}{\tau^{\sigma_s-1}-\tau^{1-\sigma_s}}$$

$$M_{1,s} = a_{1,s}^{\sigma_s-1}\frac{\tau^{\sigma_s-1}P_{1,s}^{(1-\sigma_s)}-P_{2,s}^{(1-\sigma_s)}}{\tau^{\sigma_s-1}-\tau^{1-\sigma_s}}\frac{f_s}{f_s^e}\frac{b_s^{\theta_s}(\sigma_s-1)}{\theta_s}\left(\frac{\sigma_s}{\sigma_s-1}\right)^{\sigma_s-1}(\varphi_{1,s}^{*})^{-(\sigma_s+\theta_s-1)}$$

$$M_{2,s} = \frac{\tau^{\sigma_s-1}P_{2,s}^{(1-\sigma_s)}-P_{1,s}^{(1-\sigma_s)}}{\tau^{\sigma_s-1}-\tau^{1-\sigma_s}}\frac{f_s}{f_s^e}\frac{b_s^{\theta_s}(\sigma_s-1)}{\theta_s}\left(\frac{\sigma_s}{\sigma_s-1}\right)^{\sigma_s-1}(\varphi_{2,s}^{*})^{-(\sigma_s+\theta_s-1)}$$

To derive intuitions, it is useful to express M_1 (and M_2 equivalently) as follows:

$$M_{1,s} = \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}}\frac{b_s^{\theta_s}(\sigma_s-1)}{f_s^e\theta_s}\left(\frac{\sigma_s}{\sigma_s-1}\right)^{\sigma_s-1}\times$$
$$\times\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^{*}\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^{*}\right)^{1-\sigma_s}(\varphi_{1,s}^{*})^{\sigma_s+\theta_s-1}}+\frac{E_{2,s}}{\left(\varphi_{1,s}^{*}\right)^{\theta_s}-\tau^{\sigma_s-1}\left(a_{1,s}\varphi_{2,s}^{*}\right)^{1-\sigma_s}(\varphi_{1,s}^{*})^{\sigma_s+\theta_s-1}}\right)$$

Regulatory conditions. We impose a set of regulatory conditions to ensure sensible economic outcomes. We restrict $\sigma_s > \sigma > 1$ to obtain non-negative profits. To ensure production is bounded we assume $\sigma_s - \theta_s < 0$, which is also a sufficient condition to bound profits (as it implies $\sigma_s - \theta_s - 1 < 0$).

C.1.2 Predictions

Proposition 1 (Productivity Thresholds)

(i) Demand and production subsidies do not change the exit and innovation thresholds.

(ii) Innovation subsidies raise the exit threshold, increasing market competitiveness.

(iii) Innovation subsidies reduce the innovation threshold.

Proof

We express the exit threshold as follows:

$$\left(\varphi_{1,s}^{*}\right)^{\theta_s} = b_s^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{1,s} \frac{f_s^i}{f_s}\right)^{\frac{\theta_s + 1 - \sigma_s}{1-\sigma_s}} \left(\frac{\xi_{1,s}^{1-\sigma_s}}{1 - \xi_{1,s}^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right)$$

First (Proposition 1(i)), note that the production subsidy $a_{1,s}$ and the demand subsidy $\chi_{1,s}$ do not enter this expression. Therefore, these subsidies do not affect the exit threshold productivity.

Second (Proposition 1(ii)), we model a subsidy to innovation as a reduction in $\phi_{1,s}$. As $\phi_{1,s}$ decreases, $\left(\phi_{1,s} \frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}$ increases, due to $\frac{\theta_s+1-\sigma_s}{1-\sigma_s} < 0$. Consequently, $\varphi_{1,s}^{*}$ will increase, making it harder for low productivity firms to survive. Intuitively, innovation subsidies are pushing the firms on the margin of innovating towards becoming innovators. Even before innovating, these firms are relatively more productive than other non-innovators.[52] Due to innovating, firms will lower their marginal costs, and as a result, the aggregate price index will fall. As a consequence, firms that were at the margin of exiting the market (close to zero profits) will lose from the increase in market competitiveness and exit. The exit productivity threshold therefore increases.

Third (Proposition 1(iii)), we can express the innovation threshold as a function of the exit threshold in the following way:

$$\varphi_{1,s}^{i} = \varphi_{1,s}^{*} \left(\frac{1 - \xi_{1,s}^{1-\sigma_s}}{\xi_{1,s}^{1-\sigma_s}} \frac{f_s}{\phi_{1,s} f_s^i} \right)^{\frac{1}{1-\sigma_s}}$$

The relative distance between the innovation threshold and exit threshold is $\left(\frac{1 - \xi_{1,s}^{1-\sigma_s}}{\xi_{1,s}^{1-\sigma_s}} \frac{f_s}{\phi_{1,s} f_s^i} \right)^{\frac{1}{1-\sigma_s}}$. This term will decrease as a result of introducing an innovation subsidy. A larger fraction

[52] Those who are already innovating will benefit from a lower cost of their innovation.

of producing firms will therefore innovate. Note however, that the exit threshold increases when an innovation subsidy is introduced. As such, the overall effect might be ambiguous. To analyze the total effect, we re-express the innovation threshold as:

$$\left(\varphi_{1,s}^{i}\right)^{\theta_s} = A\left(B\phi_{1,s} + (\phi_{1,s})^{\frac{\theta_s}{\sigma_s-1}}\right)$$

where $A = b_s^{\theta_s}\frac{f_s}{f_s^e}\frac{\sigma_s-1}{\theta_s+1-\sigma_s}\left(\frac{1-\xi_{1,s}^{1-\sigma_s}}{\xi_{1,s}^{1-\sigma_s}}\frac{f_s}{f_s^i}\right)^{\frac{\theta_s}{1-\sigma_s}}$ and $B = \left(\frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{1,s}^{1-\sigma_s}}{1-\xi_{1,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}} 0$, with both terms being positive.

Since $\frac{\partial\varphi_{1,s}^{i}}{\partial\phi_{1,s}} < 0$, an innovation subsidy will unambiguously decrease the innovation threshold.

Proposition 2 (Local Policy Impact on the Mass of Firms)

(i) Demand and production subsidies increase the number of operating firms.

(ii) Production subsidies have a larger effect than demand subsidies when the untreated region is large enough.

(iii) Under stronger regulatory conditions, innovation subsidies also increase the number of operating firms.

Proof

First, to understand Proposition 2(i), note that the equilibrium mass of firms in the treated city can be expressed as:

$$M_{1,s} = C\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^{*}\right)^{\theta_s} - \left(a_{1,s}\varphi_{2,s}^{*}\right)^{1-\sigma_s}\left(\varphi_{1,s}^{*}\right)^{\sigma_s+\theta_s-1}} + \frac{E_{2,s}}{\left(\varphi_{1,s}^{*}\right)^{\theta_s} - \tau^{\sigma_s-1}\left(a_{1,s}\varphi_{2,s}^{*}\right)^{1-\sigma_s}\left(\varphi_{1,s}^{*}\right)^{\sigma_s+\theta_s-1}}\right)$$

where $C = \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}}\frac{b_s^{\theta_s}(\sigma_s-1)}{f_s^e\theta_s}\left(\frac{\sigma_s}{\sigma_s-1}\right)^{\sigma_s-1}$.

$\varphi_{1,s}^{*}$ is the only term affected by the innovation subsidy. $\varphi_{1,s}^{*}$ is not affected by the demand nor the production subsidy.

From the following heuristics, it is clear that demand and production subsidies will both increase the mass of firms.[53]

- $\chi_{1,s}\downarrow \rightarrow \frac{E_{1,s}}{\chi_{1,s}}\uparrow, \rightarrow \frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^{*}\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^{*}\right)^{1-\sigma_s}\left(\varphi_{1,s}^{*}\right)^{\sigma_s+\theta_s-1}}\uparrow, \rightarrow M_{1,s}\uparrow$

[53]For the demand subsidy to have a positive effect, we need the denominator to be positive. This is almost always guaranteed. In the purely symmetric and no subsidy case, $a_{1,s} = 1$, $\varphi_{1,s}^{*} = \varphi_{2,s}^{*} = \varphi_{s}^{*}$. The denominator can be written as $\left(\tau^{\sigma_s-1} - 1\right)\left(\varphi_s^{*}\right)^{\theta_s}$ and it will be strictly positive since $\tau > 1$ by definition. If we introduce a small subsidy, the denominator will remain positive since the function is continuous.

- $a_{1,s} \downarrow \rightarrow \left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s} \uparrow, \rightarrow \frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}} \uparrow$ and $\frac{E_{2,s}}{\left(\varphi_{1,s}^*\right)^{\theta_s}-\tau^{\sigma_s-1}\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}} \uparrow, \rightarrow M_{1,s} \uparrow$

To understand Proposition 2(ii), note that a demand subsidy only enters the first term in the expression, while the production subsidy affects both terms. The partial derivatives of the mass of firms in the treated city with respect to demand and production subsidies are:

$$\frac{\partial M_{1,s}}{\partial \chi_{1,s}} = \partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial\chi_{1,s}$$

$$\begin{aligned}\frac{\partial M_{1,s}}{\partial a_{1,s}} = {} & \partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial a_{1,s} \\ & +\partial\left(\frac{E_{2,s}}{\left(\varphi_{1,s}^*\right)^{\theta_s}-\tau^{\sigma_s-1}\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial a_{1,s}\end{aligned}$$

While it is not straightforward to see that $\partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial\chi_{1,s}$ is smaller than $\partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial a_{1,s}$, as long as $E_{2,s}$ is large enough, then $|\frac{\partial M_{1,s}}{\partial a_{1,s}}| > |\frac{\partial M_{1,s}}{\partial \chi_{1,s}}|$. Intuitively, as long as the untreated region is large enough, or equivalently, as long as there are enough untreated regions, then a production subsidy will cause a greater increase in the mass of firms than a demand subsidy.

Proposition 2(iii) is more involved as the impact of innovation subsidies is more ambiguous. In Proposition 1, we showed that an innovation subsidy increases the exit threshold $\varphi_{1,s}^*$. However, there is no linear relationship between $\varphi_{1,s}^*$ and $M_{1,s}$. We can prove that an innovation subsidy will increase the mass of firms if the following condition is satisfied:

$$\frac{\left(\phi_{1,s}\frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{1,s}^{1-\sigma_s}}{1-\xi_{1,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1}{\left(\frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{2,s}^{1-\sigma_s}}{1-\xi_{2,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1} > \left(\frac{\theta_s}{\sigma_s+\theta_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}} a_{1,s}^{\theta_s}\tau^{\theta_s}$$

This condition is likely to hold when intra-national trade costs are not too large. To see this, consider a progressive increase in subsidisation towards innovation starting from no subsidy at all ($\phi_{1,s} = 1$). When $\phi_{1,s} = 1$, the left hand side of the inequality is equal to 1 (we have assumed symmetry between regions). On the right-hand side of the inequality, $\frac{\theta_s}{\sigma_s+\theta_s-1} < 1$, as $\sigma_s > 1$. Therefore, $\left(\frac{\theta_s}{\sigma_s+\theta_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}} < 1$. We also know that $a_{1,s}^{\theta_s} < 1$

if innovation subsidies are only available in cities with production subsidies (which is the empirically relevant case in our data).

Proposition 3 (Local Policy Impact on Innovation):

(i) Demand subsidies, production subsidies, and innovation subsidies all increase the number of innovators by increasing the number of operating firms.

(ii) As with Proposition 2(ii), production subsidies have a larger marginal effect compared to demand subsidies.

(iii) Innovation subsidies increase the number of innovators.

Proof *(Follows from Propositions 1 and 2)*

The expression for the mass of innovators is:

$$M^i_{1,s} = \frac{1 - G(\varphi^i_{1,s})}{1 - G(\varphi^*_{1,s})} M_{1,s} = \left(\frac{\varphi^i_{1,s}}{\varphi^*_{1,s}}\right)^{-\theta_s} M_{1,s} = \left(\frac{1 - \xi_{1,s}^{1-\sigma_s}}{\xi_{1,s}^{1-\sigma_s}} \frac{f_s}{\phi_{1,s} f^i_s}\right)^{\frac{\theta_s}{\sigma_s - 1}} M_{1,s}$$

In Proposition 1, we showed that $\frac{\partial M_{1,s}}{\partial \chi_{1,s}} < 0$ and $\frac{\partial M_1}{\partial a_{1,s}} < 0$. We also showed that the innovation threshold was invariant with respect to these subsidies. Therefore the mass of innovators must increase: $\frac{\partial M^i_{1,s}}{\partial \chi_{1,s}} < 0$ and $\frac{\partial M^i_{1,s}}{\partial a_{1,s}} < 0$.

Under the same condition that $E_{2,s}$ is large enough, we can conclude that $|\frac{\partial M^i_{1,s}}{\partial a_{1,s}}| > |\frac{\partial M^i_{1,s}}{\partial \chi_{1,s}}|$. So when the untreated region is large, or there is a high number of untreated areas, a production subsidy will be more effective than a demand subsidy in terms of boosting innovation.

In Proposition 2, we showed that under a regulatory condition, we can guarantee that an innovation subsidy will increase the mass of firms. Similarly, if the same regulatory condition holds, we can guarantee that an innovation subsidy increases the mass of innovators. Since $\left(\frac{\varphi^i_{1,s}}{\varphi^*_{1,s}}\right)^{-\theta_s}$ also increases with an innovation subsidy, the regulatory condition for an innovation subsidy to raise the mass of innovators is weaker than in Proposition 2. In other words, even if the mass of firms decreases in some cases with the introduction of an innovation subsidy, the mass of innovators can still increase.

Proposition 4 (Local Policy Impact on Revenues, Price, Exports and Quantity):

(i) All subsidies will reduce prices.

(ii) All subsidies increase city-level revenue, production and exports.

(iii) Similarly to Proposition 2, production subsidies have a larger impact than demand subsidies.

(iv) Innovation subsidies will further increase total revenue by increasing average firm revenue.

Proof City-level total revenue equals the mass of operating firms multiplied by the average revenue per firm, which we express as follows:

$$R_{1,s} = M_{1,s}\bar{r}_{1,s} = M_{1,s}\frac{\theta_s\sigma_s}{\theta_s+1-\sigma_s}\left(\left(\phi_{1,s}\frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{1,s}^{1-\sigma_s}}{1-\xi_{1,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1\right)f_s$$

To show Proposition 4(i), we can also obtain city level price index. When we introduce production subsidy $a_{1,s}\downarrow$, demand subsidy $\chi_{1,s}\downarrow$, and innovation subsidy $\phi_{1,s}\downarrow$ (innovation subsidy leads to $\varphi_{1,s}\uparrow$), we will have a price drop in the treated region according to the following price index.

$$P_{1,s}^{\sigma_s-1} = \frac{\sigma_s^{\sigma_s}}{(\sigma_s-1)^{\sigma_s-1}}\frac{\chi_{1,s}f_s}{E_{1,s}}\frac{(a_{1,s}\tau)^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{1-\sigma_s}-\left(\varphi_{2,s}^*\right)^{1-\sigma_s}}{(\tau)^{\sigma_s-1}-(\tau)^{1-\sigma_s}}$$

To see Proposition 4(ii), note that all subsidies increase the mass of operating firms (Proposition 2), thus raising total revenue. Since revenues rise and prices fall, production must also rise. As is standard in models with iceberg trade costs (no fixed cost of transport), a city will sell to all other locations, and since one of these is the foreign location (exports), an increase in production and revenue means an increase in export volumes and values.

Proposition 4(iii) follows from 4(ii) and Proposition 2(ii).

In terms of Proposition 4(iv), note that innovation subsidies encourage more firms to become innovators (Proposition 3(iii)), leading to higher average revenues per firm. Hence, revenue rises further.

C.2 Full model

In this section we provide details on theoretical derivations of the full model that are useful for our quantification exercises. We also present additional material on our algorithms.

C.2.1 Derivations

Demand for Energy Sources:

$$\max_{e_{d,s},e_{d,s'}}\left(e_{d,s'}^{\frac{\sigma-1}{\sigma}}+e_{d,s}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

$$\text{s.t. }\chi_{d,s}P_{d,s}e_{d,s}+P_{d,s'}e_{d,s'}=E_d$$

We solve for $e_{d,s}$ and $e_{d,s'}$, solar and coal installation demand.

$$e_{d,s} = \left(\frac{1}{\chi_{d,s}P_{d,s}}\right)^{\sigma} \frac{E_d}{P_{d,s'}^{1-\sigma} + \left(\chi_{d,s}P_{d,s}\right)^{1-\sigma}}$$

$$e_{d,s'} = \left(\frac{1}{P_{d,s'}}\right)^{\sigma} \frac{E_d}{P_{d,s'}^{1-\sigma} + \left(\chi_{d,s}P_{d,s}\right)^{1-\sigma}}$$

Expenditure on solar is defined as $E_{d,s} = P_{d,s}e_{d,s}$, and for non-solar is defined as $E_{d,s'} = P_{d,s'}e_{d,s'}$.

$$E_{d,s} = \frac{\chi_{d,s}^{-\sigma}P_{d,s}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma}P_{d,s}^{1-\sigma}}E_d, \quad E_{d,s'} = \frac{P_{d,s'}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma}P_{d,s}^{1-\sigma}}E_d$$

Demand for Energy-Sector Manufactured Inputs. In order to meet the optimal demands for energy sources $e_{d,s}$ and $e_{d,s'}$, the grid-planner has to choose from the available manufactured varieties that aggregate into the final energy output. The grid planner solves the following cost minimization problem:

$$\min_{q_{od,s}(\omega)} \left(\sum_o \int_{\omega\in\Omega_{o,s}} q_{od,s}(\omega)p_{od,s}(\omega)d\omega\right)$$

$$\text{s.t.} \quad \left(\sum_o \int_{\omega\in\Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s-1}{\sigma_s}}d\omega\right)^{\frac{\sigma_s}{\sigma_s-1}} = e_{d,s}$$

With solution:

$$q_{od,s}(\omega) = \frac{\left(p_{od,s}(\omega)\right)^{-\sigma_s}}{\left(P_{d,s}\right)^{1-\sigma_s}}E_{d,s}$$

Where $p_{od,s}$ is the price of a particular variety, and $P_{d,s}$ is the price index which captures the cost of producing a single unit of electricity in sector s when using a cost minimizing mix of intermediate inputs.

$$P_{d,s}^{1-\sigma_s} = \sum_o \int_{\omega\in\Omega_{o,s}} \left(p_{od,s}(\omega)\right)^{1-\sigma_s} d\omega$$

The Manufacturer Problem

Manufacturing Technology: After paying the sunk cost of entry, firms draw from a Pareto productivity distribution with city-sector specific scale parameters $(b_{o,k})$ but a common energy-sector specific shape parameter (θ_k). For example, in solar:

$$G\left(\varphi; b_{o,s}\right) = 1 - \left(\frac{\varphi}{b_{o,s}}\right)^{-\theta_s}$$

Firm Profits:

$$\pi_{o,s}(\varphi) = \max\Bigg\{0, \sum_d \left\{p_{od,s}(\varphi)q_{od,s}(\varphi) - w_o\frac{\tau_{od,s}a_{o,s}q_{od,s}(\varphi)}{\kappa_s\varphi}\right\} - w_o f_s,$$
$$\sum_d \left\{p_{od,s}(\varphi)q_{od,s}(\varphi) - w_o\frac{\tau_{od,s}a_{o,s}q_{od,s}(\varphi)}{\kappa_s\xi_{o,s}\varphi}\right\} - w_o f_s - w_o\phi_{o,s}f_s^i\Bigg\}$$

Plugging in the Marshallian demand $q_{od,s}(\varphi)$, we solve firms' profit maximization problem, and obtain

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1}\frac{w_o a_{o,s}\tau_{od,s}}{\kappa_s\varphi} \quad \text{if firm does not innovate}$$
$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1}\frac{w_o a_{o,s}\tau_{od,s}}{\xi_{o,s}\kappa_s\varphi} \quad \text{if firm innovates}$$

Substituting the optimal pricing and demand functions in the expression for firm profits, we obtain the potential value functions for each technology and exporting choice.

Without Innovation

$$\pi_{o,s}(\varphi) = \sum_d \left\{\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}}\frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}}\left(\frac{w_o a_{o,s}\tau_{od,s}}{\kappa_s\varphi}\right)^{1-\sigma_s}\right\} - w_o f_{o,s}$$

With Innovation:

$$\pi_{o,s}(\varphi) = \sum_d \left\{\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}}\frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}}\left(\frac{w_o a_{o,s}\tau_{od,s}}{\kappa_s\xi_{o,s}\varphi}\right)^{1-\sigma_s}\right\} - w_o f_s - w_o\phi_{o,s}f_s^i$$

We define $\varphi^*_{o,s}$ as the domestic market exit productivity threshold. This is the productivity that generates zero profits from serving the domestic market only. Similarly, the innovation threshold $\varphi^i_{o,s}$ is the productivity level which makes a firm indifferent between upgrading its technology or not. The expressions for these thresholds are:

$$\varphi^*_{o,s} = \frac{1}{\kappa_s}\left(\sum_d \left\{\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}}\frac{E_{d,s}}{w_o f_{o,s}}\left(\frac{w_o a_{o,s}\tau_{od,s}}{P_{d,s}}\right)^{1-\sigma_s}\right\}\right)^{\frac{1}{1-\sigma_s}}$$

$$\varphi^i_{o,s} = \frac{1}{\kappa_s}\left(\sum_d \frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}}\frac{E_{d,s}}{w_o\phi_{o,s}f_s^i}\left(\frac{w_o a_{o,s}\tau_{od,s}}{P_{d,s}}\right)^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}$$

Therefore, we have the relationship: $\varphi^i_{o,s} = \left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\frac{f_{o,s}}{\phi_{o,s}f^i_{o,s}}\right)^{\frac{1}{1-\sigma_s}}\varphi^*_{o,s}$

Free entry. Free entry implies that the sunk entry costs equals expected profits from drawing a productivity:

$$w_o f_s^e = \left(1 - G\left[\varphi_{oo,s}^*\right]\right) \mathbb{E}\left[\pi \mid \varphi > \varphi_{oo,s}^*\right]$$

$$= \left(G\left[\varphi_{o,s}^i\right] - G\left[\varphi_{o,s}^*\right]\right) \mathbb{E}\left[\pi_s \mid \varphi_{o,s}^i > \varphi > \varphi_{o,s}^*\right] + \left(1 - G\left[\varphi_{o,s}^i\right]\right) \mathbb{E}\left[\pi_s \mid \varphi > \varphi_{o,s}^i\right]$$

$$= \int_{\varphi_{o,s}^*}^{\varphi_{o,s}^i} \pi_{o,s}(\varphi) g(\varphi) d\varphi + \int_{\varphi_{od,s}^i}^{\infty} \pi_{o,s}(\varphi) g(\varphi) d\varphi$$

Replacing the expression for firm profits for each range of productivity and the expression for the Pareto distribution function we obtain an expression for the exit threshold (and therefore the innovation threshold) determined by fundamentals and subsidies.

$$\left(\varphi_{o,s}^*\right)^{\theta_s} = b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1 - \sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1 - \xi_s^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right)$$

$$\varphi_{o,s}^i = \left(\frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}} \frac{f_{o,s}}{\phi_{o,s} f_{o,s}^i} \right)^{\frac{1}{1-\sigma_s}} \varphi_{o,s}^*$$

Price index. From the definition of the price index:

$$P_{d,s}^{(1-\sigma_s)} = \sum_o \int_0^{M_{o,s}} p_{od,s}(v)^{1-\sigma_s} dv = \sum_o M_{o,s} \int_{\varphi_{o,s}^*}^{\infty} p_{od,s}(\varphi)^{1-\sigma_s} \frac{g(\varphi)}{1 - G(\varphi_{o,s}^*)} d\varphi$$

Plugging in the expression for price, and the expression for the Pareto distribution, we obtain:

$$P_{d,s}^{(1-\sigma_s)} = \left(\frac{1}{\kappa_s} \right)^{1-\sigma_s} \sum_o \left(a_{o,s} \tau_{od,s} \frac{\sigma_s}{\sigma_s - 1} \right)^{1-\sigma_s} \frac{f_s^e}{f_s} \frac{M_{o,s} \theta_s}{b_s^{\theta_s} (\sigma_s - 1)} \left(\varphi_{o,s}^*\right)^{\sigma_s + \theta_s - 1}$$

Mass of innovators. The definition for the mass of innovators $M_{o,s}^i$ is:

$$M_{o,s}^i = \frac{1 - G(\varphi_{o,s}^i)}{1 - G(\varphi_{o,s}^*)} M_{o,s} = \left(\frac{\varphi_{o,s}^i}{\varphi_{o,s}^*} \right)^{-\theta_s} M_{o,s}$$

Revenue. The average revenue $\bar{r}_{o,s}$ and total revenue $R_{o,s}$ are:

$$\bar{r}_{o,s} = \sum_d \int_{\varphi_{o,s}^*}^{\infty} p_{od,s}(\varphi) q_{od,s}(\varphi) \frac{g(\varphi)}{1 - G(\varphi_{o,s}^*)} d\varphi$$

and

$$R_{o,s} = M_{o,s} \bar{r}_{o,s} = M_{o,s} \frac{\theta_s \sigma_s}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \eta_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1 - \sigma_s}} \left(\frac{\xi_{o,s}^{1-\sigma_s}}{1 - \xi_{o,s}^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right) f_s$$

Subsidy cost

Production subsidy cost. For a firm with productivity φ in region o, its variable costs from selling to destination d are:

$$w_o \frac{\tau_{od,s}}{\kappa_s \varphi} \text{ if do not innovate, and no subsidy; } \quad w_o \frac{\tau_{od,s} a_{o,s}}{\kappa_s \varphi} \text{ if do not innovate, and with subsidy}$$

$$w_o \frac{\tau_{od,s}}{\kappa_s \xi_{o,s} \varphi} \text{ if innovate, and no subsidy; } \quad w_o \frac{\tau_{od,s} a_{o,s}}{\kappa_s \xi_{o,s} \varphi} \text{ if innovate, and with subsidy}$$

Therefore, the production subsidy size for each unit of goods sold to destination d is:

$$w_o \frac{\tau_{od,s}}{\kappa_s \varphi}(1 - a_{o,s}) = \frac{(\sigma_s - 1)}{\sigma_s} \frac{(1 - a_{o,s})}{a_{o,s}} p_{od,s}(\varphi) \quad \text{if do not innovate}$$

$$w_o \frac{\tau_{od,s}}{\kappa_s \xi_{o,s} \varphi}(1 - a_{o,s}) = \frac{\sigma_s - 1}{\sigma_s} \frac{1 - a_{o,s}}{a_{o,s}} p_{od,s}(\varphi) \quad \text{if innovate}$$

Hence, the subsidy size per unit of good is always $\frac{(\sigma_s - 1)}{\sigma_s} \frac{(1 - a_{o,s})}{a_{o,s}} p_{od,s}(\varphi)$. The total subsidy is therefore:

$$A_{o,s} = \sum_d \int_0^{M_{o,s}} \frac{\sigma_s - 1}{\sigma_s} \frac{1 - a_{o,s}}{a_{o,s}} p_{od,s}(v) q_{od,s}(v) dv = \frac{\sigma_s - 1}{\sigma_s} \frac{1 - a_{o,s}}{a_{o,s}} R_{o,s}$$

Innovation subsidy cost. The innovation subsidy cost in region o for firms with productivity $\varphi \geq \varphi^i_{o,s}$ is

$$\Phi_{o,s}(\varphi) = w_{o,s}(1 - \phi_{o,s}) f^i_{o,s}$$

Total innovation subsidy in region o is therefore $M^i_{o,s} \Phi_{o,s}(\varphi)$

Demand subsidy cost. The total demand subsidy cost in region d is:

$$X_{d,s} = (1 - \chi_{d,s}) P_{d,s} e_{d,s} = (1 - \chi_{d,s}) E_{d,s}$$

C.2.2 Uniqueness of the Equilibrium

Following the previous setup, our model is pined down by the three set of equations:

1. Grid planner cost minimization gives $2 \times N$ equations for each d and $k \in \{s, s'\}$

$$E_{d,s} = \frac{\chi_{d,s}^{-\sigma} P_{d,s}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma} P_{d,s}^{1-\sigma}} E_d, \quad E_{d,s'} = \frac{P_{d,s'}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma} P_{d,s}^{1-\sigma}} E_d$$

2. Firm profit maximization gives $2 \times N$ equations for each d and $k \in \{s, s'\}$

$$\varphi^*_{o,s} = \frac{1}{\kappa_s} \left(\sum_d \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{f_s} \left(\frac{a_{o,s} \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \right\} \right)^{\frac{1}{1-\sigma_s}}$$

3. Free entry decision $2 \times N$ equations for each d and $k \in \{s, s'\}$

$$\left(\varphi_{o,s}^{*}\right)^{\theta_s} = b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1 - \sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1 - \xi_s^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right)$$

Given expenditure on electricity E_d, solar subsidy size $\{\chi_{d,s}, a_{o,s}, \phi_{o,s}\}$, elasticity of substitution $\{\sigma, \sigma_s, \sigma_{s'}\}$, knowledge spillover κ_s, and other fundamentals $\{b_{o,k}\tau_{od,k}, \xi_k, \theta_k, f_k, f_k^e, f_k^i\}$ for each sector k. The system has $6 \times N$ unknowns: $\{\varphi_{o,k}^{*}, E_{d,k}, P_{d,k}\}$ for each d.

Substitute them in and rearrange the equations, we get $2 \times N$ equations

$$\left(b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1 - \sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1 - \xi_s^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right) \right)^{\frac{1-\sigma_s}{\theta_s}}$$

$$= \sum_d \left\{ \frac{1}{\kappa_s} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_d}{f_s} \left(a_{o,s}\tau_{od,s} \right)^{1-\sigma_s} \frac{\chi_{d,s}^{-\sigma} P_{d,s}^{\sigma_s - \sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma} P_{d,s}^{1-\sigma}} \right\}$$

Given all the fundamentals and parameters, the system has $2 \times N$ unknowns: $\{P_{d,k}\}$ for each d.

- Let $\tilde{\Phi}_{o,k}$ to represent $\left(b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s} \right)^{\frac{\theta_s + 1 - \sigma_s}{1 - \sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1 - \xi_s^{1-\sigma_s}} \right)^{\frac{\theta_s}{1-\sigma_s}} + 1 \right) \right)^{\frac{1-\sigma_s}{\theta_s}}$.
- Let $\tilde{A}_{od,k}$ to represent $\frac{1}{\kappa_s} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_d}{f_s} \left(a_{o,s}\tau_{od,s} \right)^{1-\sigma_s}$
- Let $\tilde{P}_{d,k}$ to represent $\frac{\chi_{d,s}^{-\sigma} P_{d,s}^{\sigma_s - \sigma}}{P_{d,s'}^{1-\sigma} + \chi_{d,s}^{1-\sigma} P_{d,s}^{1-\sigma}}$.

Then the equation can be written as $\tilde{\Phi}_{o,k} = \sum_d \tilde{A}_{od,k}\tilde{P}_{d,k}$. Again, we have $2 \times N$ unknowns for $\tilde{P}_{d,k}$ and we have $2 \times N$ equations. Stack this system of equations in matrix form, we get $\tilde{\mathbf{\Phi}} = \tilde{\mathbf{A}}\tilde{\mathbf{P}}$

As long as $\tilde{\mathbf{A}}$ is invertible, the system admits a unique solution. If $\tilde{\mathbf{A}}$ is not invertible, the system may have either no solution or infinitely many, cases that lie outside the scope of the model. Given that each $\tilde{P}_{d,k}$ can be uniquely determined, and that the parameter values of σ, σ_s, and $\sigma_{s'}$ are known, it follows that there exists a unique solution for each $P_{d,k}$ as well.

C.3 Quantification of the Full Model

The strategy for quantifying the full model is discussed in the main text, but we add some further technical details here. As a reminder, it proceeds in three steps. First, we use the literature and moments from the data to obtain some parameters (Step 1). Second, we estimate city productivities, sunk entry costs and fixed innovation and production costs by model inversion (Step 2). Third, we obtain the levels of the subsidies by matching our reduced form SDID estimates with their analogs from the model through minimum distance (Step 3).

C.3.1 Step 1: External Calibration

Appendix Section E.3 has details and robustness tests of estimating the own firm and spillover effects of patenting on output (production, revenues and exports) using firm-level panel data.

In estimating equation (3) we use firm revenue from the ASIE above the 90th percentile. In principle, one could allow for city specific slopes and intercepts. In practice, this is not possible as there are too few firms in each city. Hence, in our baseline approach we pool firms across cities to estimate the regressions. As a robustness test we allow for city-specific intercepts in the solar sector by including a full set of city fixed effects in equation (3). We found that the estimate of the slope, $\zeta_{0,s}$, was very similar to the baseline estimation. Since this suggests little bias to the slope coefficients, we kept to the simple values of θ_s and $\theta_{s'}$ in the main text.

One of the city-regions is the "Rest of World" outside China and we take this fully into account when modelling the general equilibrium, but we make some simplifying assumptions for this region.[54] We assume that the rest of the world also consumes energy,[55] but that it only produces coal and not solar. Moreover, there is no international trade in coal. We proxy external trade costs as the average of internal trade costs.

C.3.2 Step 2: Model Inversion

Fixed production and innovation costs

Given the externally calibrated parameters from Step 1, we can pin down the fixed costs of entry and innovation in each sector using data on average firm revenues and the share of innovating firms. Intuitively, (i) the larger the share of innovators, the lower the fixed cost of innovation relative to the fixed cost of production; and (ii) when firms are big (as measured by average firm revenues), the larger are likely to be the fixed cost of production. More precisely, we solve a system of four equations in four unknowns - the fixed costs of entry (f_s, $f_{s'}$) and innovation (f_s^i, $f_{s'}^i$) in the solar and non-solar sectors. These equations take the form:

[54] In the Conclusion we discuss ongoing work which models other major regions in the rest of the world in a richer fashion.

[55] We assume that in the pre policy period before 2007, the ratio of coal to solar consumption is the same as in China and that rest of world energy demand grows at a rate that is consistent with aggregate growth patterns.

$$\begin{cases} \frac{M_s^i}{M_s} = \left(\frac{1-\xi_s^{1-\sigma_s}}{\xi_s^{1-\sigma_s}} \frac{f_s}{\phi_s \cdot f_s^i}\right)^{-\frac{\theta_s}{1-\sigma_s}} \\ \frac{M_{s'}^i}{M_{s'}} = \left(\frac{1-\xi_{s'}^{1-\sigma_{s'}}}{\xi_{s'}^{1-\sigma_{s'}}} \frac{f_{s'}}{f_{s'}^i}\right)^{-\frac{\theta_{s'}}{1-\sigma_{s'}}} \\ \frac{R_s}{M_s} = \frac{\theta_s \sigma_s}{\theta_s+1-\sigma_s} \left[\left(\phi_s \cdot \frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1-\xi_s^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}} + 1\right] f_s \\ \frac{R_{s'}}{M_{s'}} = \frac{\theta_{s'} \cdot \sigma_{s'}}{\theta_{s'}+1-\sigma_{s'}} \cdot \left[\left(\frac{f_{s'}^i}{f_{s'}}\right)^{\frac{\theta_{s'}+1-\sigma_{s'}}{1-\sigma_{s'}}} \left(\frac{\xi_{s'}^{1-\sigma_{s'}}}{1-\xi_{s'}^{1-\sigma_{s'}}}\right)^{\frac{\theta_{s'}}{1-\sigma_{s'}}} + 1\right] f_{s'} \end{cases} \tag{5}$$

Solving this system gives values for $f_s, f_{s'}, f_s^i$, and $f_{s'}^i$.

Sunk entry costs and city productivities

The expression of electricity expenditure in each sector and city is:

$$E_{d,s} = \frac{E_d P_{d,s}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + P_{d,s}^{1-\sigma}}$$

We combine these expressions into:

$$\varphi_{o,s}^* = \frac{1}{f\left(M_{t-1}\right)} \left(\sum_d \left\{\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{\chi_{d,s} w_o f_{o,s}} \left(\frac{w_o a_{o,s} \tau_{od,s}}{P_{d,s}}\right)^{1-\sigma_s}\right\}\right)^{\frac{1}{1-\sigma_s}}$$

The expression for the exit threshold as a function of calibrated fundamentals

$$\left(\varphi_{o,s}^*\right)^{\theta_s} = b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1-\xi_s^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}} + 1\right)$$

We can this rearrange to obtain our moment conditions.

$$\begin{aligned} &\left(b_{o,s}^{\theta_s} \frac{f_s}{f_s^e} \frac{\sigma_s - 1}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}} \left(\frac{\xi_s^{1-\sigma_s}}{1-\xi_s^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}} + 1\right)\right)^{\frac{1}{\theta_s}} \\ &= \frac{1}{f\left(M_{t-1}\right)} \left(\sum_d \left\{\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{\frac{E_d P_{d,s}^{1-\sigma}}{P_{d,s'}^{1-\sigma} + P_{d,s}^{1-\sigma}}}{\chi_{d,s} w_o f_{o,s}} \left(\frac{w_o a_{o,s} \tau_{od,s}}{P_{d,s}}\right)^{1-\sigma_s}\right\}\right)^{\frac{1}{1-\sigma_s}} \end{aligned} \tag{6}$$

The expression for revenues $R_{d,s}$ as a function of the mass of firms $M_{o,s}$ is:

$$R_{o,s} = M_{o,s} \frac{\theta_s \sigma_s}{\theta_s + 1 - \sigma_s} \left(\left(\phi_{o,s} \eta_{o,s} \frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}} \left(\frac{\xi_{o,s}^{1-\sigma_s}}{1-\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}} + 1\right) f_s$$

The expression for the mass of firms $M_{o,s}$ a a function of the price indices $P_{d,s}$ is:

$$\left(f\left(M_{t-1}\right)P_{d,s}\right)^{(1-\sigma_s)}=\sum_{o}\left(a_{o,s}\tau_{od,s}\frac{\sigma_s}{\sigma_s-1}\right)^{1-\sigma_s}\frac{f_s^e}{f_s}\frac{M_{o,s}\theta_s}{b_s^{\theta_s}(\sigma_s-1)}\left(\varphi_{o,s}^*\right)^{\sigma_s+\theta_s-1} \tag{7}$$

We can express the price indices implicitly as a function of city-sector revenues and rewrite equation (6) as:

$$\begin{aligned}&\left(b_{o,s}^{\theta_s}\frac{f_s}{f_s^e}\frac{\sigma_s-1}{\theta_s+1-\sigma_s}\left(\left(\phi_{o,s}\frac{f_s^i}{f_s}\right)^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_s^{1-\sigma_s}}{1-\xi_s^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1\right)\right)^{\frac{1}{\theta_s}}\\ =&\frac{1}{f\left(M_{t-1}\right)}\left(\sum_{d}\left\{\frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}}\frac{\frac{E_d\left(P_{d,s}(\mathbf{R})\right)^{1-\sigma}}{\left(P_{d,s'}(\mathbf{R})\right)^{1-\sigma}+\left(P_{d,s}(\mathbf{R})\right)^{1-\sigma}}}{\chi_{d,s}w_o f_{o,s}}\left(\frac{w_o a_{o,s}\tau_{od,s}}{(P_{d,s}(\mathbf{R}))}\right)^{1-\sigma_s}\right\}\right)^{\frac{1}{1-\sigma_s}}\end{aligned} \tag{8}$$

There are two equations for each city. The unknowns are the city productivities $b_{o,s}$ and the sunk entry costs f_s^e. As noted in the main text, we can recover the unknowns from combining previously calibrated parameters plus city level revenues combined with the mean productivity levels estimated from the shape parameter of the Pareto productivity distribution.

C.3.3 Step 3: Matching SDID Treatment Effects

We use the SDID ATT for revenues and innovation for the three types of subsidies as empirical moments. We compare these with the model-generated versions and use minimum distance to estimate the parameters (the six subsidy values). Note that our baseline regressions on the simulated data using Two-Way Fixed Effects regressions matched to the SDID ATTs. We also ran SDID on the model-simulated data, which produced very similar results at much greater computational cost.

C.4 Welfare and Social Cost-Benefit Analysis

In each region d, there is a representative consumer that obtains utility from electricity.

$$U_d=\left(e_{d,s'}^{\frac{\sigma-1}{\sigma}}+e_{d,s}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

Given that

$$e_{d,s}=\left(\frac{1}{\chi_{d,s}P_{d,s}}\right)^{\sigma}\frac{E_d}{P_{d,s'}^{1-\sigma}+\left(\chi_{d,s}P_{d,s}\right)^{1-\sigma}}$$

We can re-express utility as:

$$U_d = \frac{E_d}{\left(P_{d,s'}^{1-\sigma} + (\chi_{d,s} P_{d,s})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}$$

Since $P_d^{1-\sigma} = P_{d,s'}^{1-\sigma} + (\chi_{d,s} P_{d,s})^{1-\sigma}$, we have

$$W_d = U_d = \frac{E_d}{P_d}$$

We compute discounted aggregate consumer welfare by aggregating across all locations and across years:[56]

$$W = \sum_{t=\tau} \beta^{t-\tau} \sum_d W_{d,t} \tag{9}$$

We use a discount rate of 2% implying $\beta = 0.98$. tau is the base year from where we are calculating the present values - usually 2006, prior to the introduction of the first local solar industrial policy.

We also provide an alternative social welfare measure that incorporates the social cost of carbon, which is of particular importance when evaluating green industrial policies. For this, we assume that the income of each city E_d is unchanged across different policy scenarios except for the damage or social cost imposed by coal production. Aggregate welfare takes therefore the following form:

$$W^{SCC} = \sum_{t=\tau} \beta^{t-\tau} \sum_d \frac{L_{d,t}}{\sum_d L_{d,t}} \frac{E_d - SCC_d}{P_d}$$

Using emissions data from IEA, we convert coal usage into additional carbon emissions, and apply the mid-range of the social cost of carbon (SCC) estimates in Carleton et al. (2022), translating emissions into monetary damages.

This is the consumer welfare gain from energy. To implement a social cost benefit calculation we also have to include benefits beyond consumer welfare, such as producer surplus. These are important since a large fraction of solar panels are exported. In addition, we need to take account of the subsidy costs which are born ultimately by Chinese citizens. For the subsidy costs we use the model-generated estimates. We do not inflate these using a deadweight cost of taxation, so the benefit-cost ratio is gross of this. For example, in our baseline calculation, social benefits outweigh costs by 65%, so as long as deadweight is less than 65%, the policies pass the cost-benefit test.

We estimate the social benefits as the change in revenues (so the increase in solar revenues less the fall in revenues from coal). We do not net off production costs are these are transfers to other Chinese citizens as workers or suppliers.[57]

[56]Note that the summation is across all Chinese city-regions, i.e., we ignore the welfare enjoyed in the region representing the rest of the world.

[57]The imported intermediates for Chinese solar are very small in value.

D Further Details on the Econometric Strategy

This section provides technical details of the SDID methodology introduced in Section 3.1. First, in SDID, treatment effects τ_c are estimated for each cohort and outcome variable separately by solving the minimization problem in Equation 10.

$$\left(\hat{\tau_c}^{\text{SDID}}, \hat{\mu_c}, \hat{\alpha_c}, \hat{\beta_c}\right) = \underset{\tau_c,\mu_c,\alpha_c,\beta_c}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu_c - \alpha_{ic} - \beta_{tc} - W_{it}\tau_c\right)^2 \hat{\omega}_{ic}^{\text{SDID}} \hat{\lambda}_{tc}^{\text{SDID}} \right\} \quad (10)$$

Here, Y_{it} is the outcome of interest (e.g. revenue), μ is the intercept, α_i and β_t are city fixed effects and time fixed effects, respectively, N is the total number of units that are either treated in cohort c or are never treated, T is total number of periods, and W_{it} is a treatment dummy variable that takes the value of one for every time period post-policy (absorbing state).

Unit weights $\hat{\omega}_{ic}^{\text{SDID}}$ are chosen, specific to each cohort and outcome variable, to make the pre-treatment trends in the outcome variable for treatment and weighted control cities as parallel as possible subject to a regularization penalty to avoid over-fitting. Specifically, they are calculated as:

$$(\hat{\omega}_{0c}, \hat{\omega_c}^{SDID}) = \underset{\omega_{0c}\in\mathbb{R},\omega_c\in\Omega}{\arg\min} \sum_{t=1}^{T_{pre}} \left(\omega_{0c} + \sum_{i=1}^{N_{co}} \omega_{ic} Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{pre} ||\omega_c||_2^2 \quad (11)$$

where N_{tr} is the number of treated units in cohort c, N_{co} the number of control units, T_{pre} the number of pre-treatment periods in the cohort, ζ is a regularization parameter [58], and $\Omega_c = \left\{ \omega_c \in \mathbb{R}_+^N : \sum_{i=1}^{N_{co}} \omega_{ic} = 1 \text{ and } \omega_{ic} = \frac{1}{N_{tr}} \text{ for all } i = N_{co}+1, \ldots, N \right\}$. While control units enter with the estimated ω_{ic} weights, the weights for treated units is uniform and equal to $1/N_{tr}$.

Time weights $\hat{\lambda}_{tc}^{\text{SDID}}$ are chosen to minimize the difference between pre-treatment and post-treatment periods for control units. Formally, these are calculated as:

$$(\hat{\lambda}_{0c}, \hat{\lambda_c}^{SDID}) = \underset{\lambda_{0c}\in\mathbb{R},\lambda_c\in\Lambda}{\arg\min} \sum_{i=1}^{N_{co}} \left(\lambda_{0c} + \sum_{t=1}^{T_{pre}} \lambda_{tc} Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} \right)^2$$

where T_{post} is the number of post-treatment periods, and $\Lambda_c = \left\{ \lambda_c \in \mathbb{R}_+^T : \sum_{t=1}^{T_{pre}} \lambda_{tc} = 1, \lambda_{tc} = T_{post}^{-1} \text{ for all } t = T_{pre}+1, \ldots, T \right\}$. While pre-periods

[58] ζ regularization parameter is defined as: $(N_{tr}T_{post})^{1/4}\hat{\sigma}$ with $\hat{\sigma}^2 = \frac{1}{N_{co}(T_{pre}-1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} \left(\Delta_{it} - \overline{\Delta}\right)^2$, where $\Delta_{it} = Y_{i(t+1)} - Y_{it}$, and $\overline{\Delta} = \frac{1}{N_{co}(T_{pre}-1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} \Delta_{it}$.

enter the estimation with λ_{tc} weights, post-treatment periods are weighted uniformly.

After estimating cohort-specific $\hat{\tau}_c{}^{SDID}$ ATTs, we aggregate these into a single statistic using a method proposed in the Appendix of Arkhangelsky et al. (2021), where each cohort's estimate is weighted by the number of treated units present in the cohort. That is:

$$\hat{\tau}^{SDID} = \sum_{c \in C} P(C = c) \cdot \hat{\tau}_c^{SDID}$$

where $c \in C$ stands for some cohort from the set of all treated cohorts, C, and $P(.)$ captures the share of treated units belonging to cohort c from all treated units. Standard errors are estimated by the bootstrap clustered at the city level.

Next, for constructing event studies, we follow a method discussed in Callaway & Sant'Anna (2021). For this, we first estimate ATTs $\hat{\tau}_{ce}^{SDID}$ specific to cohort c and event study window e. These are derived analogously to Equation 10, but instead of using $\hat{\lambda}_{tc}^{SDID} = 1/T_{post}$ weights for all post-treatment periods, we take $\hat{\lambda}_{tc}^{SDID} = 1$ where $t = e$ and $\hat{\lambda}_{tc}^{SDID} = 0$ for $t \neq e$. Unit weights $\hat{\omega}_{ic}^{\text{SDID}}$ and time weights $\hat{\tau}_c{}^{SDID}$ for pre-treatment periods are otherwise unchanged from the previous estimation.

Then, the overall ATT for the event study window, e are aggregated using the number of treated units in the cohorts with available $\hat{\tau}_{ce}^{SDID}$ estimates. That is:

$$\hat{\tau}_e^{SDID} = \sum_{c \in C} \mathbf{1}\{c + e \leq T\} \cdot P(C = c | c + e \leq T) \cdot \hat{\tau}_{ce}^{SDID}$$

where P(.) captures the share of a treated unit belonging to cohort c from all cohorts having at least e post-treatment periods before the end of our study period, T. The resulting estimates for each e study window are plotted on the horizontal axis to yield event study figures. Standard errors are estimated here too by the bootstrap clustered at the city level.

E Further Results

E.1 Welfare Results

As noted in the main text we considered many other welfare counterfactuals. Figure E.1 shows five of these. As discussed in the main text, "Equal" is where we fix the budget as equal to that of the "Real" subsidy roll-out, but give all areas the three types of policies. The similarity of tha Equal counterfactual compared to Real is due to the fact that the actual cross-city pattern does not appear to be highly distorted. One obvious distortion would be if subsidies were focused in areas where solar productivity was low. In fact, panel(a) in Figure E.2 shows that solar place productivity is quite similar in areas treated by the policy compared to those who were not. Cities with subsidies are only about 0.15% more productive than those without subsidies and this tiny difference is insignificant (p-value =0.93).

Another obvious distortion, especially if transport costs are high, would be locating subsidies in areas where demand is low. Contrary to this concern, high population citites are *more* likely to have pro-solar policies. An alternative measure of firm market access (FMA) Anderson & Van Wincoop (2003) takes into account that a firm in a given city faces demand from all other cities depending on their expenditure and prices, weighted by bilateral trade costs. Using this measure, we obtain an insignificant difference between treated and control areas (p-value = 0.98).

Hence, on both place supply (comparative advantage) and demand (market access), there do not appear be large distortions from the actual policies vs. a hypothetical common national policy.

We next look at two alternative counterfactuals based around "Equal": Devoting all the budget to demand subsidies ("Equal + Demand") vs. devoting all the budget to production subsidies ("Equal + Production"). Interestingly, in Figure E.1 the welfare impacts of these counterfactuals are quite similar to each other - about 5% for demand policies and 4% for production policies. It is unsurprising that these are lower than the "Equal+Innovation" welfare as we already showed how innovation policies cost were very cost effective. This also explains why these two new scenarios generate lower welfare effects than the 8% baseline effect of actual real policies that include these innovation policies. But why do pure production policies not outperform demand policies, given we found them to generate so much more output and innovation not just at the city level in Section 3.1, but also at the national level in Section 6? The answer is simply due to the greater cost of production than demand subsidies. Although the "bang is bigger" from production subsidies, so is the social buck, as can clearly be seen from panel (d) in Figure 11. The welfare and cost benefit calculations net these out.

E.2 Direct Data on Subsidies

The ASIE dataset covers all large industrial firms in China between 1998 and 2013 and contains some (although limited) direct information on firm's total subsidies, which we use empirically to cross-validate some of our findings. The limitations of ASIE subsidy data include, first, reported subsidies are not only those allocated by city governments, but also those from national and provincial. Second, they are not confined to solar activites. Third, the subsidy variable is completely missing in 2008, 2009 and 2010. Fourth, even when matched for 2004-2007 and 2011-2013, there are missing subsidy values for about a quarter of firms. Fifth, ASIE covers only larger firms, so we only match a subsample of our population. On average, we match 21.3% of firms and cover 43.2% of total solar revenues in 2004-2007 and 2011-2013 periods. To estimate total solar subsidies, we assume that the subsidy to revenue ratio for the unmatched firms was the same as the matched firms and scale up yearly subsidy totals with the ratio of total revenue for all solar firms to the total revenue of firms with non-missing ASIE subsidy data.[59] Finally, note that our structurally based estimates of subsidies take into account hidden subsidies that firms may not declare in ASIE, which means that they may be higher than ASIE.

Figure E.3 plots out our estimate of the subsidy data from ASIE for solar firms across years. Two things stand out. First, there is a clear jump in 2007 when the first local policies were introduced, giving independent confirmation that solar firms were not receiving many other subsidies prior to our identified policies. Second, the magnitude of solar subsidies is lower than our model based estimates. In 2010, for example, our model estimates that total solar subsidies was RMB 3 billion compared to RMB 2 billion in Figure E.3. This suggests that declared ASIE subsidies are missing some hidden subsidies.

We also ran SDID regressions on the subsidy data. Here, for firms that have some information in ASIE, we imputed missing observations with linear imputation.[60] To address the missing years between 2008 and 2010, we simply dropped observations in these years and the seven cities which became treated in this period.[61] We also winsorized at the one percent level.

The results are presented in Table E.18. This confirms that cities that introduced supply side policies generated increases in observed subsidies. The ATT effects are largest for the innovation and production subsidy bundle, mirroring the findings in the main text for other outcomes. Since the ASIE data refers to solar firms and not demand subsidies, the absence of any demand policy effect is a placebo, confirming our expectation of no effect.

[59] We confirmed in the raw ASIE data the subsidy to revenue ratio is statistically unrelated to size for solar firms.

[60] To account for firms not present in the data, we scaled up city-year-level subsidy totals by the number of solar firms operating in the city-year relative to the ones covered by ASIE.

[61] We do this so that we would not have to add these cities incorrectly to another cohort's treated group.

E.3 Firm-level results: Productivity impacts of innovation

We have focused on city-level results throughout the paper because the policy variation we exploit "lives" at this level. However, since these city-level aggregates are built up from firm-level panel data, we can also examine firm-level results directly. There are at least two reasons to do this. First, we want to analyze whether the assumptions we have been making in the model hold up qualitatively at the firm level. Second, we can use some of these relationships as moments in disciplining the structural quantitative analysis (see Section 5).

One underlying assumption is that innovation as measured by patenting increases productivity and therefore output. We assess this by running models of the form:

$$\ln(Y_{f,i,t}) = \pi_1 \ln(\text{PAT}_{f,i,t-1}) + \pi_2 \ln(\text{K}_{f,i,t-1}) + \vartheta_f + \tau_t + u_{f,i,t} \tag{12}$$

where $Y_{f,i,t}$ is an outcome (e.g., productive capacity, revenues or exports) of firm f in city i at time t, PAT are the number of solar patents, K is the capital stock, ϑ_f is a firm fixed effect, τ_t is a full set of time dummies and $u_{f,i,t}$ an error term. We lag the right-hand side variables by one period to mitigate contemporaneous feedback effects and we cluster the standard errors by firm.

Column (1) of Table E.19 shows that there is indeed a positive and significant relationship between ENF solar panel production capacity and past patenting. A doubling of the number of patents is associated with a 2% increase in output. In column (2) we include the capital stock (from Orbis).[62] We see that the inclusion reduces the coefficient marginally to 1.8% but it remains significant at the 1% level. Including other controls, such as employment, makes no difference to this result.[63]

Panel capacity from ENF is unavailable after 2013, so we next use revenues, which is available throughout the sample period to 2020. The sample size is six times larger, but the qualitative results are similar. The magnitude of the patents coefficient is larger, however, implying that a doubling the number of patents is associated with an increase in revenue of 6% in column (3) and 5% in column (4) of Table E.19. Finally, we use export value as the dependent variable in the last two columns and show even larger associations between patents and exporting. An alternative measure using patenting stock rather than flows yields highly comparable results across all six columns.[64]

Our model and the "neighbouring city" spillover analysis in subsection 3.2.3, suggests knowledge spillovers across cities. Can we observe this in the firm-level analysis? And are

[62] As there are missing values in the capital variable, we impute it using the mean capital stock in the respective year. An alternative specification without the imputation yields a slightly smaller albeit significant coefficient on the patent coefficient. The estimated effect on capital is the same.

[63] If we include lagged ln(employment) on the right-hand side it often has an insignificant coefficient and the coefficient(standard error) on patents stays significant in all columns.

[64] We construct this by using the depreciated sum of the count of patents for each firm since 1985 (using the perpetual inventory method with a depreciation rate of 0.15 as is conventional).

there within city spillovers? To investigate this, we expand the specification to include spillovers. Column (1) of E.20 repeats the baseline specification of column (3) of Table E.19. Column (2) then includes patents by other firms in the same city and column (3) includes the patents by other firms in the same province. These enter with positive and significant coefficients.[65] Column (4) includes both spillover terms together and finds evidence consistent with within city and between city spillovers.[66]

E.4 Solar patents taken out by non-solar entities

We now investigate the effect of subsidies using the total number of *solar*-related patents in the city. As noted in Section B.4 this is based on text in the patents using keywords from SIPO. Compared to the main approach in the text which aggregates the patents of solar producing firms, this has the advantage that it does not rely on the ENF data set to define what is a solar firm. However, it comes with the cost that the entities patenting are not all the same as those whose revenues and production we are using in the other SDID regressions.

There are some solar patents filed by entities outside our ENF dataset such as universities, government labs, individuals and "non-solar firms". The last category would include firms who are not producing solar panels, but may be operating in technologically related industries.

The first row of Table E.21 provides a robustness check utilising this alternative strategy by applying the SDID method to city-level solar patents and the same period as our main results. The results show the familiar pattern, with innovation subsidies having the strongest effect, production subsidies the second strongest effect, and demand subsidies showing no significant effect. The magnitude of these estimates appear to be smaller than the estimated effect on ENF firms' (solar) patents in the last row of Table E.5. A possible explanation for this is that the patents here may include a host of technologies which support solar technology but are not among the core technologies affected by solar subsidies.

Given that the data can be extended before 2004 as well – the start of the ENF production sample – in the second row of Table E.21, we estimate ATTs for the longer 2000-2020 period

[65] It may seem surprising that the coefficient is larger, but these are proportional effects, so a doubling of the city or province number of patents is a much larger increase than a doubling of the firm's own patent. An increase of a single patent is a 58% increase for a firm (average patents are 1.7) which is predicted to have a 3.25% increase in revenues. Taking the values from column (4) which includes both city and province spillover shows that a single patent by another firm in the same city (province) increases the spillover pool by only 2% as the number of average patents is considerably larger with 51.7 (267.4). This means the increases of a single patent is predicted to increase firm level revenue for each firm by 0.11% and 0.03% in the city and province respectively. Especially as these will apply to all firms in the city and province respectively this is a large learning spillover, but smaller than the own-patent effect as we would expect.

[66] We further tested robustness by incorporating the revenue in the city and province. For example, when including the revenue of the city (again excluding the revenue of the firm itself) the effect size of the spillover reduces only marginally to 7.6% from 8.4%. The coefficient on the revenue of the city is 4.9% and significant. The picture is similar for other specifications.

as well. We find that the ATTs are both quantitatively and qualitatively similar to the estimates derived for the time frame of our main sample.

E.5 Adjusting for Multi-city firms

In the main section of the analysis, we use the address of firms' headquarters to determine their location and treatment status. We have on factory locations for 45% of firms in the ENF production data (their three main factories).[67] For these firms, we find that only 7.3% of firms have factories in multiple cities. Production activity in these cases is likely to be dispersed among the multiple factory locations, and – as Chinese law requires firms operating in multiple cities to set up separate legal entities in each city – the subsidies applying to the firm's activity may also vary from region to region.

Consequently, we adjust for this variation in production and treated status within firms. Specifically, we assume that the firms' overall output is distributed equally among its reported factories and each factory is treated by the subsidies of the city where it is located. After allocating production activity to cities with these assumptions, we then rerun our city-level SDID estimations. We concentrate on production outcomes (shown in Panel D of Table 2), as these are available for the same set of firms (and time period) that have factor location information (i.e. ENF production firms), but we observe qualitatively similar results if we restrict the analysis to this sample for other outcomes as well. Table E.22 reports the results after adjustment. We see that while the estimate magnitude of the effects has slightly decreased in this specification, our qualitative conclusions are unchanged.

E.6 Solar subsidy policies above the city level

As discussed in the main text, solar subsidy policies in China are focused overwhelmingly at the city level. We did not identify any subsidy policies at the lower level - i.e., among the 2,862 Chinese counties or 41,034 townships. However, there *were* some policies at higher levels above the city level (national and provincial), that could in principle bias our estimates. We adress these in turn.

E.6.1 National-level policies

National level policies that affect all cities equally are absorbed by the time dummies in our empirical exercises.[68] We did identify two national policy with material subnational

[67] 93% of firms report the city of their headquarter among factory locations, which supports our assumption that the headquarters address and production activity are closely related. We do not have information on the exact distribution of production activity across factory locations to investigate the relationship further.

[68] In PKULaw, we identified a total of eight national subsidies, all of which are demand subsidies. The central component of six national policies is a country-wide feed-in-tariff (FIT) policy, while the other two focus on a preferential value-added tax policies from solar power generation.

variation. First, consider the implementation of feed-in tariffs (FITs) for installed solar capacity. Although FITs were introduced at the national level in July 2011, a geographic differentiation was introduced in 2013, dividing the country into three tariff zones based on solar irradiance levels. Tariff rates were subsequently reduced in 2013, 2016, 2017, and 2018.[69] Because these adjustments vary by location and over time, they could present a potential challenge to our identification strategy. To address this concern, we restrict our analysis to the primary tariff zone, which includes 220 of the 358 cities in our dataset encompassing 37 of the 42 cities that ever introduced a solar subsidy policy. This restriction improves the comparability of treated and untreated units by holding the FIT regime constant. These results are shown in Table E.23. Our core findings remain robust within this more homogeneous subsample, reinforcing confidence in our main estimates.

A second national policy was the "Top Runner" program. Announced in 2015, but implemented from 2017 onwards, this policy provided a demand subsidy by mandating a certain amount of solar investment had to meet higher standards. It was accomplished via procurement auctions for utility-scale solar development and bidders were evaluated on the efficiency of their technology (in addition to price), in order to enhance innovation. To make sure our results are not affected by this policy, we show in Table E.24 that all key results are robust to ending the estimation in 2013, well prior to the introduction of Top Runner.

E.6.2 Province-level policies

There are 33 provinces in China. In PKULaw, we identified a total of 18 province-level solar subsidies, 17 were demand subsidies (impacting 101 cities in the provinces' jurisdiction) and one was an innovation subsidy (impacting 8 cities). To assess these policies' potential influence, we re-ran our city-level analysis on a restricted sample excluding any cities in these treated provinces.[70]

Table E.26 shows that the results are not significantly different from our baseline estimates in Table 2. Innovation subsidy ATTs in column (2) are essentially the same. The magnitude of demand subsidy ATTs in column (1) do increase somewhat, however, and are significant at the 5% level in Panel E (exports). The direction of this change is intuitive. 79 out of the 101 cities dropped (because they could be influenced by province-level demand subsidies) were in the "donor pool" (i.e. places we classified as not introducing demand subsidies). As we have argued there are some positive effects of these hidden demand policies, this causes us to underestimate the treatment effect in our baseline as they were included in the control group. Our key takeaway from Table E.26 is that the results are robust. Demand

[69] For a detailed discussion of these policies, see Auffhammer et al. (2021).

[70] For demand subsidies, the restricted sample contains 257 of 358 cities, including 22 cities of out the 30 cities that were treated at some point by a city-level demand subsidy. For innovation subsidies, the restricted sample contains 347 cities, including 8 of the 11 cities which were treated at some point by a city-level innovation subsidy.

policies still have ATTs that are much smaller in magnitude and precision than production or innovation subsidies.

E.7 Adding controls to SDID

Our baseline SDID analysis does not control for additional variables, since the city and time fixed effects should effectively absorb most of the relevant confounding influences. City-year specific shocks that are correlated with policy introduction could in principle bias our results, which motivates the SDID approach and is why we presented many placebo tests showing no effect of the subsidies on GDP, non-solar patents, etc. (subsection 3.3). We also considered specifications controlling for a number of observables, such as GDP, population, income, local tax revenue, etc. These are potentially "bad controls" if the policies affect the growth of the city. However, since solar is a relatively small part of the economic activity of a city, such controls may be useful in picking up cities which are subject to unobservable shocks correlated with the introduction of solar policies that our SDID approach is not fully capturing. Although GDP per capita tended to be positively correlated with the outcomes, its inclusion made almost no difference to the magnitude or significance of our treatment effects. Table E.27 shows the results of including such controls on all our main specifications. Although the sample is slightly smaller due to missing values on a few of the smaller cities, there is almost no discernible impact. These findings are robust to splitting up GDP from population and including other observables. All this suggests our econometric procedure is doing a good job at dealing with unobservable shocks.

E.8 Calculating Weights with Multiple Outcome Variables

As described in Section 3.1, synthetic difference-in-differences calculates unit weights (per cohort and outcome) by minimizing the difference between the average path of treated units and the weighted average of synthetic control units in the pre-treatment region. When the algorithm is implemented for each outcome separately, weights are free to vary across results. Here, we show that we can also calculate a single set of unit weights using multiple outcomes, which ensures balanced in the pre-treatment region for this broader set of variables. See Sun et al. (2025) for a discussion on how this approach can lower bias bounds in synthetic control analyses.

In our case, we calculate the single set of unit weights, for each cohort, as:

$$(\hat{\omega}_0, \hat{\omega}^{SDID}) = \arg \min_{\omega_0 \in \mathbb{R}, \omega \in \Omega} \sum_k \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it}^{(k)} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it}^{(k)} \right)^2 + \sum_k {\zeta^{(k)}}^2 T_{pre} ||\omega||_2^2$$

where difference compared to equation (11) is that the loss function is summed over k outcome variables, $Y_{it}^{(k)}$.[71] All main outcome variables are used for the construction of weights which have at least as long coverage as the outcome variable studied in a particular estimation.[72] In Table E.28, we report ATT estimates for all outcome variables and policies. In Figure E.4, we also present dynamic event study graphs for all outcome variables and production subsidies.[73] Both overall ATT values and the event studies point to qualitatively similar conclusions than the estimates presented in the main section.

E.9 Compositional Changes and Dynamic Effects

In Section 3.1, we used aggregate event studies to discuss our policies' dynamic effects. While these figures summarize the overall movement of all treated cities succinctly, they may be also affected by compositional effects - stemming from changes in the composition of cohorts contributing to different years' ATTs - beyond dynamic effects (Callaway & Sant'Anna 2021). In this section, we use two additional strategies which help us isolate solar policies' dynamic effects from cohort composition.

First, following a strategy recommended by Callaway & Sant'Anna (2021), we select a set of cohorts and study dynamic effects only within a study window where these cohorts have estimates.[74] As the composition of cohorts is stable within this window, this strategy yields unbiased estimates for these cohorts' average dynamic effects, but has the downside that it requires dropping a lot of data to select the subset of cohorts. The logic that we follow in making this selection is that we would like to use as many cohorts as possible while also having at least one treated period for all of our outcome variables.[75] Based on this, aggregate event studies using cohorts treated between 2007 and 2013 are reported in Appendix Figures E.5, E.6, E.7, E.8, and E.9. They should be interpreted as the event studies presented in Section 3.1, except for the addition of a red vertical line, which indicates the end of the study window until which there are no compositional changes. The patterns we observe on these figures are broadly consistent with what we have seen previously.[76]

[71] The outcomes are standardized over the full sample to ensure that contribution to the loss function is not dependent on the scale of the variable.

[72] So, for example, when effects on the solar exports outcome variable is studied – which has a coverage of 2004-2016 – we include yearly patents, revenue and firm count in addition to solar exports to the construction of unit weights, but do not include panel capacity as that is available only until 2013.

[73] For the result focusing on panel capacity, which uses five variables for constructing unit weights, we use unadjusted revenues rather adjusted ones.

[74] In other words, the beginning of the study window is the minimum number of pre-periods that cohort members have and the end of the study window is the minimum of the members' post-periods.

[75] Note that patenting, revenue and firm count outcome variables are available until 2020, while exporting data ends in 2016 and ENF production data in 2013. Therefore, the study window will have four years shorter post-treatment periods for exports and seven fewer years for ENF variables than for the other outcomes.

[76] The one difference is that the long-term effects of the policy start to stabilize rather than increase continually. This may indicate that the apparent increasing effect in our earlier graphs was due to due to early policy cohorts having larger effects than later cohorts.

A second approach is to examine an event studies for each individual cohort. These cohort-specific estimates are unaffected by compositional changes and so, they should represent pure dynamic effects too. First, we focus on the 2007 cohort, which was the first time production subsidies were introduced at the beginning of The Eleventh Five-Year Plan. These are shown in Appendix Figures E.11 through E.15. The broad conclusions of our discussion remain, with these graphs showing again more of a stabilised effect than a continued increase. For outcome variables that have coverage until 2020, we also inspect cohort-specific dynamic effects using the 2013 cohort, which was at the end of our previously selected study window. The results in Figures E.16 through E.18 are consistent with what we have seen for the 2007 cohort.

Overall, these results suggest that composition is not driving our results.

Table E.3: **Estimation of all outcomes in levels instead of IHS**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel A: All patents (2004-2020)				
Subsidy policy ATT	6.310	−7.076	20.046**	25.613*
Mean = 13.128	(9.949)	(14.578)	(9.569)	(14.873)
Panel B: Number of solar firms (2004-2020)				
Subsidy policy ATT	1.199	−0.257	2.505*	2.900
Mean = 2.872	(0.898)	(0.617)	(1.462)	(2.122)
Panel C: Revenue (million RMB) (2004-2020)				
Subsidy policy ATT	135	−0.95	329**	397**
Mean = 157	(123)	(109)	(148)	(179)
Panel D: Panel production capacity (MWh) (2004-2013)				
Subsidy policy ATT	319.567**	138.574	366.728**	480.764***
Mean = 82.449	(128.377)	(127.902)	(147.783)	(175.088)
Panel E: Solar export value (million dollars) (2004-2016)				
Subsidy policy ATT	22.1*	4.6	26.9**	31.9*
Mean = 19.27	(12.4)	(13.7)	(12.7)	(17.3)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables in levels, winsorised at 1%. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms. All regressions are based on a balanced panel of admin 2 regions covering the period where the outcome variable is available. Patents, firm count, and revenue outcomes are based on a sample of 6,086 observations covering 2004–2020, solar export value is based on 4,654 observations covering 2004–2016, panel production capacity is based on 3,580 observations covering 2004–2013.

Table E.4: **Estimation of all outcomes using log(1+Y) instead of IHS**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel A: All patents (2004-2020)				
Subsidy policy ATT	0.437**	0.204	0.753***	0.926***
	(0.170)	(0.239)	(0.197)	(0.327)
Panel B: Number of solar firms (2004-2020)				
Subsidy policy ATT	0.165**	0.023	0.299**	0.318***
	(0.073)	(0.033)	(0.117)	(0.112)
Panel C: Revenue (2004-2020)				
Subsidy policy ATT	1.803	-0.446	3.560**	4.604*
	(1.160)	(0.500)	(1.793)	(2.363)
Panel D: Panel production capacity (2004-2013)				
Subsidy policy ATT	1.895***	0.493	2.267***	2.683***
	(0.477)	(0.406)	(0.508)	(0.680)
Panel E: Solar export value (2004-2016)				
Subsidy policy ATT	3.192***	1.153	4.298***	6.092**
	(1.231)	(1.145)	(1.498)	(2.366)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables are log(x+1)-transformed. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms. All regressions are based on a balanced panel of admin 2 regions covering the period where the outcome variable is available. Patents, firm count, and revenue outcomes are based on a sample of 6,086 observations covering 2004–2020, solar export value is based on 4,654 observations covering 2004–2016, panel production capacity is based on 3,580 observations covering 2004–2013.

Table E.5: **Splitting patent outcomes into different types**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patents	0.496**	0.236	0.871***	1.060***
	(0.200)	(0.275)	(0.227)	(0.367)
☐ Design patents	0.186	0.277	0.237	0.151
	(0.138)	(0.216)	(0.173)	(0.253)
☐ Invention/utility model patents	0.529***	0.201	0.937***	1.097**
	(0.201)	(0.274)	(0.232)	(0.373)
• Solar patents	0.523***	0.261	0.776***	0.904**
	(0.168)	(0.228)	(0.204)	(0.367)
• Non-solar patents	0.296	0.023	0.707***	0.818**
	(0.180)	(0.220)	(0.242)	(0.388)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time period for the estimation: 2004-2020. Each coefficient represents one SDID regression. The coefficient is the ATT which averages the staggered treatment effect for all cohorts. Chinese patents can be classified as design patents, utility model patents and invention patents. Utility model and invention patents contain IPC codes and can therefore be further classified into solar patents and non-solar patents. All regressions are without controls.

Table E.6: **Solar panel and cell results 2004-2013: production, capacity and firm numbers**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel production	2.140***	0.705**	2.513***	3.078***
	(0.471)	(0.341)	(0.525)	(0.702)
Cell production	1.831***	1.298*	2.024***	2.455**
	(0.592)	(0.664)	(0.707)	(1.010)
Cell capacity	1.928***	1.310*	2.066**	2.322*
	(0.672)	(0.709)	(0.842)	(1.197)
Panel firm counts	0.558***	0.146	0.677***	0.806***
	(0.125)	(0.109)	(0.140)	(0.184)
Cell firm counts	0.380**	0.229	0.422**	0.540**
	(0.152)	(0.213)	(0.183)	(0.262)
Observations	3,580	3,580	3,580	3,580

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2013. Each column is one SDID regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table E.7: **Unadjusted Revenue - SDID Estimates by Outcome and Subsidy Type**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Revenue	1.033**	0.144	1.777**	2.618**
	(0.441)	(0.173)	(0.753)	(1.145)
Observations	6,086	6,086	6,086	6,086

Notes: The main results have our estimates solar-only revenues, whereas these are the results using the raw revenue data for solar firms (including revenue from non-solar products). * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 42 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table E.8: **Exports: Total, non-solar exports and number of solar exporters**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Export value	2.513**	0.654	3.327**	4.429**
	(1.185)	(1.131)	(1.438)	(2.147)
Non solar export value	1.388	−0.736	3.094***	3.560**
	(0.924)	(0.979)	(1.026)	(1.641)
Exporters firm count	0.220**	0.046	0.314***	0.400**
	(0.095)	(0.107)	(0.107)	(0.167)

Notes: * 0.1 ** 0.05 *** 0.01. First row is total exports of solar firms (including non-solar exports); second row is non-solar exports and third row is the count of solar exporters. Each unit is one of the 358 admin 2 level regions in China. 43 cities are treated by any subsidy. Time: 2004-2016. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table E.9: **Cross-city spillovers**

	(1) *Any subsidy*	(2) *Demand Subsidy*	(3) *Production Subsidy*	(4) *Innovation subsidy*
All patents	0.398***	0.349***	0.348***	0.477***
	(0.105)	(0.099)	(0.122)	(0.183)
Firm count	0.112**	0.078*	0.120*	0.197**
	(0.047)	(0.041)	(0.066)	(0.100)
Revenue	0.696***	0.316*	0.764***	1.026***
	(0.177)	(0.178)	(0.215)	(0.349)
Panel capacity	0.424	0.149	0.501	0.456
	(0.275)	(0.220)	(0.350)	(0.444)
Solar export value	1.272**	0.464	1.575**	1.737*
	(0.582)	(0.459)	(0.659)	(1.000)

Notes: * 0.1 ** 0.05 *** 0.01. Dependent variables are reported in columns. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. This sample here is restricted by dropping the 43 regions that have been treated directly by any subsidy. From the remaining regions, 103 cities' neighbours received any kind of subsidy. Time: 2004-2013 for panel capacity, 2004-2020 for patents, firm count and revenues. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The revenue numbers are adjusted to account for multi-product firms following the mechanism described in Section B.7. All regressions without controls.

Table E.10: **Estimated effect without treatment-adjacent cities**

	(1) *Any subsidy*	(2) *Demand Subsidy*	(3) *Production Subsidy*	(4) *Innovation subsidy*
All patents	0.710***	0.361	0.966***	1.124***
	(0.223)	(0.253)	(0.230)	(0.321)
Firm count	0.240***	0.05	0.390***	0.423***
	(0.078)	(0.038)	(0.127)	(0.150)
Revenue	1.259***	0.152	1.864***	2.579***
	(0.383)	(0.293)	(0.519)	(0.758)
Panel capacity	2.153***	0.627	2.498***	2.923***
	(0.536)	(0.496)	(0.358)	(0.663)
Solar export value	4.138***	1.56	4.844***	6.130**
	(1.073)	(1.154)	(1.647)	(2.510)
Observations	3,341	3,341	3,341	3,341

Notes: * 0.1 ** 0.05 *** 0.01. Dependent variables are reported in columns. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. This sample here is restricted by dropping the XXX un-treated cities neighboring cities that received any kind of subsidy. Time: 2004-2013 for panel capacity, 2004-2020 for patents, firm count and revenues. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The revenue numbers are adjusted to account for multi-product firms following the mechanism described in Section B.7. All regressions without controls.

Table E.11: **Pollution - PM 2.5 concentration**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
PM 2.5 concentration	-0.611	-1.192^{**}	-0.167	-0.161
	(0.441)	(0.581)	(0.394)	(0.584)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	38.58	38.58	38.58	38.58

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. Time: 2004-2020. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The outcome variable is annual average $\mu g/m^3$ concentration of $PM_{2.5}$. It is in levels and is winsorized at 1%. Its source is the 0.1 x 0.1 degree resolution V5. GL.02 data set, from which, we calculate area-weighted averages for cities. All regressions without controls.

Table E.12: **Pollution - CO_2 emissions**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Annual CO_2 emissions	-0.038^{**}	-0.042^{*}	-0.028	-0.020
	(0.015)	(0.023)	(0.017)	(0.028)
Observations	4,872	4,872	4,872	4,872

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 348 admin 2 regions in China with available data. Time: 2004-2017. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The outcome variable is annual CO_2 emissions and it is transformed using IHS. Its source is the county-level annual data set of Chen et al. (2020), which we remap to our admin 2 regions. All regressions without controls.

Table E.13: **Learning-by-doing patents**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.358^{***}	0.220	0.495^{*}	0.680^{***}
	(0.131)	(0.168)	(0.207)	(0.358)
Observations	5,728	5,728	5,728	5,728

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls. 25.6% of the utility + invention patents are classified as LBD patents.

Table E.14: **Productivity: comparing policy effects on outputs vs. inputs**

Panel A	(1)	(2)	(3)	(4)
Period: 2004-2020	*Any subsidy*	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	0.994**	0.060	1.772***	2.502***
	(0.448)	(0.278)	(0.615)	(0.819)
Labor	0.743*	0.024	1.441**	1.793**
	(0.423)	(0.231)	(0.592)	(0.906)
Capital	0.494	−0.199	1.223**	1.646**
	(0.346)	(0.175)	(0.509)	(0.785)
Observations	6,086	6,086	6,086	6,086
Panel B	(1)	(2)	(3)	(4)
Period: 2004-2013	*Any subsidy*	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	1.726***	0.288	2.157***	2.560***
	(0.543)	(0.208)	(0.617)	(0.961)
Panel production capacity	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Labor	1.418**	0.132	1.771***	2.001**
	(0.575)	(0.241)	(0.680)	(0.966)
Capital	1.142**	0.103	1.450**	1.730*
	(0.510)	(0.250)	(0.596)	(0.899)
Observations	3,580	3,580	3,580	3,580

Notes: *0.1 ** 0.05 *** 0.01. Each observation is city (admin 2 level region) and there are 358 cities in China. 43 cities are treated by a subsidy. The time period of panel A is 2004-2020, and 2004-2013 for panel B. Each column contains one Synthetic Difference In Differences (SDID) estimate of the Average Treatment of the Treated (ATT), which averages the staggered treatment effects across all cohorts (years in which there were solar policies). Column (1) has any solar policy, column (2) the demand (installation) subsidies, column (3) production subsidies and column (4) innovation subsidies. Bootstrapped standard errors below the ATT. The revenue numbers are adjusted to account for multi-product firms following the mechanism described in Section B.7 and all regressions are without controls.

Table E.15: **Productivity as an outcome**

	(1)	(2)	(3)	(4)
	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue/Capital	0.447***	0.241*	0.495**	0.655**
	(0.163)	(0.131)	(0.245)	(0.302)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls. The ratio is transformed using IHS and cities with zero production are coded as zeros.

Table E.16: **Placebo: City-level total patents**

	(1)	(2)	(3)	(4)
	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Patent	−0.064	0.004	−0.118	−0.034
	(0.438)	(0.965)	(0.309)	(0.811)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Outcome is total patents (mainly non-solar) Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table E.17: **Placebo: GDP per capita**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
GDP per capita	0.028	0.027	0.034	0.038
	(0.195)	(0.201)	(0.468)	(0.568)
Observations	5,491	5,491	5,491	5,491

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. The number of observation is smaller because not all cities have GDP per capita data.

Table E.18: **Subsidy value**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Subsidy value (million RMB)	9.207*	-0.558	10.848*	15.351
	(5.267)	(1.250)	(5.644)	(11.179)
Observations	2,457	2,457	2,457	2,457
Mean of Dep. var.	1.608	1.608	1.608	1.608

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. Time periods included in the estimation: 2004-2007 and 2011-2013. 7 regions treated by any subsidy between 2008 and 2010 are excluded. Each column is one SDID regression. The coefficient is the ATT, which averages the staggered treatment effect for all cohorts. All regressions are without controls.

Table E.19: **Firm level regressions: Patents associated with higher subsequent Output and exports**

	(1) Log(Capacity)	(2) Log(Capacity)	(3) Log(Revenue)	(4) Log(Revenue)	(5) IHS(Exports)	(6) IHS(Exports)
Solar Patents$_{t-1}$	0.020***	0.018***	0.058***	0.049***	0.135***	0.129***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)
Capital Stock$_{t-1}$		0.077***		0.257***		0.256***
		(0.024)		(0.031)		(0.043)
Observations	2,527	2,527	11,861	11,861	8,973	8,973
No. of Firms	520	520	1,104	1,104	1,297	1,297
Sample Period	2004-2014	2004-2014	2004-2020	2004-2020	2004-2015	2004-2015
Firm FE	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Notes: * 0.1 ** 0.05 *** 0.01. Firm level panel data. The standard errors are clustered at the firm level. The sample size varies due to different data availability for the variables. Columns 5 and 6 utilize the IHS transformation because some firms do not export, even though they are known to operate. To maintain sample consistency, missing values in the capital stock variable are imputed with the mean for that year, and an indicator variable is included for these observations. Neither the coefficients nor the standard errors change significantly when imputation is not performed. To make the estimates represent an elasticity, the solar patents are transformed using IHS as some firms are operating but do not have any patents and capital stock is log-transformed.

Table E.20: **Firm level panel data: Knowledge Spillovers**

	Log(Revenue)							
Solar Patents$_{t-1}$	0.058***	0.057***	0.056***	0.056***	0.049***	0.048***	0.048***	0.048***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Solar Patents		0.084***		0.056**		0.060**		0.044*
by other firms in City$_{t-1}$		(0.030)		(0.025)		(0.027)		(0.025)
Solar Patents			0.138**	0.100*			0.090**	0.061
by other firms in Province$_{t-1}$			(0.054)	(0.050)			(0.043)	(0.038)
Capital Stock$_{t-1}$					0.257***	0.252***	0.251***	0.250***
					(0.032)	(0.032)	(0.032)	(0.032)
Observations	11,861	11,861	11,861	11,861	11,861	11,861	11,861	11,861
Num Firms	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104
Firm FE	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Notes: * 0.1 ** 0.05 *** 0.01. Firm level panel data. The sample period is 2004-2020. The standard errors are clustered at the province level.

Table E.21: **City-level total solar patents**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Solar patents	0.444***	0.114	0.662***	1.029***
(2004-2020)	(0.150)	(0.138)	(0.213)	(0.219)
Solar patents	0.470***	0.146	0.703***	0.991***
(2000-2020)	(0.148)	(0.132)	(0.191)	(0.205)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region and there are 358 admin 2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one SDID regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table E.22: **Results with within firm multi-city adjustment on ENF production sample**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity	1.415***	−0.052	1.816***	1.730**
	(0.505)	(0.282)	(0.547)	(0.745)
Panel production	1.281**	−0.272	1.714***	2.279***
	(0.537)	(0.324)	(0.614)	(0.722)
Cell production	1.494**	0.786	1.734**	2.083***
	(0.586)	(0.631)	(0.713)	(0.980)
Cell capacity	1.659**	0.958	1.855**	2.031*
	(0.657)	(0.674)	(0.823)	(1.134)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region. Time: 2004-2013. Each coefficient is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The revenue numbers are adjusted to account for multi-product firms following the approach described in Section B.7.

Table E.23: **Main Feed-In-Tariff Zone sub-sample: SDID Estimates by Outcome and Subsidy Type**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel A: All patents (2004-2020)				
Subsidy policy ATT	0.588***	0.381*	0.804***	0.915**
	(0.162)	(0.208)	(0.264)	(0.404)
Panel B: Number of solar firms (2004-2020)				
Subsidy policy ATT	0.207**	0.041	0.351***	0.296**
	(0.088)	(0.047)	(0.132)	(0.130)
Panel C: Revenue (2004-2020)				
Subsidy policy ATT	0.853***	0.137	1.469***	1.988***
	(0.330)	(0.226)	(0.497)	(0.651)
Panel D: Panel production capacity (2004-2013)				
Subsidy policy ATT	2.070***	0.421	2.357***	2.644***
	(0.497)	(0.503)	(0.558)	(0.786)
Panel E: Solar export value (2004-2016)				
Subsidy policy ATT	1.775**	1.093	1.793*	1.996
	(0.894)	(1.158)	(1.026)	(1.509)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All regressions are based on a sub-sample of cities in the main national zone of feed-in-tariffs (covering period where the outcome variable is available). Patents, firm count, and revenue outcomes are based on a sample of 3,740 observations covering 2004–2020, solar export value is based on 2,860 observations covering 2004–2016, panel production capacity is based on 2,200 observations covering 2004–2013. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables are IHS-transformed. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms.

Table E.24: **SDID Estimates by Outcome and Subsidy Type focusing on earlier years (2004-2013)**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel A: All patents				
Subsidy policy ATT	0.636**	−0.366	0.940**	1.379***
	(0.308)	(0.438)	(0.369)	(0.443)
Panel B: Number of solar firms				
Subsidy policy ATT	0.378***	0.097	0.448***	0.467***
	(0.139)	(0.077)	(0.167)	(0.179)
Panel C: Revenue				
Subsidy policy ATT	1.726***	0.288	2.157***	2.560***
	(0.543)	(0.208)	(0.617)	(0.961)
Panel D: Panel production capacity				
Subsidy policy ATT	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.465)	(0.575)	(0.773)
Panel E: Solar export value				
Subsidy policy ATT	4.025***	2.256	4.421***	5.472**
	(1.332)	(2.090)	(1.412)	(2.369)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables are IHS-transformed. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms. All regressions are based on a balanced panel of admin 2 regions covering the period where the outcome variable is available. All regressions are based on a balanced panel of 3,580 observations covering the 2004-2013 period.

Table E.25: **SDID Estimates by Outcome and Subsidy Type – Top Runner cities excluded (in columns (1) -(4)) or scored as demand subsidies (in column (5))**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*	(5) *Demand subsidy w Top Runner cities*
Panel A: All patents (2004–2020)					
Subsidy policy ATT	0.444**	0.240	0.789***	0.938***	0.208
	(0.200)	(0.227)	(0.228)	(0.353)	(0.183)
Panel B: Number of solar firms (2004–2020)					
Subsidy policy ATT	0.205**	0.033	0.367***	0.405**	0.006
	(0.086)	(0.044)	(0.138)	(0.159)	(0.026)
Panel C: Revenue (2004–2020)					
Subsidy policy ATT	1.111***	0.184	1.853***	2.802***	0.055
	(0.351)	(0.224)	(0.521)	(0.708)	(0.200)
Panel D: Panel production capacity (2004–2013)					
Subsidy policy ATT	2.002***	0.144	2.431***	2.928***	0.587
	(0.528)	(0.286)	(0.600)	(0.831)	(0.467)
Panel E: Solar export value (2004–2016)					
Subsidy policy ATT	3.092***	0.947	4.263***	6.282**	0.957
	(0.998)	(0.992)	(1.380)	(2.558)	(1.034)

Notes: Each cell reports the SDID ATT estimate for the outcome named in the panel title and the subsidy type in the column header; standard errors are in parentheses. Outcome variables are IHS-transformed. Columns 1–4 exclude 21 cities where Top Runner policies have been implemented. This leads to the following number of observations: Panels A–C: 5,729; Panel D: 3,370; Panel E: 4,381. Column 5 uses the full sample of cities and marks Top Runner cities as if they were treated by demand subsidies since the implementation of the Top Runner program. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table E.26: **Excluding cities treated by province-level subsidies, SDID Estimates by Outcome and Subsidy Type**

	(1) *Demand subsidy*	(2) *Innovation subsidy*
Panel A: All patents (2004–2020)		
Subsidy policy ATT	0.417	1.219***
	(0.274)	(0.359)
Panel B: Number of solar firms (2004–2020)		
Subsidy policy ATT	0.066*	0.546***
	(0.037)	(0.157)
Panel C: Revenue (2004–2020)		
Subsidy policy ATT	0.505*	2.984***
	(0.288)	(0.936)
Panel D: Panel production capacity (2004–2013)		
Subsidy policy ATT	0.062	3.314***
	(0.303)	(0.633)
Panel E: Solar export value (2004–2016)		
Subsidy policy ATT	3.002**	6.864***
	(1.377)	(2.642)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each cell reports a separate SDID regression estimating the ATT for the corresponding solar subsidy policy, reported in the column's header, and outcome variable, reported in the panel's title. Outcome variables are IHS-transformed. Panel A uses the total number of patents from solar firms, panel B the number of solar firms, panel C the total revenue of solar firms, panel D the panel production capacity of solar firms, and panel E the value of solar exports from solar firms. All regressions are based on a balanced panel of admin 2 regions restricted to cities which were not treated by province-level subsidies of the column's type. Patents, firm count, and revenue outcomes are based on a sample of 3,740 observations covering 2004–2020, solar export value is based on 2,860 observations covering 2004–2016, panel production capacity is based on 2,200 observations covering 2004–2013.

Table E.27: **Controlling for GDP per capita**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patents	0.490**	0.232	0.862***	1.042**
	(0.217)	(0.262)	(0.248)	(0.407)
□ Design patents	0.187	0.276	0.234	0.150
	(0.131)	(0.192)	(0.175)	(0.238)
□ Invention/utility model patents	0.528**	0.198	0.938***	1.083***
	(0.221)	(0.260)	(0.260)	(0.412)
• Solar patents	0.530***	0.261	0.785***	0.907**
	(0.202)	(0.245)	(0.223)	(0.366)
• Non-solar patents	0.254	−0.061	0.739***	0.801**
	(0.182)	(0.215)	(0.217)	(0.349)
Firm count	0.210***	0.030	0.375***	0.411***
	(0.073)	(0.034)	(0.121)	(0.155)
Revenue	0.997***	0.076	1.761***	2.478***
	(0.351)	(0.200)	(0.506)	(0.690)
Panel capacity	2.072***	0.564	2.468***	2.901***
	(0.460)	(0.537)	(0.535)	(0.619)
Solar export value	3.166***	1.132	4.259***	6.024**
	(1.150)	(1.068)	(1.587)	(2.755)
Export value	2.485**	0.617	3.303**	4.390*
	(0.973)	(1.142)	(1.325)	(2.258)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region. Here we control for log GDP per capita, and this data is available for 284 cities (update: available for 314 cities now). 43 regions are treated by any subsidy. Time: 2004-2020. Each coefficient is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The revenue numbers are adjusted to account for multi-product firms following the approach described in Section B.7.

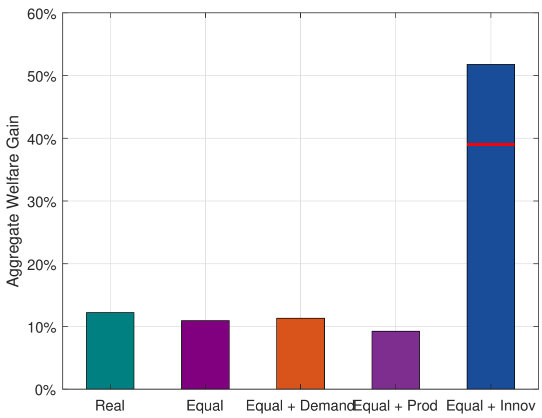
Table E.28: **Calculating unit weights with multiple outcome variables**

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.319	0.180	0.556**	0.655*
	(0.206)	(0.259)	(0.236)	(0.358)
Firm count	0.187**	−0.009	0.359***	0.379**
	(0.092)	(0.045)	(0.126)	(0.169)
Revenue	0.897**	−0.011	1.664***	2.215***
	(0.386)	(0.266)	(0.473)	(0.691)
Solar export value	2.130**	−0.138	3.406***	4.580*
	(0.964)	(0.884)	(1.285)	(2.465)
Panel capacity	1.622***	0.089	2.067***	2.416***
	(0.578)	(0.260)	(0.571)	(0.720)

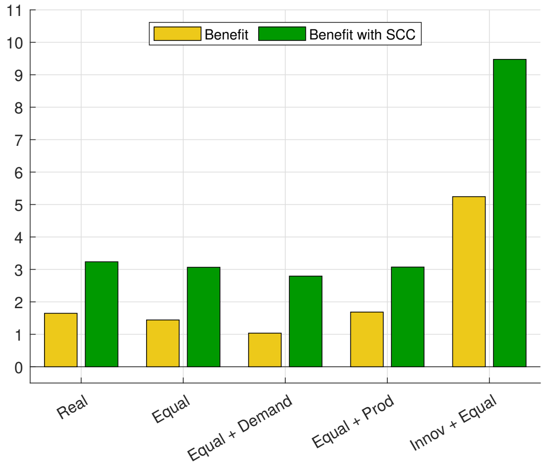
Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin 2 level region. 43 regions are treated by any subsidy. Time: 2004-2020. Each coefficient is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. Unit weights are constructed using multiple outcomes. The revenue numbers are adjusted to account for multi-product firms following the approach described in Section B.7. For results focusing on panel capacity, unadjusted revenue is used for constructing unit weights.

Figure E.1: **Welfare Gains and Cost-Benefit analysis under different policy designs**

(a) Consumer Welfare gain from Electricity consumption

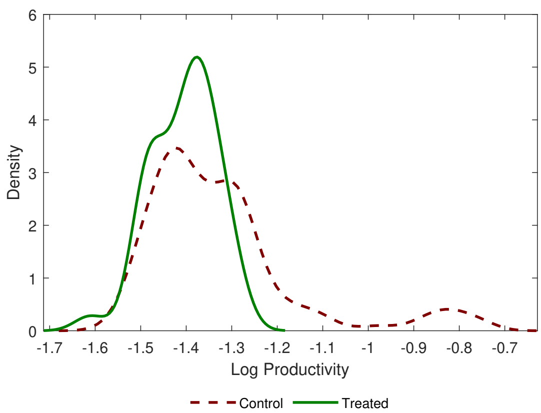


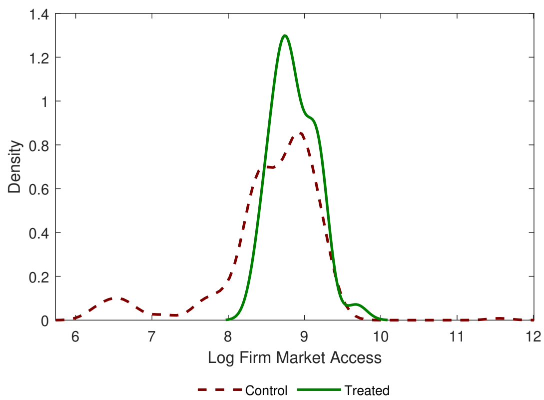
(b) Cost Benefit Analysis



Note: Welfare (W) calculated as in equation (9). First, second and last bars are the same as Figure 12 - see notes there. Each bar is the additional welfare gain relative to the no-subsidy baseline. The left hand panel is without social cost of carbon and right hand panel includes it. The first (teal) bar corresponds to the "Real Subsidy" policy roll-out. This corresponds to a fiscal spend, that we keep constant when considering all other scenarios. "Equal" (pink) has a uniform set of demand, production and innovation policies in all cities. "Innovation + Equal" (blue) gives sufficient innovation subsidy so that all Chinese firms innovate and then divides the remaining budget equally between production and demand subsidies. The new bars are (i) "Demand + Equal" which gives all areas only demand policies and (ii) "Production + Equal" gives all areas only production policies.

Figure E.2: **Characteristics of cities with solar subsidies**





Note: These figures show the distribution of two characteristics of citites which have at any point introduced local solar subsidies ("treated" vs. those that did not "control"). The left hand side panel shows the distribution of estimated city-specific solar productivity. Productivity ($b_{o,s}$) is estimated by model inversion as described in section 5.2.2. The right hand side panel shows the distribution of firm market access defined as in Anderson & Van Wincoop (2003).

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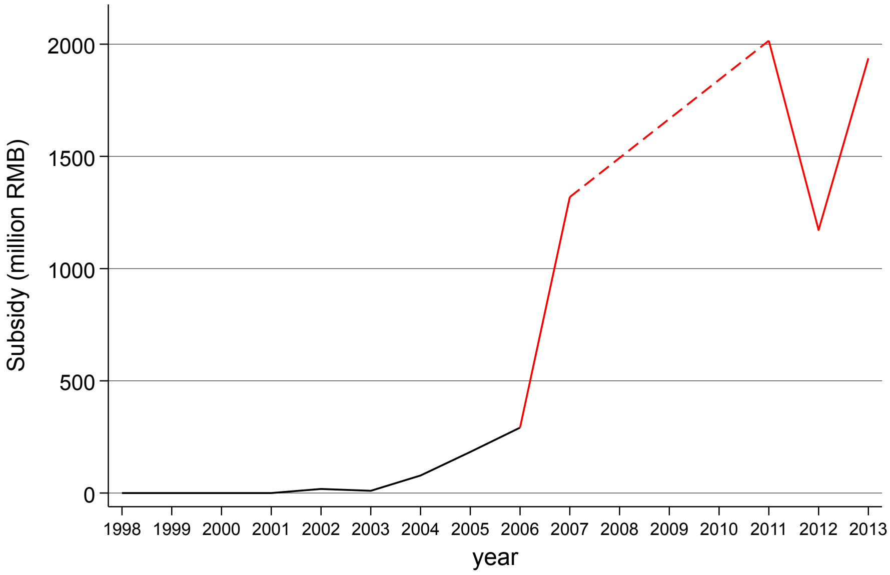
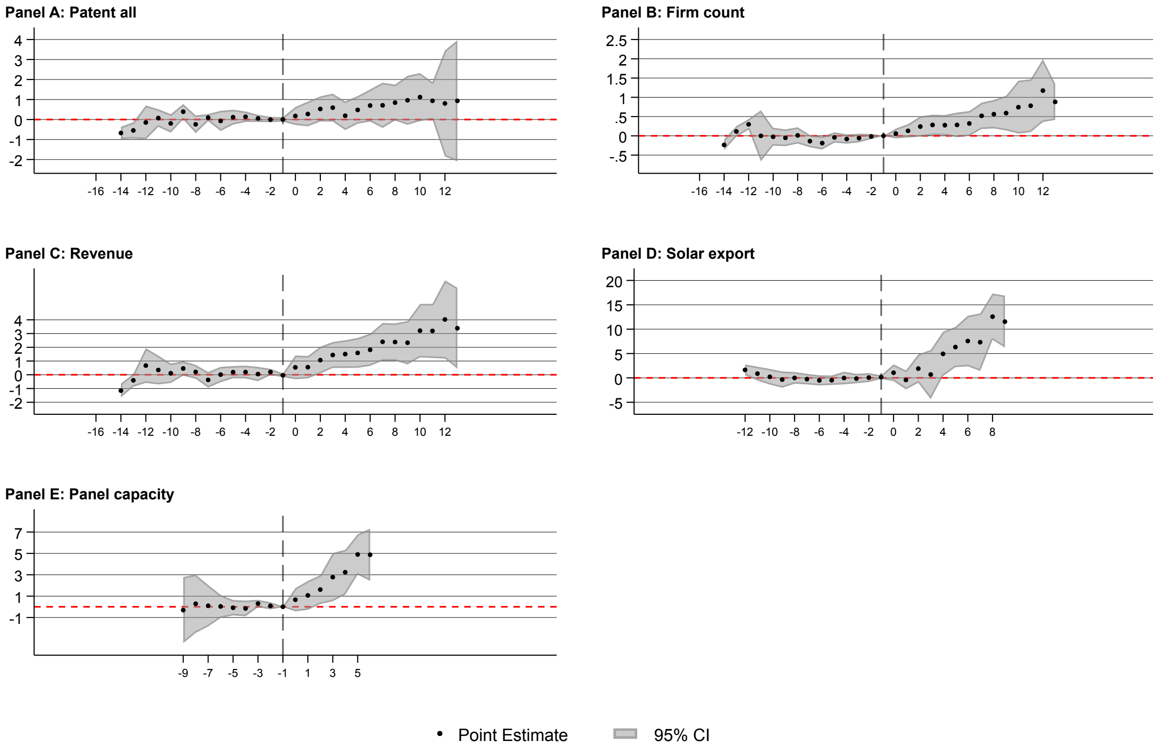
Figure E.3: **Total subsidy value allocated to solar firms (1998-2013)**



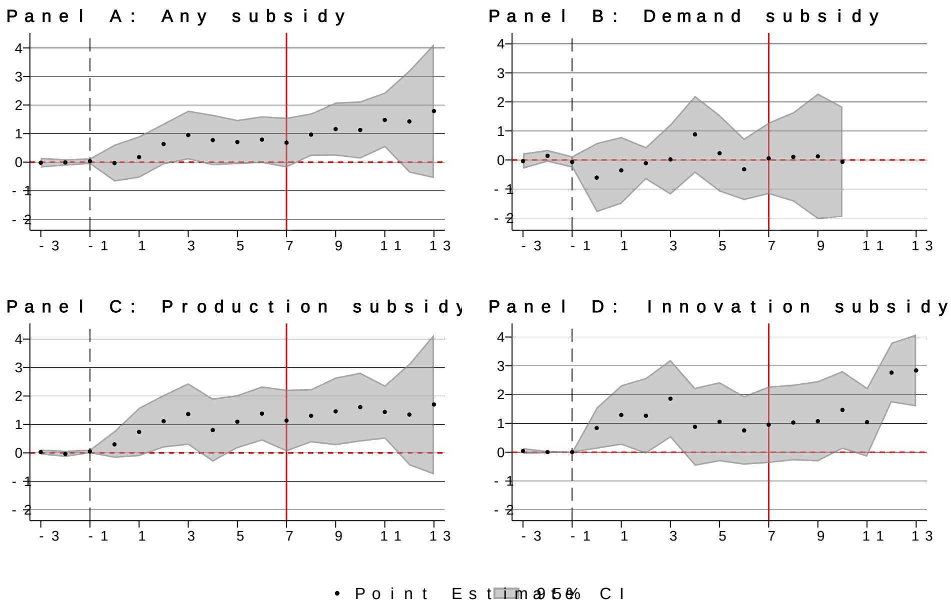
Note: The figure shows the yearly sum of subsidies allocated to solar firms as reported in the ASIE data set. Values before 2007 are in black, values after 2007 are in red. Between 2008 and 2010, no subsidy data is available from ASIE. To mark this, yearly totals for 2007 and 2011 are connected with a dashed line.

Figure E.4: **Calculating unit weights with multiple outcome variables - Production subsidy (Dynamic event studies)**



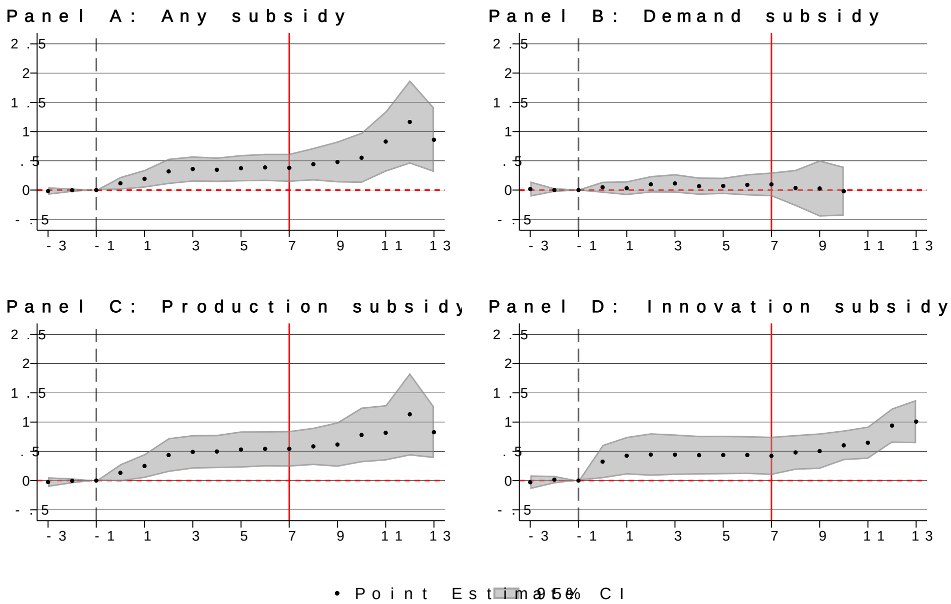
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Unit weights are constructed using multiple outcome variables. The outcome variable in all panels is IHS-transformed. The treatment variable is production subsidy in all panels. The outcome variable varies by panel: panel A focuses on all patents, panel B focuses on firm count, panel C focuses on revenue, panel D focuses on solar exports, panel E focuses on panel capacity. Panel E uses unadjusted revenue for constructing unit weights. 95% confidence intervals are plotted around point estimates.

Figure E.5: **All Patents by Solar Firms - Cohorts between 2007 and 2013**



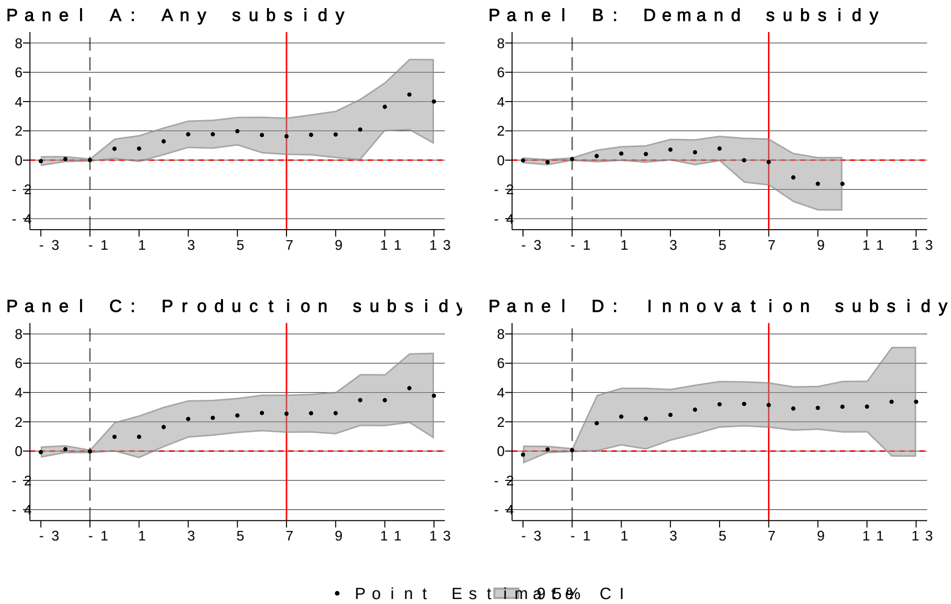
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total number of patents by solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Figure E.6: **Firm Count - Cohorts between 2007 and 2013**



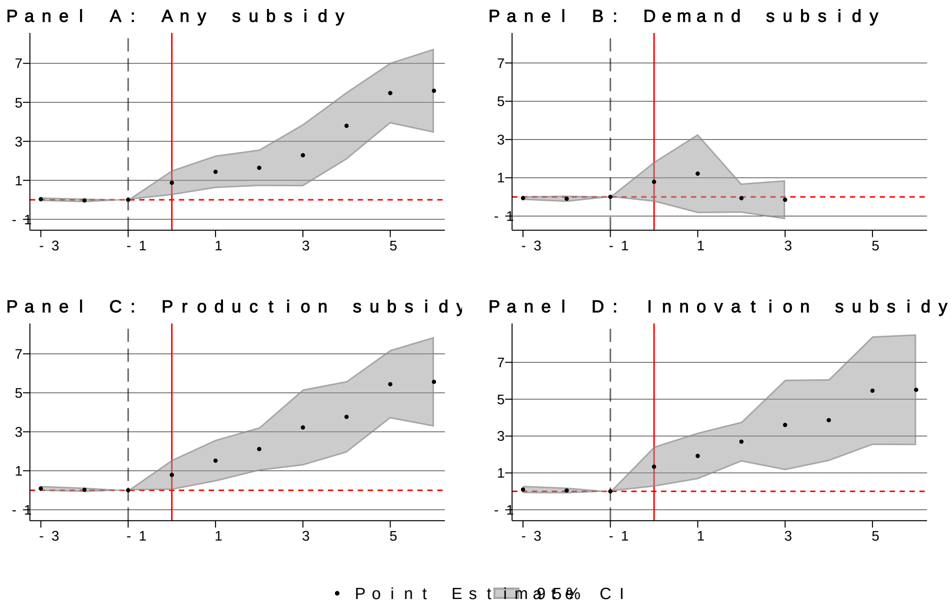
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total number of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Figure E.7: **Revenue - Cohorts between 2007 and 2013**



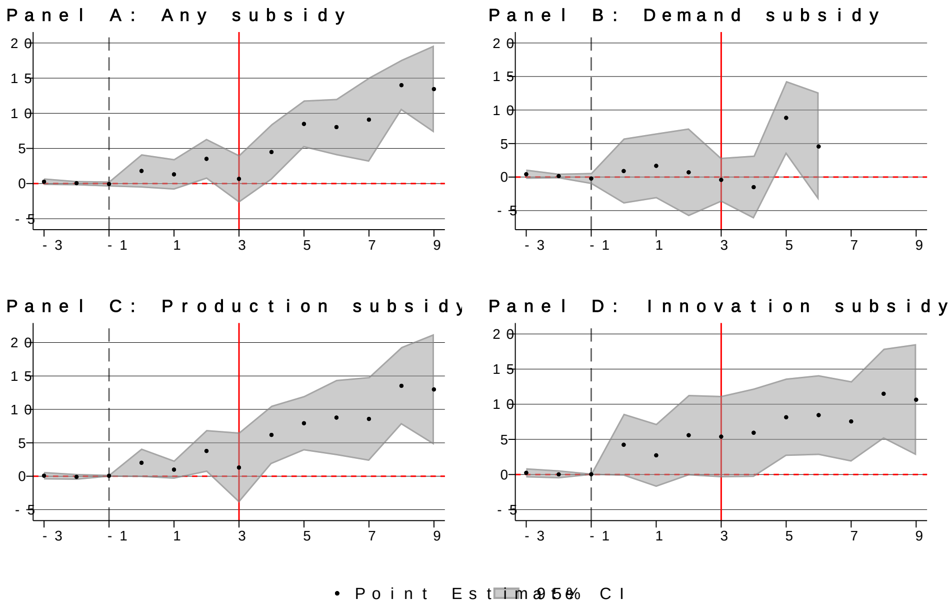
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total revenue of solar firms (with IHS transformation and adjustment leveraging export data). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Figure E.8: **Panel Production Capacity - Cohorts between 2007 and 2013**



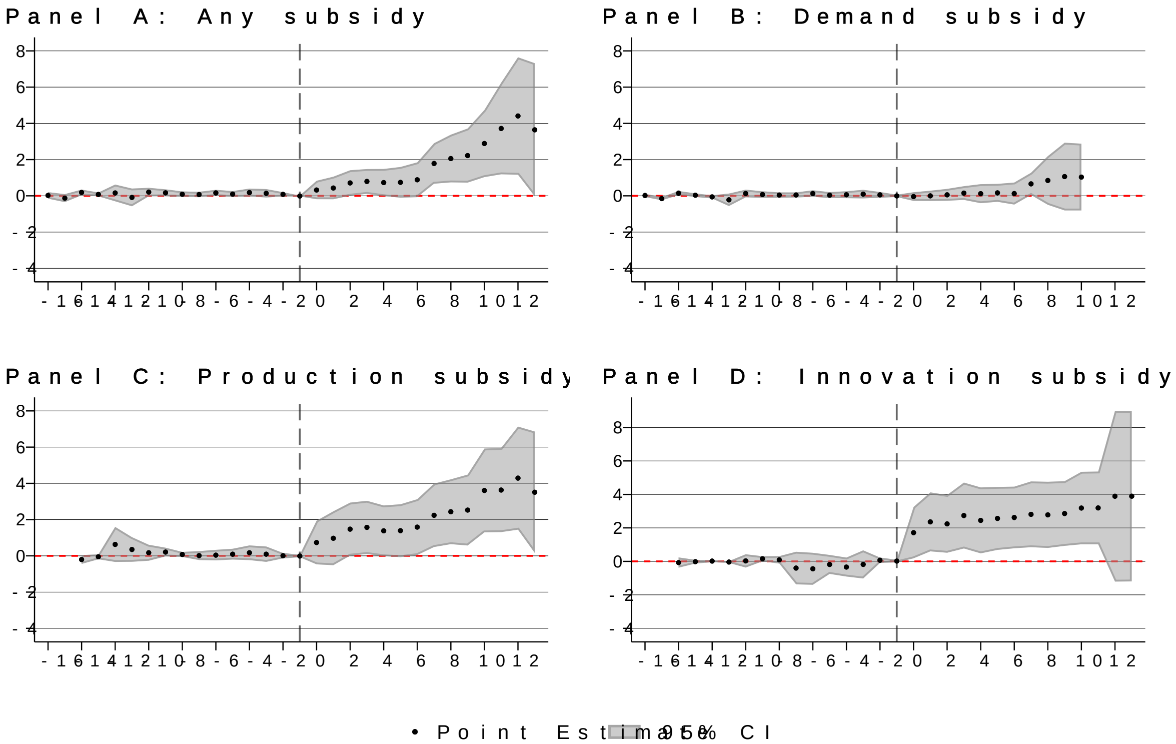
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total panel capacity MWh of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Figure E.9: **Solar Export Value - Cohorts between 2007 and 2013**



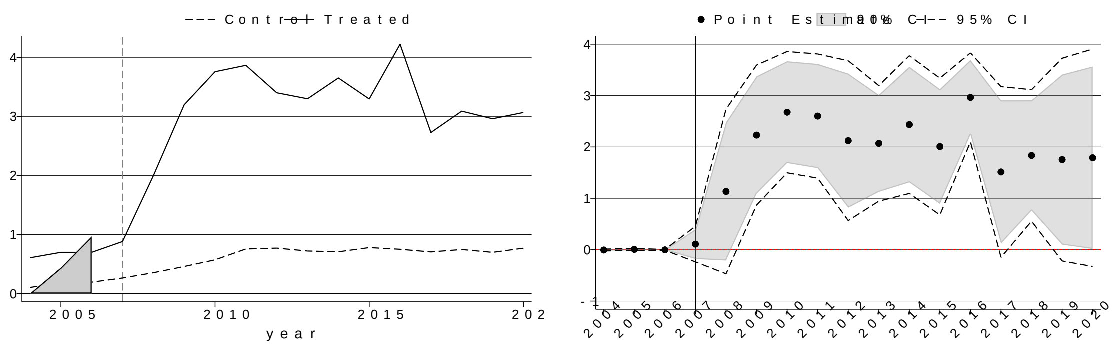
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total solar export value of solar firms (with IHS transformation, million dollars). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates

Figure E.10: **Event Studies using unadjusted Revenue (i.e. no correction for multi-product firms)**



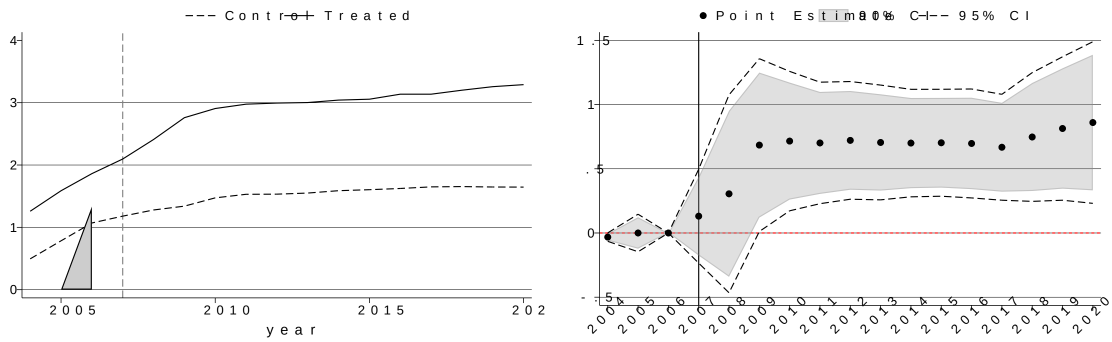
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 3.1. The outcome variable in all panels is the total reported revenue of solar firms (with IHS transformation). The treatment variable varies by panel: panel A uses any subsidy, panel B demand subsidy, panel C production subsidy and panel D uses innovation subsidy. 95% confidence intervals are plotted around point estimates.

Figure E.11: **Number of patents by solar firms - Any subsidy (2007 example)**



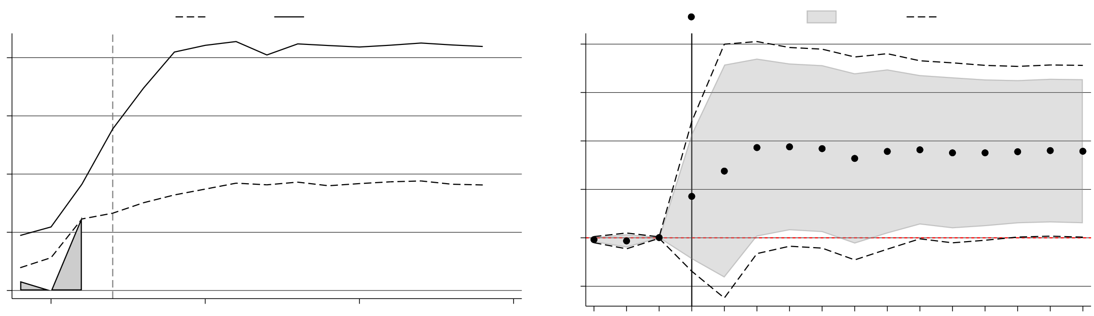
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is firm patents (with IHS transformation). These are estimates for the cohort of cities treated in 2007. There are 358 cities and 3 are treated in 2007.

Figure E.12: **Number of solar firms - Any subsidy (2007 example)**



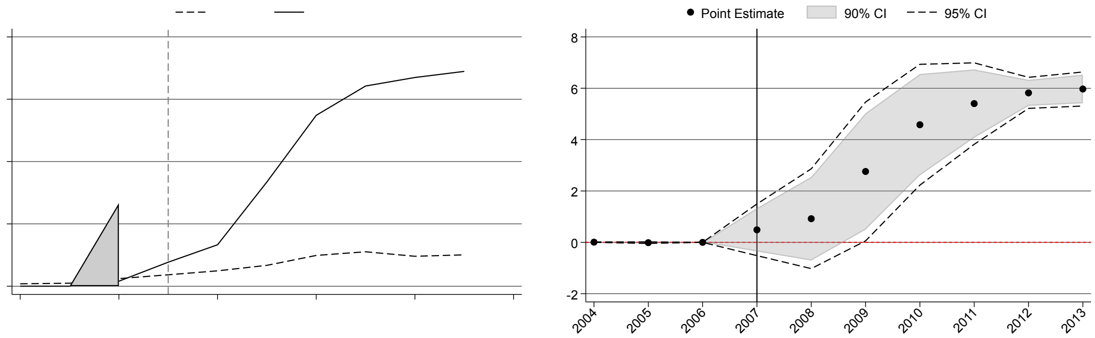
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is number of solar firms (with IHS transformation). These are estimates for the cohort of cities treated in 2007. There are 358 cities and 3 are treated in 2007.

Figure E.13: **Revenue by solar firms - Any subsidy (2007 example)**



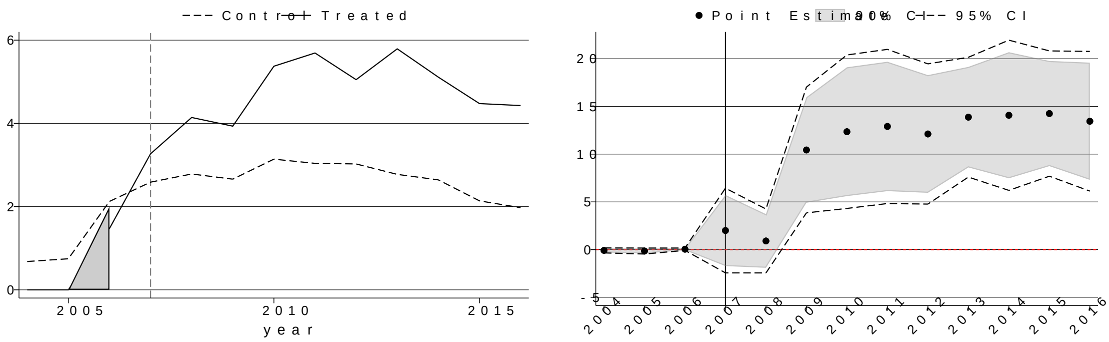
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total revenue of solar firms (with IHS transformation). These are estimates for the cohort of cities treated in 2007. There are 358 cities and 3 are treated in 2007.

Figure E.14: **Total panel capacity by solar firms - Any subsidy (2007 example)**



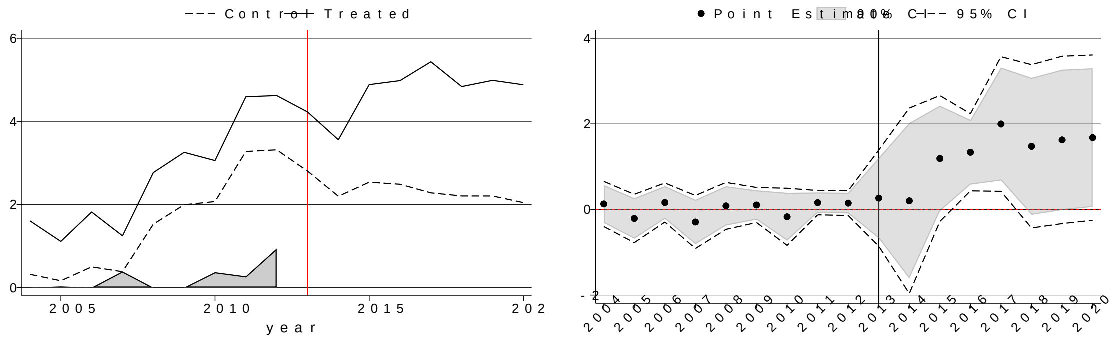
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total panel capacity of solar firms (with IHS transformation). These are estimates for the cohort of cities treated in 2007. There are 358 cities and 3 are treated in 2007.

Figure E.15: **Solar exports by solar firms - Any subsidy (2007 example)**



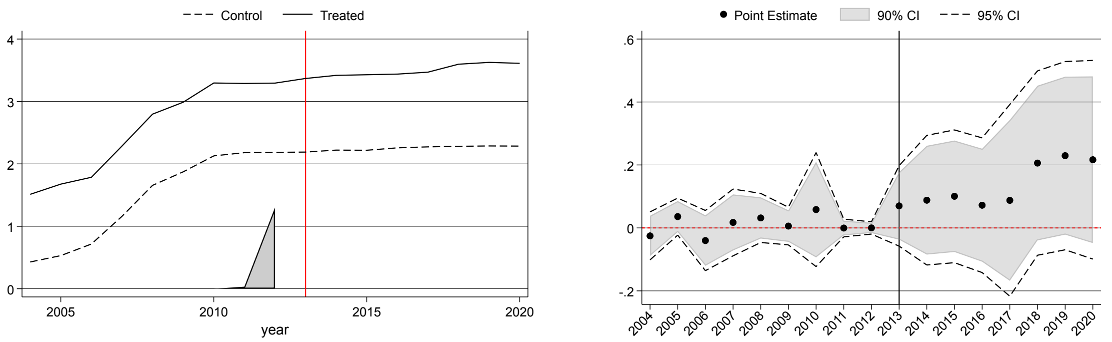
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total solar exports of solar firms (with IHS transformation). These are estimates for the cohort of cities treated in 2007. There are 358 cities and 3 are treated in 2007.

Figure E.16: **Number of patents by solar firms - Any subsidy (2013 example)**



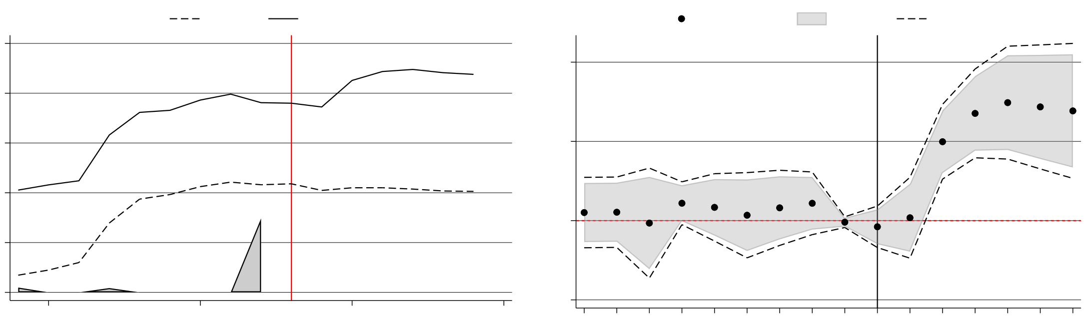
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is firm patents (with IHS transformation). These are estimates for the cohort of cities treated in 2013. There are 358 cities and 3 are treated in 2013.

Figure E.17: **Number of solar firms - Any subsidy (2013 example)**



Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is firm patents (with IHS transformation). These are estimates for the cohort of cities treated in 2013. There are 358 cities and 3 are treated in 2013.

Figure E.18: **Revenue by solar firms - Any subsidy (2013 example)**



Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total revenue of solar firms (with IHS transformation). These are estimates for the cohort of cities treated in 2013. There are 358 cities and 3 are treated in 2013.