Chinese Innovation, Green Industrial Policy and the Rise of Solar Energy

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Abstract

The rapid decline in global cost of solar panels from the early 2000s coincided with China's growing dominance in solar photovoltaics (PV) and its adoption of green industrial policies. We evaluate the effectiveness of local, city-level policies to encourage growth and innovation in the Chinese solar industry. Using new data on solar subsidy policies, patenting, production and trade and a synthetic-difference-in-differences approach, we show that production subsidies caused large increases in solar PV output, innovation and the productivity. Cities combining production subsidies with R&D support had an even larger impact. We can reject negative spillovers to other cities, finding that business stealing effects are outweighed by knowledge spillovers. Although demand subsidies targeted at solar generation reduced pollution, they had little impact on local solar output and innovation, as additional demand was largely obtained from other Chinese cities. We interpret these results through the lens of a quantified general equilibrium model with heterogeneous manufacturers, intra-national and international trade costs and endogenous choices of R&D, entry/exit and trade. Our results suggest substantial benefits to China from its solar policy, even abstracting from the climate change externality. We draw implications for green industrial policies in other countries, suggesting such interventions can foster growth in clean energy.

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1 Introduction

Of all the changes required to halt climate change, none is more important than the energy transition. This is because energy (electricity, heat and transport) accounts for 73.2% of global greenhouse gas emissions.[1] Recent improvements in renewable energy technologies have made solar and wind cost-competitive with fossil fuel technologies in many parts of the world. Between 1990 and 2019, the average annual growth rate of solar energy supply exceeded that of any other energy source.[2] The rise of solar offers a "ray of hope" that we may be able to curb emissions without large-scale reductions in energy usage.

But what underpins the dramatic cost reductions in solar energy that are driving global diffusion? Understanding this is central to ensuring that the transition to clean energy continues and may also yield insights into how to encourage other clean sources of energy (such as wind, tidal and hydrogen).

It is striking that the fastest reductions in solar photovoltaic (PV) costs since the mid-1970s have occurred in the last decade and a half, coinciding with the take-off of the solar industry in China (Figure 1). We observe that between 2004 and 2013, Chinese solar firms increased their annual production by 76% per year, and by 2016, China's dominance of global solar manufacturing had become all-encompassing. The country produced 52% of polysilicon, 81% of silicon wafer, 59% of silicon cell, and had 70% of crystalline module capacity worldwide (Ball et al., 2017).

Chinese firms were not just becoming dominant in production. They were also innovating extensively in solar technologies and processes. For example, there has been a 23% increase per year in patenting by solar firms between 2004 and 2019. This impressive performance also emerges when citation weighting for quality, looking at productivity and success in frontier solar technology competitions.

These marked increase in solar innovation and production were accompanied by the implementation of a series of major pro-solar policies by local governments in China, including production, innovation, and installation/demand subsidies. In this paper, we assess empirically the contribution of such place-based industrial policies to the development of the solar

[1]Climate Watch, The World Resources Institute (2020)

[2]IEA (2021), Renewables Information: Overview. Solar PV grew at an average of 36% annually, followed by Wind (22.6%), Biogases (11.31%), Solar Thermal (10.52%), and Liquid biofuels (9.58%). The rest of renewables (Municipal waste, Geothermal, Hydro, Tide, wave & ocean, and Solid biofuels) grew at a rate lower than 5%.

industry in China. To do so, we exploit variation in the implementation of solar policies across city-regions. Subsidies to solar manufacturing and generation were managed and allocated by local governments. As a result, the timing, size, and targeting of policy support varied significantly depending on the city-region. To account for potential non-random implementation of policies, we use a synthetic difference-in-differences approach (Arkhangelsky et al., 2021).

We find that Chinese cities that introduced local solar policies enjoyed positive and long-lasting benefits (up to at least 13 years after initial treatment). Notably, we estimate that the number of patents filed by solar manufacturers in treated cities increases by over 50% per year in the long run. We find similarly sizeable impacts on the number of solar manufacturers in treated cities, their total revenue, and total solar panel production. The magnitudes are small and insignificant for demand subsidies, but large for production subsidies, especially when combined with innovation subsidies.

To perform this analysis, we construct a novel longitudinal database covering city-level solar policies and city-level solar industry innovation, production and exporting outcomes. To measure policy support, we use a comprehensive data set of China's legal information (the PKULaw database), which includes all laws, regulations, and any related legal information implemented by the central and local governments since 1949. We build on recent attempts to use this or similar data sets to generate micro-level quantitative measures of industrial policy in China (e.g. J. Chen & Xie 2019, Wang & Yang 2021) by using text analysis to identify all regulations that pertain to solar photovoltaics and classify these by type (e.g., subsidies) and target (installation, production, innovation).

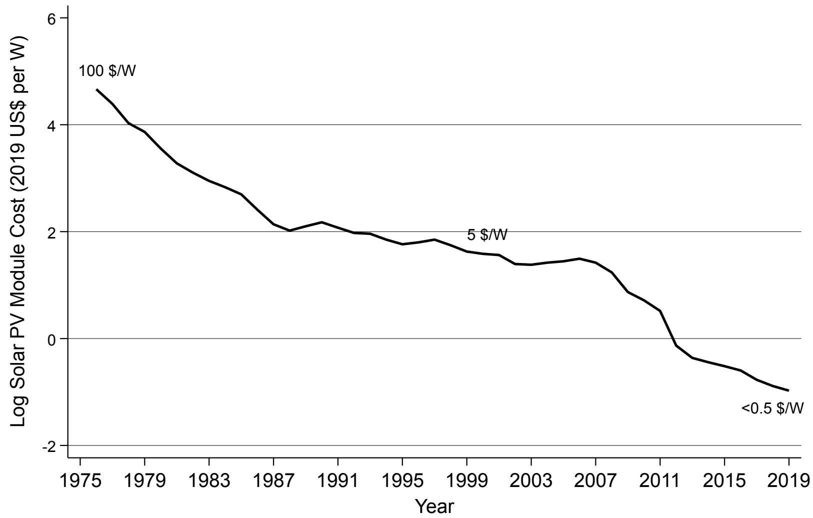
To estimate the effectiveness of local solar subsidies, we gather a variety of city-level solar industry outcome data from a wide range of sources. We identify solar manufacturers in China using an industry directory (ENF) which covers the near-universe of solar-related companies worldwide from 2004-2021 and contains detailed company location information. From 2004-2013 we capture production and capacity information for solar manufacturers using market research reports undertaken by ENF, which include measures of solar module (and cell) production and capacity in Mega Watts per hour (MWh).

To complement the production data, we are able to obtain revenue (and other financial information such as capital assets, employees and cost of goods sold) of solar firms over the 2004-2020 period using company accounts data drawn from a variety of sources such as BVD Orbis, ASIE, and the National Firm Registry (a Census). To study innovation, we obtain patenting activity for our sample of solar manufacturers from the State Intellectual Property Office

(SIPO) and PATSTAT. We classify these patents in several ways (IPC codes, SIPO classification, and text analysis) to identify solar patents and their innovative nature. We then aggregate this firm-level information to the city level using the location of each firm's headquarters as recorded in the ENF database. Most firms in the ENF data set operate exclusively in one city.

The structure of the paper is as follows. Section 2 provides background information on the evolution of China's solar industrial policy and our approach towards measuring it. Section 3 details the rest of the data, Section 4 gives the basics of our model and Section 5 our empirical strategy. The main results are in Section 5, some extensions in Section 6, and Section 7 concludes. Online Appendices give more details of the Institutional Background (A), the Data (B), details of the Theory (the full model in C, Simulation Results in D and a simplified model in E) and Further Results (F).

Figure 1: Global average price of solar PV modules (in 2019 US$) per Watt



Source: LaFond et al. (2017) & IRENA Database

1.1 Related Literature

Our paper speaks to several literatures. Most directly, there is a long literature that attempts to theoretically explain the channels through which industrial policies could facilitate economic development (Murphy et al. 1989, Bartelme et al. in press, Buera et al. 2021, Buera et al. 2013, Itskhoki & Moll 2019, Harrison & Rodríguez-Clare 2010 and Rodrik 2004).

Although there are many case studies, there is a more recent econometric literature that attempts to overcome challenging measurement and endogeneity problems to establish the causal effect of industrial policies (Criscuolo et al., 2019; Aghion et al., 2015; Lane, in press; Kalouptsidi, 2018; Choi & Levchenko, 2021; J. Chen & Xie, 2019). For a review on the empirical evidence on industrial policy, see Lane (2020).

In this context, our primary contribution is to show that subsidies to production lead to increases in innovation as measured by patenting activity. Previous work has documented the link between production subsidies and sustained firm growth (Manelici & Pantea, 2021), or between technology adoption subsidies, technological upgrading, and long-term outcomes (Choi & Shim, 2023). Our main result showcases a link between production subsidies and sustained innovative activity. This is consistent with theories of learning by doing, whereby current production, enabled by policy support, affects future productivity and hence innovative activity. We show evidence of a mechanism through learning by doing through textual analysis of patent data, a machine learning algorithm trained on manual inspection of a large number patent documents.[3]

We are able to draw this link as a result of our novel approach to the measurement of industrial policy. Recent work by Juhász et al. (2022) has used text analysis to identify policies which likely constitute industrial policy. We extend this approach to detect specific subsidies and their targets (demand, production, innovation). As a result, we are able to study how different forms of industrial policy have varying effects on a range of industrial outcomes and, in doing so provide suggestive evidence of the underlying mechanisms that generate these effects.

Second, there is a growing literature on directed technical change (e.g. Acemoglu et al. 2012, 2016, 2019), with a particular emphasis on environmental innovation (e.g. Aghion et al. 2016; Way et al. 2022). Most of the literature has focused on the role of tax-adjusted energy prices (Popp, 2002, 2019; Newell et al., 1999), but there are a few papers looking at other policies (see the survey by Dechezlepretre & Hemous 2023) such as regulation and R&D subsidies (e.g. Howell 2017). We are one of the very few papers (alongside Arkolakis & Walsh 2023) to examine a range of direct subsidy policies in a particular green industry.

A third group of papers focuses on the policy reasons for the incredible growth rates of China since 1980, and especially 2000. Song et al. (2011) focus on finance; König et al. (2022) and Wei et al. (2023) focus on innovation policy; Barwick et al. (2021) look at industrial policy in Chinese shipbuilding and Wang & Yang (2021) look more generally at multiple policies.

[3]We also detail a model where subsidies can stimulate innovation through enabling firms to cover the fixed cost of innovation.

These papers focus on national policies, Bai et al. (2020) like us focus on local policies, they emphasise the 'special deals' that local bureaucrats make with their local leading firms.[4]

Finally, there is a literature on the solar industry itself. Nemet (2019) has an excellent discursive history of the global industry and the role of policy. Econometric papers include Gillingham & Bollinger (2021); Bollinger & Gillingham (2019); Gonzales et al. (2022); Gillingham & Tsvetanov (2019) and De Groote & Verboven (2019). The focus of these papers is more on household incentives and none are specifically on China.

2 Institutional Background: China's Industrial Policy Towards Solar PV

We now give a brief history of the intervention of the Chinese state in the solar industry back to the early 2000s, borrowing extensively from the excellent account in Ball et al. (2017) (more details are in Appendix A). First, we describe the increasing prominence of solar in the Chinese government's Five-Year Plans, which outline national economic priorities and sectoral industrial policies. Second, we describe the decentralised policy-making which led to considerable local heterogeneity in policy support towards the solar industry. Finally, we discuss the challenges with measuring industrial policy and our novel measurement approach.

2.1 Solar PV in the Government's Five-Year Plans

The Chinese government outlines its vision for sectoral industrial policies in its Five-Year Plans. These plans reflect the priorities of the central government, and provide guidance for policy-makers at all levels of government. The solar industry has occupied an increasingly prominent position in the Five-Year Plans, beginning with the Tenth Five-Year Plan (2001-2005), where it received only a brief mention[5]. By contrast, the Eleventh Five-Year Plan (2006-2010) featured an increased emphasis on R&D and mentioned funding for solar manufacturing and innovation for the first time. This was further built on in the Twelfth (2011-2015) and Thirteenth (2016-2020) Five-Year Plans – the later of which was accompanied by a specific Solar Energy Development Plan issued by China's National Energy Administration.

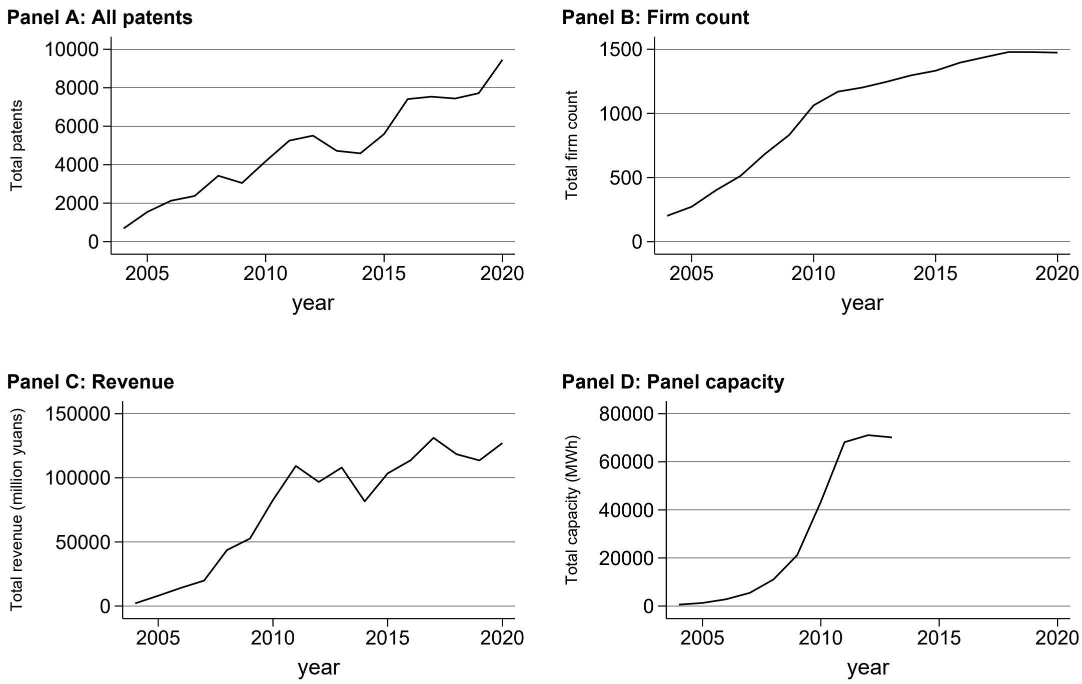
Figure 2 traces the evolution of the Chinese solar industry over this time period, using our

[4] This relates to place-based policies more generally - see, for example, Gruber & Johnson (2019); Greenstone et al. (2010); Kline & Moretti (2014).

[5] "Actively developing new and renewable energy sources such as wind power, solar power, and geothermal energy. Promoting energy conservation and comprehensive utilization technologies."

data on the universe of solar manufacturers in China (see Section 3). Panel A shows that solar patents went through a revolution, rising from a few hundred in 2004 to over 10,000 in 2020. Panel D shows that there was near zero panel production capacity in 2004, but this rose to about 70,000 MWh by 2013. Similarly, Panel C shows that revenues of solar firms rose from close to zero to over 100 billion Yuan by 2019 spread across over 1,500 firms (Panel B).[6]

Figure 2: 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 and panel capacity, obtained from ENF Market Research reports. The sample is our near-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 mechanism described in Section B.8

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[6]It might seem surprising that the number and revenues of solar firms can be non-zero in 2004 when production capacity is zero. This is mainly because some solar firms are multi-product (there are also some firms who produce non-solar PV such as cells, but this is a small number). Hence, they may earn revenues on non-Solar products and services. We address this issue by utilizing additional firm-level data on exports to adjust revenue numbers of multi-product firms. The results are essentially unchanged compared to using the raw revenue figures. See Appendix B.8 for a discussion of the adjustment mechanism. We further validate the approach by utilizing a separate adjustment in which we set to zero firm counts and revenues if solar production capacity was zero. The results were essentially unaltered. Since we can only do this exercise pre-2014 due to the ENF data constraint, we prefer to use a consistent approach in our baseline and not impose this additional restriction.

2.2 Policy Support toward Solar Manufacturing

Whilst the Five-Year Plans provide national policy guidance, the power to implement industrial policy is dispersed across different levels of government in China, resulting in considerable uncertainty about the extent and nature of policy support for the industry.

Qualitative research by Ball et al. (2017) based on interviews with government officials, business leaders, managers and academics, provides some clarity. Their work suggests that subsidies to solar manufacturing were managed and allocated by local governments, following the national guidance embedded in the Five-Year Plans. Since at least 2006, many city bureaucrats have competed to build up solar manufacturing, offering tax incentives, discounts for land acquisitions, and cash investments. Bai et al. (2020) give a rich description of the local policy landscape in China. City bureaucrats have strong administrative competence and compete aggressively on offering special deals to private firms.

Ball et al. (2017) estimate a lower bound of around $300 million spending in solar R&D subsidies by national and local governments between 2001 and 2015, compared to $1.44 billion of private R&D solar spending. They also find evidence of considerable regional heterogeneity in solar R&D funding.

2.3 Measuring Solar Industrial Policy

This still leaves open the question of how we can identify and measure the dispersed implementation of industrial policies - particularly when there may be no one organisation who has oversight of the full range of implemented policies. Given these, and other challenges, some researchers have relied on model-based approaches to detect industrial policy subsidies (Kalouptsidi, 2018).

In this paper, we follow an approach based on text analysis of policy documents, similar to that of Juhász et al. (2022)[7]. We extract data on industrial policy towards solar manufacturing, innovation, and installation from PKULaw's Laws & Regulations dataset (https://www.pkulaw.com/law/). The Laws & Regulations database 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 pertaining to solar photovoltaics. The first sub-national solar policy we

[7]We manually inspect and classify all solar policies, while Juhász et al. (2022) use an automated classification algorithm

identified was in 2006.

The dataset contains information on the title, validity, administrative level, department, release date, and implementation date of each policy. We additionally scrape the original policy documents, which contain the text of each regulation or announcement. We manually inspect the full text of each policy and classify them into types. We focus on subsidy policies where there is direct financial support. We further disaggregate subsidy policies according to whether they target demand (solar installation), production and/or innovation.

Table 1 illustrates the criteria we follow to classify policy documents and provides examples of key text extracts that guided the classification. The table shows that there have been 78 subsidy policies in total (sometimes a policy is a bundle of demand and supply subsidy policies which is why the sum of the disaggregated policy numbers exceeds 78). City-level demand subsidies are the most common - there have been 61 of these between 2006 and 2021. There are 27 production subsidy policies, 12 of which also contain innovation subsidies. We did not find any cities that introduced solar innovation policies without production subsidies. So when we compare across policies we are implicitly comparing standalone demand or production policies to a bundle of a production and innovation policy. We return to this when interpreting the empirical results.

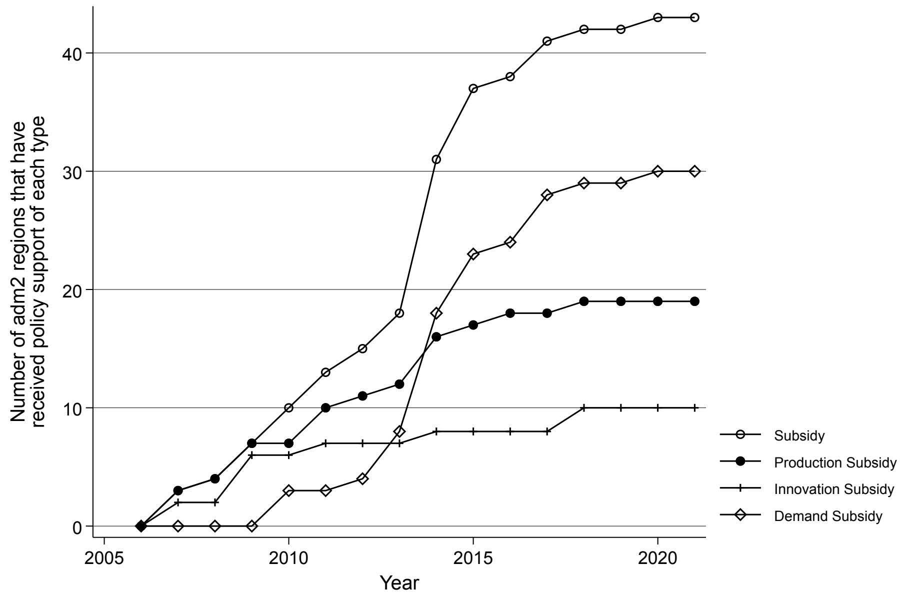
Table 1: City-level solar policies

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 (admin2 region) level over the 2006-2022 period. There are 358 cities. 43 cities are treated by some subsidy by the end of our sample.

Figure 3 presents the time series of city subsidy policies. As we are unable to accurately measure the end date of policies, this captures the cumulative number of cities which have at some point implemented a solar industrial policy. The total policy line (hollow circles) shows that there was a steady increase in the number of cities using solar policies since 2006. In 2010 only 10 cities had solar policies, but this had reached 18 by 2013. There was then almost a doubling to 32 in 2014, driven by an increase in demand policies (hollow diamonds). The number of cities with policies levels off after 2017, finishing at 43 (out of 358 cities across China) by 2022.

Figure 3: Number of cities treated with Solar supply & demand subsidy policies



Note: All policies are at the admin2 region level. There are in total 358 admin2 regions in China (we remove Taiwan, Hongkong and Macao from the analysis). The time series for 'Subsidy' includes any of demand, production, or innovation subsidies.

Interestingly, the solid dots show that early policies were production subsidies (usually bundled with innovation policies) - the first demand policy only began in 2010. By the end of our sample period 19 cities had production subsidies and 10 also had innovation subsidies. By contrast, a full 30 cities had demand subsidies.

Note that in our PKULaw dataset we cannot accurately identify the end date of policies. Therefore, we exploit the staggered timing of the date of first adoption of any policy in the city. Despite this caveat, almost all cities report that their policies were still in place at the end of our sample period. Moreover, cities often implement multiple policies, so it is unlikely a city completely abandons policy support towards solar. Hence, our treatment of policy support as an absorbing state.[8]

Our approach complements recent attempts to provide micro-level quantitative measures of industrial policy in China. J. Chen & Xie (2019) use the Chinese Law and Regulation Database, which is a subset of our PKULaw dataset, to provide a micro-level measure of the number of industrial policies at the Chinese prefectural-city level. We extend these recent approaches by using the universe of laws and regulations targeting the solar industry and by analyzing policy documents to identify targeting (production, innovation, or installation) as well as spatial heterogeneity. In addition, our manual text classification allows us to carefully distinguish financial support in the form of subsidies from solar industry announcements, records, or other type of policies that do not include explicit support to manufacturers. [9]

3 Data

This section provides an overview of our data set on the Chinese solar industry. More details are in Appendix B.

We gather a variety of firm-level outcome data that we aggregate at the city-level and combine with our policy support indicators. First, we construct a sample of solar manufacturers over time using the historical directories of solar panel producers from ENF Solar Industry Directory, available from 2010 until 2021 (henceforth, *ENF register*). The ENF Solar Industry Directory is a register of 50,800 worldwide photovoltaic companies. Because it is the leading solar website, most companies self-register on ENF's platform. ENF additionally reviews daily news regarding the solar industry, as well as available lists of key solar exhibitions, to incorporate the remaining new solar companies. It also relies on government organisations and a variety of web-searching techniques to complete the full list of firms. To detect firm exit, ENF uses automatic scanning of company updates, which triggers careful checks from ENF database experts to update manufacturers' information, or to report firms as ceasing their activities. Hence, ENF is able to reasonably capture a snapshot of all solar panel manufacturers each year.

We obtain our first measure of panel and cell production from the last edition of ENF's Chinese Cell & Panel Manufacturers Report. This dataset (henceforth, *ENF production*) allows

[8]Ideally, we would look at the persistence of effects after the policy was removed to test for permanent effects as in Kline & Moretti (2014).

[9]We analyzed these type of 'exhortation' policies, but generally found them to have no effects on our outcome variables.

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. We match *ENF production* and *ENF register* for their overlapping period based on firm name and extensive contact details information (address, phone, website, fax, and email). Together, we are left with a sample of 1,718 Chinese solar panel manufacturers, operating at some point between 2004 and 2021, which includes production and capacity data for each manufacturer during the 2004-2013 period. Both ENF datasets contain detailed address information, which allows us to geo-locate all firms through the Google and Baidu APIs, and assign them their corresponding city.

In order to expand the time horizon of our analysis and estimate long-run effects on production beyond 2013, we use Bureau Van Dijk's Orbis dataset, which gives us rich financial data, including total assets, revenue, employees, and cost of goods sold, 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 aggregate all production, capacity, and revenue figures from ENF cell and panel manufacturers at the city-level.

We validate the entry and exit information on ENF register using the Chinese firm registration information, which we access through the Qichacha platform (https://www.qcc.com/). The Qichacha platform gathers detailed firm-level information, spanning from registration to exit, and is updated periodically following government requirements. It 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. This allows us to obtain the number of operating solar manufacturers in each city and year.

The Qichacha platform also contains detailed intellectual property information from the former State Intellectual Property Office (SIPO). We extract, 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. We aggregate the patents filed by our sample of ENF manufacturers to the city-level.

To understand the nature of the underlying innovation, we classify the patents filed by our sample of manufacturers into several categories. First, we rely on the SIPO classification of patents into Invention, Utility Model and Design patents[10]. Invention patents have longer protection periods, require paying higher filing costs, and involve a more cumbersome administrative process. They are therefore generally of higher quality and a more innovative nature.[11] Second, using IPC codes, we further classify invention and utility model patents into solar and non-solar patents.[12] Third, since it is well known that the threshold for obtaining a patent in China is lower than in the US and Europe, we weight patents by their future citations as a measure of quality. We also examine the impact of policies on productivity as an alternative measure to patents. Note that having a lower threshold for a patent in China enables us to obtain a much larger sample of activity (we have over 10,000 new patents in 2020 alone) than we would be able to examine in the US or Europe. This captures many of the more incremental valued learning by doing patents which would be missed in more developed nations - an advantage of our setting.

The maps in Figure 4 illustrate the spatial variation in solar patents and subsidies across Chinese cities, which we exploit in our empirical analysis. 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. 82 of the 358 city-regions in China had some patenting by solar firms in 2019, compared to only 25 in 2004.

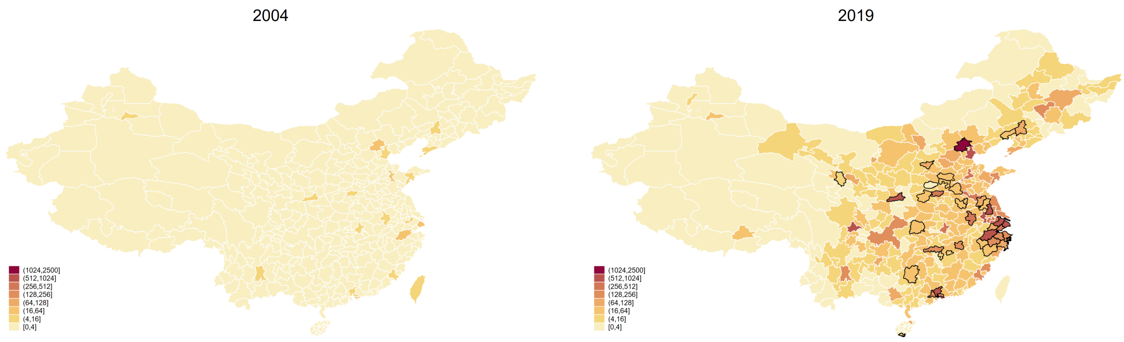
Finally, in order to explore if policy support encouraged learning by doing, we also use text mining techniques to classify invention and utility model patents based on the text in patent abstracts. We classify patents into learning-by-doing patents (those that include a productivity-increasing process innovation) and non-learning-by-doing patents (which often reflect either the invention of new products or basic science research around the chemistry and material

[10]An invention patent refers to a new technical solution or improvement for a product or method. Unlike utility model patents, which are restricted to products, invention patents can apply to both products and methods. The protection period for invention patents is the longest in the domestic patent classification, up to 20 years. A utility model patent involves a new technical and practical solution regarding the shape, structure or combination of a product or products. The protection period for utility model patents is of 10 years. Design Patents cover product improvements of an aesthetic nature, which are suitable for industrial application. Broadly, all original designs around a product's appearance could apply for a design patent. The protection period of design patents is of 15 years.

[11]The firms in our solar manufacturers dataset file mostly invention and utility model patents. Only 10% are design patents.

[12]We follow the categorisation into solar developed in Shubbak (2019).

Figure 4: Number of solar patents in each city and subsidy policy

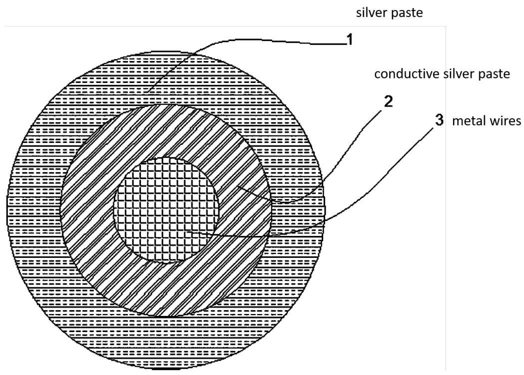


Note: Each white-bordered region represents an admn2 level city region. Black circled cities are treated by any subsidy policy. We use a heat map scale, where cities colored in a stronger red are filing more solar patents

science that informs the production of wafers and cells). To do so, we build on the work of Liu (2023), who classified a sample of Chinese solar patents into process and product related innovations by hand-reading the full patent text. Leveraging his work as a training dataset, we classify the remaining patents in our much larger sample using machine-learning techniques.

Figure 5 shows an example of a learning-by-doing patent. The patent abstract alludes to reducing production costs, minimizing production errors, and being suitable for mass production compared to prior art. In the data Appendix B, we provide additional learning-by-doing and non-learning-by-doing patent examples and their abstracts.

Figure 5: Learning by doing patent example



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*"

4 Model

To provide an intuition for the impact of place-based industrial policies on the evolution of the solar industry, we develop a model of electricity demand, production of power-plant components (such as solar panels), exporting, and innovation in China. The model builds on Bustos (2011) and Shapiro & Walker (2018). More details and derivations can be found in Appendices C and D.

The model features multiple city-regions which we index by d (for "destination") when referring to the region that is generating or consuming electricity and o when referring to the region that is producing the components of power plants. Each region d has a representative consumer who demands electricity services e^d. To satisfy this demand, a grid-planner in each region builds and runs power plants of different types s, combining their output to supply final electricity services. To simplify, we assume that there is no trade in electricity across regions.[13] To build power plants, the grid planner purchases (differentiated) sector-specific

[13]Future work will incorporate some of the limited cross-regional transmission links for electricity in China. This will enable origin producers outside of the subsidized destination region to respond to demand subsidies without shipping their panels across China. It will reinforce our results on the differences between demand and

power plant manufactured components (e.g. solar panels) from producers in all origin regions o. Manufacturers of power plant components such as solar PV producers have heterogeneous productivity and make decisions about entry, exit, production, and international exporting. They also have the opportunity to innovate or 'upgrade their technology' –increase their productivity for a fixed cost.

By using a heterogeneous firm framework, we are able to get predictions for the impact of subsidies on a range of industry outcomes, including firm numbers, output, and exports and innovation. By incorporating internal economic geography (a key feature that distinguishes our model from approaches such as Bustos 2011) we can generate separate predictions for the impact of subsidies targeting demand (installation of solar panels or use of solar panels to generate electricity) as opposed to the supply side (production or innovation). For example, increased use of solar due to demand subsidies in one city can be met by increased supply from other cities (subject to transport costs). Since there are no 'local content' requirements, this mutes the effect of demand subsidies on the growth of solar production in the same city.

We make several key simplifications in the model. First, electricity services are only used for final consumption, not as an input to production. Second, we abstract from the production, trade and consumption of goods and services other than electricity. Third, we take as exogenous the demand function for electricity in each city. We therefore abstract from the response of population or industrial production to changes in energy prices across space. Fourth, power plants are not durable. Fifth, we assume the electricity sector is a small fraction of the city's labor market so we can take city wages are exogenous. We make these simplification to focus on the problem of a solar panel producer, since this is the center of our empirical analysis and where we have the richest data.

4.1 The Grid Planner Problem

In each region d, there is a representative consumer that obtains utility from electricity services e. We abstract from consumption of other goods and services for simplicity, as our focus is on the production of varieties of power plant components.

$$U_d = u\left(e_d\right) \tag{1}$$

supply policies, being similar to a reduction in iceberg trade costs across city-pairs linked by the transmission grid.

This representative consumer provides L_d effective units of labour for the purpose of producing electricity. L_d reflects both the population of region d and the human capital of the local population. As noted we consider L_d to be, for now, exogenous to the model - implying that we abstract from the migratory response of labour to changes in electricity prices.

Electricity services in region d are the combined electrical output of many power plants of different energy sectors which are built and operated by a regional 'grid-planner'. Given that we focus on subsidies to the solar industry which do not apply to other electricity sectors, we assume these sectors to be solar s and non-solar s'. The electrical output of solar ($e_{d,s}$) and non-solar ($e_{d,s'}$) plants are combined using a CES technology (where the elasticity of substitution is denoted $\sigma = 1/(1-\rho)$):

$$e_d = \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho}\right)^{1/\rho} \tag{2}$$

This assumption captures in a reduced-form-way the differential timing and flexibility of generation from different electricity sources. For example, solar is not a perfect substitute for coal because it only provides electricity whilst the sun is up. Coal on the other hand, can produce electricity all day and therefore meet nighttime demand. $\kappa_{d,\text{sector}}$ allows for the overall productivity of different electricity sources to differ across regions, capturing differences in solar potential or mineral resources across regions. Note that the grid-planner can only use power plants located within their own region d and cannot trade electricity across regions.

To generate electricity in each sector $e_{d,s}$, the 'grid planner' in region d combines sector-specific intermediate manufactured inputs using a CES aggregator.

$$e_{d,s} = \left(\sum_o \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega\right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{3}$$

Here, $q_{od,s}(\omega)$ denotes the quantity of the variety ω of goods in sector s from region o used by the grid-planner in region d. Note that each variety ω is produced in a single region only and by a single firm. The elasticity of substitution across varieties is represented by the sector-specific parameter σ_s, whereas σ represents the elasticity of substitution across different energy sectors.

We conceive this CES aggregate of intermediate inputs as a 'power plant'. For example, in order to install a solar power system providing solar electricity services, the planner combines different varieties of solar cells or panels, a racking system, and the necessary associated power inverters, charge controllers, batteries, and wiring as needed. These intermediate inputs can be sourced from all regions of the country.

The grid-planner chooses the overall quantity of electricity services to produce, the mix of solar and non-solar electricity, and the mix of intermediate inputs for each energy sector in order to maximise their profits taking as given the price of final electricity in their region (p_d) and the price of all intermediate inputs. In practice, since utility depends only on electricity services (and is strictly increasing in e_d), and as production of final electricity services is constant returns to scale, we can equivalently solve this as a problem in which the grid-planner supplies as much electricity as possible in the minimal cost way given the income of the representative household I_d.

With this framing, the grid-planner problem can be solved in two stages. First, the grid-planner chooses the mix of intermediates (e.g. varieties of solar panel) in order to minimise the cost of generating a given level of electricity in sector s.

$$\min_{q_{o,d}(\omega)} \left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{od,s}(\omega) p_{od,s}(\omega) \right)$$

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

This yields the price (and the optimal intermediate inputs mix) of generating one unit of electricity using solar and non-solar electricity in region d: $P_{d,s}$ and $P_{d,s'}$.

Given these price indices, the grid-planner chooses a mix of solar and non-solar electricity generation to maximise electricity output.

$$\max_{e_{d,s}, e_{d,s'}} \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho} \right)^{1/\rho}$$

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

Solving this nested CES problem yields the following demand for each intermediate input variety:

$$q_{od,s}(\omega) = \left(\frac{p_{od,s}(\omega)}{P_{d,s}} \right)^{-\sigma_s} \left(\frac{\kappa_{d,s}}{P_{d,s}} \right)^{\sigma} \frac{I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}} \tag{4}$$

4.1.1 Demand-Side Industrial Policy

We model *demand* subsidies targeting sector s as a policy which subsidizes the final price $P_{d,s}$ the local grid planner pays - that is, a factor $\chi_{d,s}$ which multiplies $P_{d,s} e_{d,s}$ in the grid-planner problem where $\chi_{d,s} < 1$. This captures in a reduced form way policies such as feed-in tariffs which guarantee a higher per-unit electricity price for solar power plant operators when selling their electricity to the grid. Demand for each variety becomes:

$$q_{od,s}(\omega) = \left(\frac{p_{od,s}(\omega)}{P_{d,s}}\right)^{-\sigma_s} \left(\frac{\kappa_{d,s}}{\chi_{d,s} P_{d,s}}\right)^{\sigma} \frac{I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} \left(\chi_{d,s} P_{d,s}\right)^{1-\sigma}} \tag{5}$$

A solar demand subsidy in location d will lead to a shift in the composition of electricity production towards solar. This, in turn, will result in an increase in the demand for solar intermediate inputs in location d. Assuming that all prices are fixed (i.e. considering just the partial equilibrium response) this will lead to the same proportionate increase in region d demand for all solar intermediate varieties. Demand subsidies implemented in region d therefore influence demand for varieties produced in all regions of China, indirectly impacting firm decisions.

4.2 The Manufacturer Problem

Intermediate inputs for each sector are produced by firms in different regions of China. Each "origin" city-region o has a continuum of potential manufacturing firms i in each sector s, which operate under monopolistic competition.

4.2.1 Manufacturing Technology

Firm i, who produces intermediate goods for electricity sector s (e.g. solar panels for the solar electricity sector), uses effective units of labor $L_{o,s,i}$, with unit cost $w_{o,s}$. Firm subscripts i are dropped from now onward for notational simplicity. To operate, a firm must pay a sunk cost $w_o f_{o,s}^e$, which we express in terms of effective units of labour.[14] Upon paying the entry cost, the firm draws an initial level of productivity φ, from a Pareto productivity distribution, whose cumulative distribution function is:

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

Each firm in operation produces a differentiated variety of sector-specific intermediate good. We therefore equivalently index firms by either their productivity φ or the variety they produce ω. To produce $q_{o,s}(\varphi)$ units of a variety, a firm requires an amount of effective labor

$$l_{o,s} = f_{o,s} + \frac{q_{o,s}}{\varphi}$$

[14]This sunk cost could be understood as the cost incurred in initial product definition and development.

where $f_{o,s}$ is the fixed cost of production, expressed in terms of effective units of labour, and $\frac{1}{\varphi}$ is the marginal cost of production.

4.2.2 Innovation

After observing its initial productivity φ, a firm can choose to upgrade its technology (innovate), which increases the fixed cost of production by an extra $f^i_{o,s}$, but reduces its marginal cost, now: $\frac{1}{\xi_{o,s}\varphi}$, with $\xi_{o,s} > 1$

4.2.3 Internal Trade and Exporting

In addition to innovating, a firm can also choose whether to sell to a foreign region, which we index by $\tilde{d}$. We assume there are no fixed costs of trade within China. Due to the CES preferences this means that firms sell to every Chinese city. On the other hand, a firm must pay an international exporting fixed cost $f^x_{o,\tilde{d},s}$ if it wants to sell to the foreign market. Thus, firms face an additional discrete choice of whether to export or serve only the domestic market.

Trade (intra-China and international) is subject to iceberg trade costs such that in order for $q_{od,s}(\varphi)$ to arrive to destination d, a firm in o needs to produce $\tau_{od,s}q_{od,s}(\varphi)$ units of the variety, with $\tau_{od,s} \geq 1$. Trade costs are normalised, such that they are equal to 1 if and only if $d = o$.

4.2.4 Supply-Side Industrial Policy (Production and Innovation subsidies)

Firms are directly or indirectly subject to three different types of subsidies which are set by local governments: production, innovation and demand subsidies

We model *production* subsidies targeting sector s as a reduction in input costs for targeted firms, whose marginal cost becomes $\frac{a_{o,s}}{\xi_{o,s}\varphi}$ where $a_{o,s} < 1$. This captures the sort of production subsidy given as an example in Table 1, where the cost of the entire production run is proportionately reduced.

We model the *innovation* subsidy targeting sector s as a reduction in the fixed cost involved in technological upgrading. The innovation fixed costs for an innovator facing a subsidy are $\phi_{o,s}f^i_{o,s}$, with $\phi_{o,s} < 1$. This corresponds to the example innovation subsidy in Table 1, where firms are given a fixed payment for incurring a fixed cost (establishing an R&D centre).

4.2.5 Firm profits

We now derive an expression for firm profits after paying the entry cost and drawing the productivity. This comes from combining the firm technology and industrial policy as described above. Since profits depend on the exporting and innovation decision of the firm, their profits here are a maximum over three alternative profits - if they neither innovate or export, if they export but don't innovate, and if they both export and innovate. We ignore the case in which the firm innovates but does not export as this appears not to be an empirically relevant case in our data.

$$
\begin{aligned}
\pi_{o,s}(\varphi) = \max\Bigg\{ & \sum_{d \neq \tilde{d}} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\varphi} \right\} - w_o f_{o,s}, \\
& \sum_{d} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\varphi} - w_o f^x_{o,\tilde{d},s} \right\} - w_o f_{o,s}, \\
& \sum_{d} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\xi_{o,s}\varphi} - w_o f^x_{o,\tilde{d},s} \right\} - w_o f_{o,s} - w_o \phi_{o,s} f^i_{o,s} \Bigg\}
\end{aligned}
$$

In each case, profits are given by revenues in each destination minus the costs of production, which consist of marginal costs, the fixed cost of exporting and the fixed cost of production. Marginal costs depend on productivity, the production subsidy, trade costs, productivity and innovation decisions. The fixed cost of production depends on the innovation subsidy and the innovation decision.

4.2.6 Firm optimal choices

Firms maximise profits by making decisions about price, which regions to export to, whether to innovate, whether to exit and whether to enter in the first place. To solve, we can break this problem down into stages.

Given the firm's choice over innovation and exporting, we can solve for the firms optimal price by taking the FOC of firm profits with respect to $p_{od,s}(\varphi)$, and replacing the optimal $q_{od,s}(\omega)$ above, we obtain the usual result that manufacturer's price as a constant markup over marginal costs. For example, if the firm is exporting and innovating, price would be given by:

$$
p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{w_o \tau_{od,s} a_{o,s}}{\xi_{o,s}\varphi} \tag{6}
$$

Replacing the optimal pricing and demand functions in the expression for firm profits, we can obtain the potential value functions for each technology and exporting choice (full details in Appendix C). Optimal profits are therefore:

$$\Pi_{o,s}(\varphi) = \max \left\{ \sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} a_{o,s}}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f_{o,s}, \right.$$
$$\sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} a_{o,s}}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s},$$
$$\left. \sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} a_{o,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s} - w_o \phi_{o,s} f^i_{o,s} \right\}$$

Note that the demand subsidies show up in this expression through $E_{d,s}$, which depends on the demand subsidy in region d. Given that they price optimally, firms make exporting and innovation decisions to maximise this expression. This results in a set of productivity cut-offs which determine whether a firm will i) stay in the market after drawing a productivity φ, ii) export to the international market $\tilde{d}$, and iii) innovate.

Domestic market exit threshold: We define $\varphi^*_{oo,s}$ as the domestic market exit productivity threshold. This is the productivity that generates zero profits from serving the domestic market only.

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

Exporting threshold: Let $\varphi^*_{o\tilde{d},s}$ describe the productivity level which makes a firm earn zero profits from exporting to foreign country $\tilde{d}$, and therefore indifferent between serving $\tilde{d}$ or limiting its supply to the domestic market. We also assume that the marginal exporting firm is not innovating.

$$\varphi^*_{o\tilde{d},s} = \frac{\tau_{o\tilde{d},s} a_{o,s}}{P_{\tilde{d},s}} \left(\frac{E_{\tilde{d},s}}{f^x_{o,\tilde{d},s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o^{\sigma_s} \sigma_s^{\sigma_s}} \right)^{\frac{1}{1-\sigma_s}}$$

Innovation threshold: Let $\varphi^i_{od,s}$ be the productivity level which makes a firm indifferent between upgrading its technology or not. This is given by:

$$\varphi^i_{oo,s} = \left(\sum_{d} \frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{w_o \phi_{o,s} f^i_{o,s}} \left(\frac{w_o \tau_{od,s} a_{o,s}}{\chi_{d,s} P_{d,s}} \right)^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}$$

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.

4.3 Industry Equilibrium

An equilibrium in this model is characterised by the following: First, Households maximise utility. Second, the grid-planner minimises cost, Third, firms maximise profits. This implies that they will price according to the pricing formula above; make exit, export and innovation decisions according to the productivity thresholds above, and enter if the expected profits are weakly greater than the sunk cost of entry. Fourth, there is free entry, or zero expected profits. This means that the sunk cost of entry equals the expected profits from entry[15].

$$w_o f^e_{o,s} = \left(1 - G\left[\varphi^*_{oo,s}\right]\right) \mathbb{E}\left[\pi \mid \varphi > \varphi^*_{oo,s}\right] \tag{7}$$

Fifth, final electricity service market clears, and finally, the market for power plant components also clears.

These conditions determine the equilibrium price indices, number of firms, aggregate production and revenue, and mass of exporters and innovators in each region. The price indices in all regions and for the solar and non-solar sector satisfy the following system of equations:

$$\sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o f_{o,s} \sigma_s^{\sigma_s}} \frac{\kappa^{\sigma}_{d,s} I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}} \left(w_o \tau_{od,s}\right)^{1-\sigma_s} \right\} =$$

$$\left(\frac{f_{o,s}}{f^e_{o,s}} b^{\theta_s}_{o,s} \frac{\sigma_s - 1}{\sigma_s - \theta_s - 1} \left\{ \left(\frac{\sigma_s - \theta_s - 1}{\sigma_s - 1} - 1 \right) \left(\frac{1 - \xi^{1-\sigma_s}_{o,s}}{\xi^{1-\sigma_s}_{o,s}} \right)^{\frac{\theta_s}{\sigma_s - 1}} \Phi^{-\theta_s} - \left(\frac{f^*_{o\tilde{d},s}}{f_{o,s}} \right)^{\frac{1-\sigma_s+\theta_s}{1-\sigma_s}} \Theta^{-\theta_s} - 1 \right\} \right)^{\frac{1-\sigma_s}{\theta_s}}$$

Where

$$\Phi = \left\{ \frac{\sum_d E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}}{\sum_{d \neq \tilde{d}} E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}} \right\}^{\frac{1}{1-\sigma}} = \left\{ \frac{\sum_d \frac{\kappa^{\sigma}_{d,s} \tau^{1-\sigma_s}_{od,s} I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}}}{\sum_{d \neq \tilde{d}} \frac{\kappa^{\sigma}_{d,s} \tau^{1-\sigma_s}_{od,s} I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}}} \right\}^{\frac{1}{1-\sigma}}$$

$$\Theta = \left(\Phi^{1-\sigma} - 1\right)^{\frac{1}{1-\sigma}}$$

The above system of equations features only fundamentals, wages, and income towards electricity in each region. While wages and therefore total income are potentially still endogenous, we assume that wages are fixed in response to policy. This assumption is justified by

[15] for the production to be bounded, it is required that $\theta_s + 1 - \sigma_s > 0$

conceptualising the solar industry as a small part of the rest of the economy, which remains 'unmodelled'. Because the solar industry is relatively small, we assume that changes in solar industrial policy will not affect the total economy enough to change wages. Therefore, changes in policy, even if they lead to labour moving into the solar sector, will not affect total income in the economy since total labour times wages remains unchanged. Further, we assume that income towards electricity services represents a fixed share of total income and therefore also remains invariant to policy.

Full derivations and the expressions for the rest of key aggregate objects (derived from the price indices) can be found in the Theoretical Appendix.

In the next section we impose additional simplifications to derive analytical solutions and evaluate how our key aggregates of interest change with respect to each type of solar subsidy.

4.4 Comparative Statics: Closed Form Solutions in a Simplified Model

We are interested in how the solar industry will respond to changes in local industrial policy. We consider a number of comparative static predictions of the model with respect to policy parameters. We consider three types of subsidies: production, demand, and innovation and several outcomes: innovation, revenue, production, the number of firms, exports and prices.[16]

given the complexity of the model, the endogenous equilibrium outcomes are generally not closed form solutions. Consequently, in the next section, we quantify the model and derive these predictions numerically. In this section, we derive comparative statics analytically where we can obtain closed form solutions. We use a simplified version of the model in which there is only a single sector (solar electricity), two symmetric regions with the same trade costs and underlying productivity, and no international trade. Hence, we drop the sector subscript s from all equations in this section. Where relevant we index the treated city by "1", and the non-treated city by "2". The qualitative results from this simple model are essentially the same as the simulations in the full model.

PROPOSITION 1 (PRODUCTIVITY THRESHOLDS): *Demand and production subsidies leave the exit and innovation thresholds unchanged. Innovation subsidies make the market more competitive and increase the exit threshold. In addition, innovation subsidies reduce the innovation threshold.*

[16]We observe empirical proxies for all of these outcomes except price. Because price is so important for the welfare implications we keep track of this as well.

In the simplified model, we can derive expressions for the exit, φ_1^*, and innovation, φ_1^i, thresholds in the treated city-region, which depend only on exogenous parameters and policy variables.

$$\left(\varphi_1^*\right)^\theta = b^\theta \frac{f_1}{f_1^e} \frac{\sigma - 1}{\theta + 1 - \sigma} \left(\left(\phi_1 \frac{f_1^i}{f_1} \right)^{\frac{\theta+1-\sigma}{1-\sigma}} \left(\frac{\xi_1^{1-\sigma}}{1 - \xi_1^{1-\sigma}} \right)^{\frac{\theta}{1-\sigma}} + 1 \right)$$

$$\varphi_1^i = \varphi_1^* \left(\frac{1 - \xi_1^{1-\sigma}}{\xi_1^{1-\sigma}} \frac{f_1}{\phi_1 f_1^i} \right)^{\frac{1}{1-\sigma}}$$

PROOF *See Appendix D*

The demand subsidy, χ_1, the and production subsidy, a_1, do not enter these expressions. Intuitively, these subsidies scale up profits proportionately at all levels of productivity. Therefore the relative benefits of each choice (exit, produce without innovating, innovate) remain unchanged and hence the thresholds do not shift. A consequence is that production and demand subsidies will not change the average productivity of operating firms.

An innovation subsidy is modeled here as a decrease in ϕ_1, i.e. a reduction in the fixed cost of innovating. This will lead to an increase in the exit threshold (φ_1^*), meaning the least productive firms will exit. This can be seen by noting that when ϕ_1 decreases $\left(\phi_1 \frac{f^i}{f}\right)^{\frac{\theta+1-\sigma}{1-\sigma}}$ increases because $\frac{\theta+1-\sigma}{1-\sigma} < 0$. Intuitively, only firms who are already innovating or on the margin of innovating will benefit from the innovation subsidy. They will lower their prices with lower costs and, since these are already the most productive firms, they make the market more competitive, pushing the least productive firms out of the market.

As we show in Appendix D, the innovation threshold can be written in the following form

$$\left(\varphi_1^i\right)^\theta = A \left(B\phi_1 + (\phi_1)^{\frac{\theta}{\sigma-1}} \right)$$

Where A and B are positive constants that do not depend on the innovation subsidy. In this form, it is straightforward to see that $\frac{\partial \varphi_1^i}{\partial \phi_1} > 0$. That is, an innovation subsidy (lower ϕ_1) will decrease the innovation threshold. Overall, the average productivity of operational firms will increase, and a greater share will be innovators.

PROPOSITION 2 (MASS OF FIRMS): *Demand subsidies and production subsidies will increase the number of operating firms. Production subsidies will have a larger effect than demand subsidies when the untreated region is large enough. Under stronger regulatory conditions, innovation subsidies will also increase the number of operating firms.*

The equilibrium level mass of firms can be represented as (see details in Appendix D)

$$M_1 = C\left(\frac{\tau^{\sigma-1}\frac{E_1}{\chi_1}}{\tau^{\sigma-1}\left(\varphi_1^*\right)^\theta - \left(a_1\varphi_2^*\right)^{1-\sigma}\left(\varphi_1^*\right)^{\sigma+\theta-1}} + \frac{E_2}{\left(\varphi_1^*\right)^\theta - \tau^{\sigma-1}\left(a_1\varphi_2^*\right)^{1-\sigma}\left(\varphi_1^*\right)^{\sigma+\theta-1}}\right)$$

Where C is a constant - $C = \frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}\frac{b^\theta(\sigma-1)}{f^e\theta}\left(\frac{\sigma}{\sigma-1}\right)^{\sigma-1}$

PROOF *See Appendix D*

The mass of firms in city-region 1 depends on demand from both the treated region 1 and the untreated region 2. These two regions correspond to the two terms in this expression. The demand subsidy χ_1 enters only in the numerator of the first term. An increase in the subsidy, which is a reduction in χ_1, increases household expenditure in the treated region and therefore increase the overall mass of firms in the treated region, M_1.[17] The mass of firms in region 2 will also increase.

The production subsidy will impact units produced to sell both in the home region and in the untreated region. Therefore, the production subsidy enters both terms of this expression. The mass of firms will increase both due to increased profits which can be earned selling domestically and increased profits from selling in the untreated region.

Since the demand and production subsidies enter differently into the first term of this expression, it is not immediately obvious whether a production or demand subsidy will have a larger impact on the mass of firms in region 1. However, as long as expenditure in the untreated region E_2 is large enough, then production subsidy will be more effective because treated firms can sell outside the treated region. A "large enough" untreated city-region is isomorphic to there being a large number of untreated locations, which is the case in our data (of the 358 city-regions, only 42 ever had any subsidy policies - see Figure 3).

If we consider the relative impact of production and demand subsidies on treated as opposed to the untreated region, a production subsidy will unambiguously increase the mass of firms in region 1 relative to region 2, whereas a demand subsidy will increase the mass of firms in both.

The innovation subsidy only influences the mass of firms through the changes to the threshold

[17]For the demand subsidy to have an positive effect, we need the denominator to be positive. This is almost always guaranteed. In the purely symmetric and no subsidy case, $a_1 = 1$, $\varphi_1^* = \varphi_2^* = \varphi^*$. The denominator can be written as $\left(\tau^{\sigma-1} - 1\right)\left(\varphi^*\right)^\theta$ and it will be strictly positive since $\tau > 1$ by definition. Then if we introduce some small subsidy, the denominator will remain to be positive since the function is continuous.

$\varphi^*_{1,s}$. From Proposition 1, we know that an innovation subsidy will increase the exit threshold $\varphi^*_{1,s}$. However, there is no linear relationship between $\varphi^*_{1,s}$ and $M_{1,s}$. It can be shown that (see Appendix D) an innovation subsidy will increase the mass of firms under a regulatory condition which is likely to hold if the trade cost is not too large.

PROPOSITION 3 (INNOVATION): *Demand subsidies, production subsidies, and innovation subsidies all increase the number of innovators by increasing the number of operating firms. Consistent with Proposition 2, production subsidies have a larger marginal effect compared to demand subsidies.*

PROOF *See Appendix D*

More detailed proofs are in the Appendix, but this follows directly from Propositions 1 and 2. From Proposition 1, we know that demand and production subsidies do not affect the exit and innovation thresholds, so the share of innovators does not change. From Proposition 2, we know the but the total mass of firms increases following these subsidies, so the number of innovators must rise. The relative size of this effect for the two subsidy types will be driven entirely by their impact on the mass of firms. If the same condition above holds such that production subsidies have a larger impact on the mass of firms, then they will also have a larger impact on innovation.

Since innovation subsidies increase the exit threshold and reduce the innovation threshold they will increase the share of operating firms that are innovators. As long as the same condition above holds such that innovation subsidies increase the mass of firms, the total number of innovators will also increase.

PROPOSITION 4 (REVENUES AND PRODUCTION): *All subsidies increase city-level total revenue through the increase of the mass of operating firms. Similarly to Proposition 2, production subsidies have a larger impact than demand subsidies. Innovation subsidies will further increase total revenue by increasing average firm revenue*

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

PROOF *See Appendix D*

City-level total revenue equals the mass of operating firms multiplied by the average revenue per firm. All subsidies increase the mass of operating firms, thus raising total revenue. Innovation subsidies encourage more firms to become innovators, and reduce the number of less productive firms leading to higher average revenues per firm.

Finally, since prices are non-decreasing in subsidies, the impact on production will be in the same direction as revenues and generally larger as prices will tend to fall.

4.5 Comparative Statics in the Full Version of the Model: Quantification and Simulation

In this section, we look at the full model which has multiple energy sectors (solar and non-solar) as well as an international export market. We keep to initially symmetric regions, and consider the introduction of different subsidies. This allows us to examine the effect of each type of subsidy on treated and untreated regions. Although we present numerically simulated solutions, it is worth noting that the propositions derived analytically in the previous subsection continue to hold.

In setting values for the model parameters, we are guided by a set of regulatory conditions: Production needs to be bounded; the innovation threshold is larger that the exporting threshold, and the exporting threshold is larger than the exit threshold; the elasticity of substitution across energy sectors (solar vs non-solar) is smaller than the one within each energy sector (across varieties). Finally we normalise income towards electricity services and set it equal to one. Recall, that we assume that this is policy invariant and we therefore treat it as exogenous in our model. The values we select for the numerical simulation are given in Table 2.

Figure 6 presents the results of our numerical simulation, where we gradually increase subsidies up to 1%. In other words, $a_{1,s}$, $\chi_{1,s}$ and $\phi_{1,s}$ gradually decrease from 1 (no-subsidy economy) to 0.99. The solid blue line represents the change in outcomes as the production subsidy changes. The dashed red and dotted yellow line represent analogously changes in outcomes when demand and the combination of innovation and production subsidies respectively are increased. Note that in the data, we never observe innovation subsidies alone - they are always in cities that also have some sort of production subsidy. Thus, the dotted yellow line represents the evolution of outcomes as the combination of production and innovation subsidies changes.

The outcomes on the y-axis of each panel in Figure 6 are the mass of innovators (a), the mass of solar firms (b), revenue (C), panel production (D), and price (E), all for the solar energy sector.

There are several clear findings. First, as a result of an increase in subsidy support, the mass of innovating forms, the total mass of firms, the mass of exporters, revenue, and production

Table 2: Parameter Values used in simulation of the full model

Parameter		Value
	Preference Parameters	
σ	Elasticity of substitution across energy sectors (solar vs non-solar)	4
$\sigma_s, \sigma_{s'}$	Elasticity of substitution across power plant input varieties (e.g. solar panel models)	5
	Production Technology Parameters	
$\theta_s, \theta_{s'}$	Shape parameter of Pareto distribution (dispersion of productivity draws within energy)	6
$b_{o,s}, b_{o,s'}$	Location parameter of Pareto distribution (city's productivity)	1
$f_s^e, f_{s'}^e$	Sunk entry cost	1
$f_s, f_{s'}$	Production fixed cost	1
$f_s^i, f_{s'}^i$	Innovation fixed cost	1
$\xi_{o,s}, \xi_{o,s'}$	Productivity gain from innovating	1.1
	Trade Parameters	
τ_i	Iceberg trade costs (Intra-China)	1.1
τ_f	Iceberg trade costs (foreign)	1.2
$f_s^x, f_{s'}^x$	Exporting fixed cost	1

all increase, while prices decline. Second, and consistent with the intuition from our analytical results in the simplified model, there are stark differences the effectiveness of solar subsidies. Although all types of subsidies are effective, supply-side subsidies (production and innovation) have stronger effects than demand subsidies across all outcomes. As there are more untreated than treated cities in our simulation (as is the case empirically in China) firms treated with supply-side subsidies are able to benefit from selling to multiple markets. They benefit from a business stealing effect from solar firms in other cities. In contrast, demand subsidies increase output for firms in other cities who can supply the treated city, which means the local production effects are smaller in the origin city.

A third result, from Figure 6 is that combining production and innovation subsidies (dotted yellow line) is more effective than implementing production subsidies alone (solid blue), particularly in increasing the number of innovators (consistent with Proposition 3). The extra impact from innovation subsidies is also noticeable on revenue and Production (panels (c) and (d) respectively), albeit more modestly.

In Figure E.1 we conduct similar exercises looking at the aggregate effects of the local subsidies. The qualitative conclusions are quite similar, although as expected, the magnitude of the effects are smaller (especially for the production subsidies due to the negative business stealing effect in other cities).

4.6 Summary on the Model

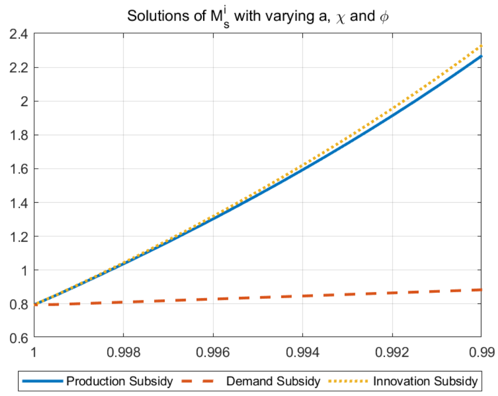
We have detailed a model with heterogeneous manufacturers supplying the (differentiated) components of clean (solar) and dirty electricity to a local grid planner under imperfect competition. These manufacturers make endogenous choices over innovation, exporting, entry, exit and supplying the city-region they are located in as well as other cities in China and overseas (subject to transport costs). We then introduce three types of subsidy (demand, production and innovation) and examine the change in equilibrium of this multi-region model.

Both the analytical results and the numerical simulations generate clear predictions. Across our outcomes of interest, which capture solar industrial activity, we predict that all subsidies will generate positive effects. City-level innovation, revenues, production, firm numbers and exports all increase. However, the strength of the impact varies according to the type of subsidy. Noticeably, the local demand subsidy effect is weakest due to the possibility of meeting the increased derived demand for solar panels from outside the subsidized city-region.

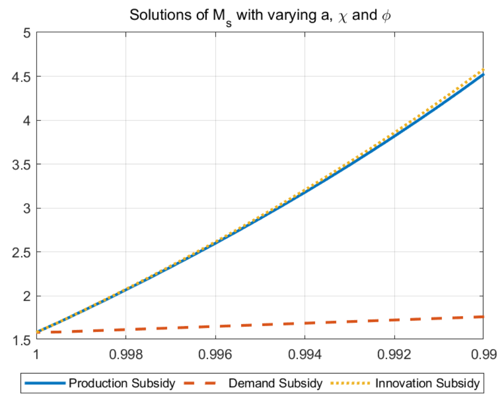
In the next section we will show evidence in support of all these empirical predictions.

Figure 6: Effect of Different Subsidies on City-level Outcomes

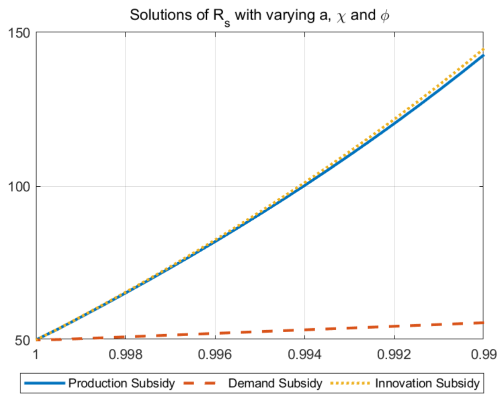
(a) Innovation



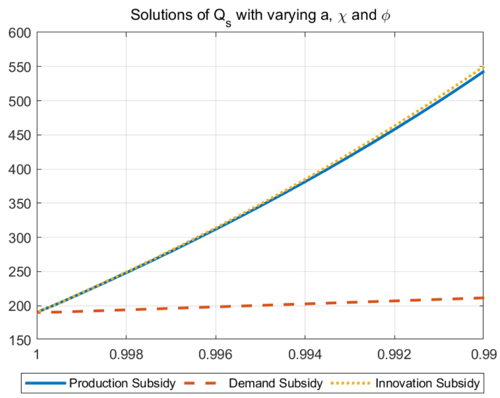
(b) Number of firms



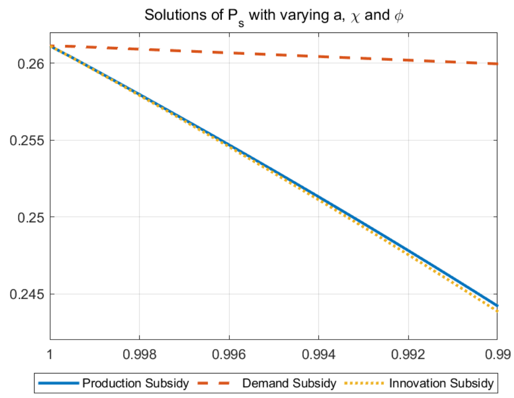
(c) Revenue



(d) Quantity



(e) Price



Note: These are numerically simulated effects of the full model of different city-level subsidies on solar outcomes. Each of the panels looks at a different outcome, with the level on the y-axis. The x-axis changes the level of the subsidy from the no-subsidy economy normalized at 1 up to a 1% subsidy (0.99). The different lines represent different types of subsidy: production (a), demand (χ) and innovation (ϕ). Details in text and Appendix C.

5 Empirical Strategy

Our objective is to study whether solar industrial policy was effective in increasing innovation and production in the Chinese solar industry. Our treatment is the first time a city implements a solar-related industrial policy. Once a city implements such a policy, it becomes an absorbing state. This choice follows from our argument in Section 2, which suggests that no Chinese city has completely removed all solar subsidies once it has started a subsidy program.

There are several challenges in evaluating causal effects of solar industrial policies. First, implementation of policies is not random. For example, 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 try and catch up. We are helped here by the fact that the Chinese solar industry started prior to the first policy interventions in 2006. Having pre-2006 outcome data will help us in constructing control cities for the treatment cities.

Second, the impact of policies may vary over time. For example, R&D expenditure may take time to lead to new innovations. We would like to capture these potential dynamic effects because a key aim of industrial policy is often to "kick-start" an industry (Juhász 2018, Choi & Levchenko 2021), and also because concerns have been raised that subsidies may have boosted local solar manufacturing and domestic jobs in the near term but that these benefits were not sustained (Ball et al., 2017). Our approach should also be robust to these potential dynamic effects of policy intervention, in light of the recent work on two-way fixed effects with differential treatment timing (Callaway & Sant'Anna 2021, Sun & Abraham 2021).

To help address these concerns we employ the Synthetic Difference-In-Differences (SDID) methodology proposed by Arkhangelsky et al. (2021). The approach combines a familiar difference in differences approach, with a synthetic control approach to construct a counterfactual group for each treated unit by taking a weighted average of all possible control units. The weights are chosen such that the pre-trends of the treatment and control group are approximately parallel.

In our setting, cities are treated by solar policies in different years. We therefore first estimate cohort-specific ATTs by applying the SDID for a given treatment year. We select synthetic controls which are specific to a given cohort (a set of cities that implement a solar industrial policy in year t) and a given outcome of interest (e.g., revenues). Given the likelihood that treatment effects will be evolving over time, we construct the synthetic control using only the never-treated cities (i.e., cities that never implement a solar industrial policy in our study period).

Formally, we estimate the treatment effect τ by solving the minimization problem in equation 8, where Y_{it} is the outcome of interest, μ is the intercept, α_i and β_t are city fixed effects and time fixed effects, respectively, and W_{it} is a treatment dummy variable that takes the value of one for every time period post-policy (absorbing state). The weights $\hat{\omega}_i^{\text{sdid}}$ are chosen to make the pre-treatment trends in the outcome variable for treatment and control cities as parallel as possible. The weights $\hat{\lambda}_t^{\text{sdid}}$ allow us to estimate our treatment effects by placing more importance on those pre-treatment periods that better predict post-treatment outcomes.[18]

$$\left(\hat{\tau}^{\text{SDID}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{\text{SDID}} \hat{\lambda}_t^{\text{SDID}} \right\} \tag{8}$$

After estimating cohort-specific ATTs, we then aggregate all the cohort effects using the weighted average proposed in Arkhangelsky et al. (2021), which pools effects across all cohorts and time periods and provides us with the ATTs reported in Tables 3, 4, 5, and 6. Standard errors are estimated by the bootstrap clustered at the city level.

Finally, we study the dynamic effects of the policy by aggregating cohort-specific ATTs into event study estimates following a methodology discussed in Callaway & Sant'Anna (2021). Specifically, for some event study window, e, we calculate the ATT as:

$$ATT(e) = \sum \mathbf{1}\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e)$$

where $g \in G$ stands for some cohort from the set of all treated cohorts, G, $ATT(g, g + e)$ captures the ATT estimate for cohort g e years after treatment - i.e. at time $g + e$ - and P(.) captures the probability of a treated unit belonging to cohort g from all cohorts having at least e post-treatment periods before the end of our study period, T. [19] These event study estimates are in Figures 7, 8, 9, and 10.[20]

Since our approach requires matching on pre-trends, it is worth briefly discussing the time period for which we have data available and during which solar industrial activity was taking

[18] For estimating ω, we use constrained least squares on the pre-treatment data with a tuning parameter to avoid over-fitting. Using potential control units, we estimate λ using least squares.

[19] We estimate $P(G = g | G + e \leq T)$ for cohort g by dividing the number of treated units in the cohort by the number of all treated units that have at least e post-treatment periods.

[20] As discussed in Section 6.8, these event studies may be affected by compositional effects beyond dynamic effects. In this section, we explore the importance of these effects in more detail.

place in China. The first solar policies began in 2007 when specific financial support was allocated across provinces, cities, and municipalities. Our production, revenues, patents, and capacity measures all commence in 2004. Morever, whilst the 2006-2010 period saw the fastest growth in the industry and decline in the price of solar modules, initial growth occured during the period of the Tenth Five-Year Plan (2001-2005). We therefore are able to compare outcome trends across cities where the solar industry existed even if it was at a nascent stage.

Each subsection focuses on different groups of outcomes (innovation, firm numbers, output and exports). We visualize the results in event studies and then show average results across all cohorts of policies in all years. Some more detailed cohort-specific event studies are relegated to the Appendix and referred to when necessary in the text.

5.1 Innovation

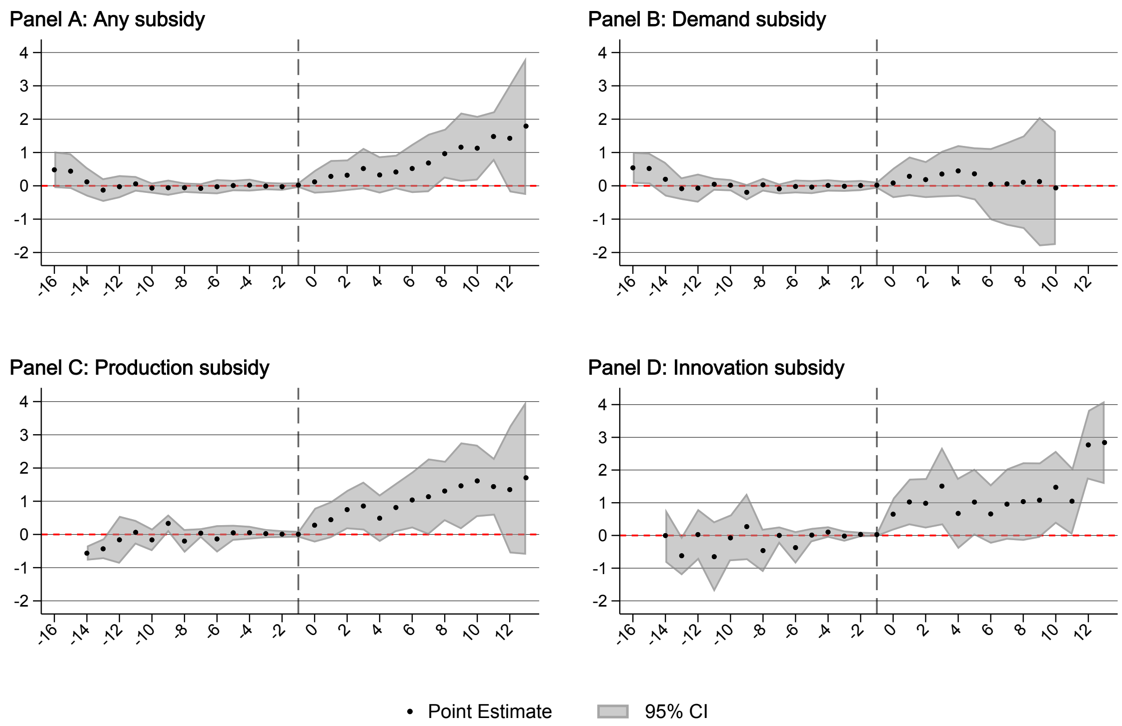
We begin with what we regard as the most novel findings, focusing on the impact of subsidies on innovation using the number of patents filed by solar firms in the same city. Figure 7 depicts our estimates of for the four treatment types. As introduced in the previous section and discussed in more detail in Section 6.8, these graphs combine all available cohorts into one estimate relative to treatment year.[21] The dots (point estimates) capture the difference between treatment and control and we show the 95% confidence intervals (bootstrapped standard errors allowing for clustering by city). The top left Panel A shows the effects on the patents filed by solar firms in cities that were treated with any subsidy policy. After the implementation of the policy, there is a gradual increase in the patenting activity in treated compared to control cities. Importantly, there are no signs of pre-trends in the years preceding the introduction of the policies, suggesting our SDID method is doing a good job of matching treatments with controls.

Panel B of Figure 7 examines demand subsidies. In contrast to the overall picture, we see no significant effects in any of the post-treatment years as a result of the demand policies. Panels C and D have the results for production and innovation subsidy respectively. These are obviously driving the overall results in Panel A, with slightly larger effects for innovation policies in line with the model of the previous section. The impacts gradually increase in the years after the treatment. Importantly, the number of patents does not revert to baseline even 13 years

[21] These pooled estimates use all the available post-treatment information. As a result, the estimates mask compositional changes that are further discussed in Section 6.8.

after the policy was introduced, which implies that firms were not simply bringing forward activity that would have occurred even in the absence of the policy. Even though the errors bands become wider, the impact remains significant even ten years after the implementation for all categories but the demand subsidy.

Figure 7: 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 5. The outcome variable in all panels is total patents of solar firms (with arcsinh 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.

Table 3 shows the aggregate ATT, which combines the treatment effects for all cohorts of policies. Column (1) reports the "any subsidy" treatment shown in 7, but for all policies in all years. Since the dependent variable is transformed through the Inverse Hyperbolic Sine (IHS), the ATT effect implies an increase of approximately 64%[22] in the number of patents in a city that introduces a solar subsidy. To put this in context, the average number of annual

[22]To calculate the percentage increase, we use $e^{\beta} - 1$. However, this is only an approximate estimator to give us an intuitive sense of magnitude. This estimator is accurate only if the outcome value is relatively large. It is also important to notice that the inverse hyperbolic sine transformation is not scale invariant, which is why we have checked against other transformations such as using levels.

patents by solar firms in a city is 13.1, so this would imply an increase to 21.5, or about 8.4 extra solar patents per year.

There has been much recent discussion over the interpretation of models with the IHS transformation that we are using here (e.g. Aihounton & Henningsen 2021, J. Chen & Roth 2023 and Mullahy & Norton 2022). We also find that nontrivial magnitudes arise from alternative transformations of the patent count such as using Poisson count data models, simple levels or the log(1+Patents) transformation.

Columns (2)-(4) of Table 3 disaggregate the any solar policies in column (1) into the three alternative types of subsidy. In column (2), we observe that although the ATT of demand subsidies is positive, it is less than half the size of the first column (0.236) and is not statistically significantly different from zero. By contrast, the production subsidy in column (3) is highly significant with an ATT of 0.871, which is larger than column (1). And in the final column, the ATT for Innovation subsidies is 1.060, the largest in the Table and over twice the size of the any subsidy effect in column (1).

Table 3: All Patents

	(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)
Observations	6,086	6,086	6,086	6,086

Notes: *0.1 ** 0.05 *** 0.01. Each observation is a city (admin2 level region) and there are 358 cities in China. 43 cities are treated by any subsidy. The time period is 2004-2020. 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 clustered by city. All regressions without controls.

Taking Table 3 as a whole, we see a very striking pattern. Subsidies seem to work in increasing innovation, and the magnitude of the effects are consistent with the simple theory we have laid out. The effects are largest for innovation subsidies and negligible for demand subsidies. But production subsidies also generate positive, significant and non-negligible effects on innovation over the longer-run, which is consistent with the aim of green industrial policies.

The influence of production subsidies on firm innovation occurs through two channels. First, production subsidies lower the marginal cost of production, allowing firms to incur the fixed cost associated with innovating. Second, through expanding their production, firms may engage in learning by doing. Some of these efficiency improvements are captured in patenting (which is easier to do in the Chinese patent office than in those of richer countries like the USPTO or EPO). In our extensions in Section 6, we use text-mining techniques to classify patents and replicate our results using as an outcome variable the number of patents whose abstracts reflect process efficiency improvements (which we denote as 'learning-by-doing patents'). The fact that we find positive effects for these patents is suggestive of subsidies enabling learning-by-doing and the subsequent filing of the resulting productivity improvements.

In our Section 6 extensions, we also explore whether some of the city-level estimates we document may include business stealing effects across cities, which could mute the aggregate impact of solar industrial policies. We find no evidence of negative cross-city spillovers.

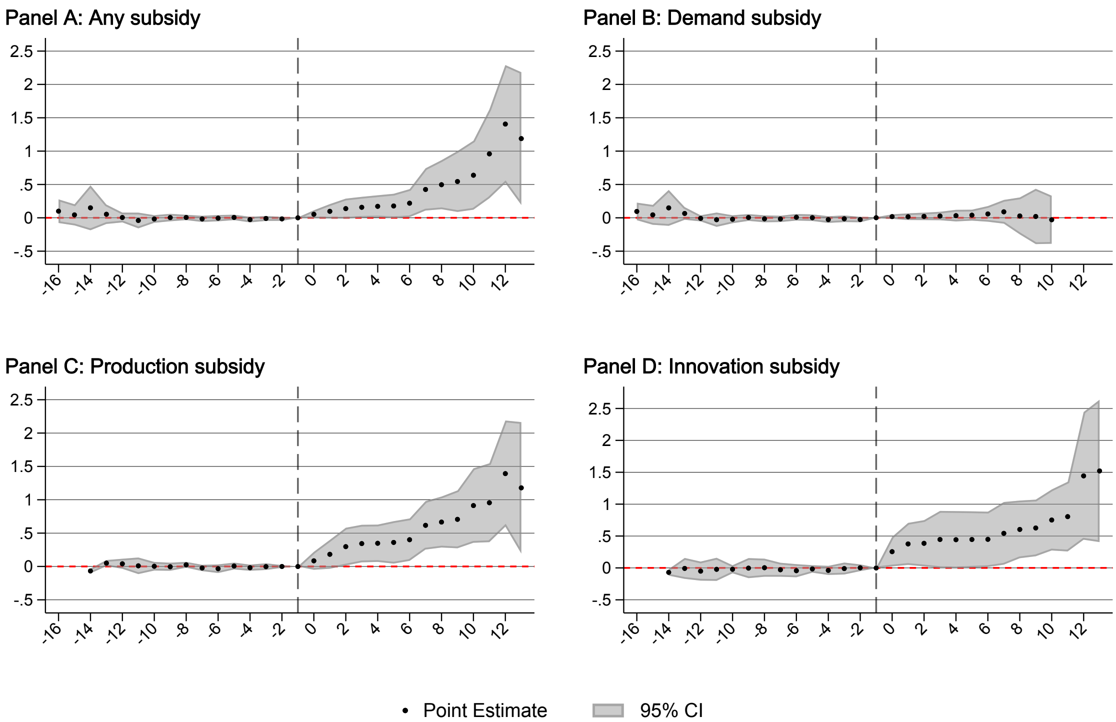
5.2 Number of Solar Firms

Our model posits that the mechanism through which production subsidies positively impact innovation is through first increasing the scale of activity of firms. We now proceed to evaluate the impact of solar subsidies on production activity at both the extensive and intensive margins.

We begin with the simplest measure, that of the number of solar firms in a city. Figure 8 replicates the analysis of Figure 7, but using the number of solar firms as the outcome. Note that the "doppleganger" cities used as controls can be different to those in Figure 7 as the SDID routine picks the best controls for each outcome variable separately. Similarly to the previous analysis we see parallel trends between treatment and control and a large positive and significant impact on the number if firms after a city introduces pro-solar policies. Again the effects persist for at least 13 years, and are highly significant even in the long-run.

Table 4, which parallels Table 3, presents the ATT for firm numbers. The overall effect in column (1) is significant, but smaller in magnitude than for patents (0.186 compared to 0.496). We see a similar qualitative pattern when looking across the policies. The demand subsidy effects are positive, but small and statistically insignificant. The production and innovation subsidies are, by contrast large and significant.

Figure 8: Firm Count



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. The outcome variable in all panels is the number of solar firms (with arcsinh 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.

Table 4: Firm Count

	(1)	(2)	(3)	(4)
	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Firm count	0.186***	0.060	0.288***	0.381***
	(0.064)	(0.043)	(0.090)	(0.135)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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 and variable is transformed using IHS.

5.3 Output: Revenues and Production

To assess the intensive margin effects on production we use two different sources of data. From 2004 to 2013, we can accurately measure solar panel capacity and production in MWh using the ENF's market research reports (*ENF production* dataset)[23]. These reports are constructed based on detailed surveys of factory conditions. They therefore represent highly accurate measures of solar activity.

As noted in Section 3, ENF stopped collecting such detailed information after 2013. Consequently, we also examine the sales of solar firms using company accounts data. We use the *ENF register* which contains a list of all solar firms (used in the previous subsection) and match in accounts data from a variety of sources, in particular BVD Orbis, which is reasonably comprehensive for our companies. This gives us revenue data for solar firms during the 2004-2020 period, which we aggregate to the city-by-year level.

Figure 9 displays the pooled impact solar policies on solar manufacturers' revenue. The results show that solar manufacturers' total revenue (measured in RMB millions and transformed using the IHS) increases more in treated than in control cities after the subsidies. There are again statistically significant effects at the 95 % level for the any, production and innovation subsidy groups that persist throughout a decade after implementation. The demand subsidy is associated with zero or slightly negative effects although they are never statistically significant.

Table 5 presents the pooled ATT across all city-cohorts. As before, there is a strong, positive and significant effect on revenue of 1.0 in column (1). Note that this is about five times larger than the effect on the number of firms in Table 4, which suggests that revenue per firm has increased as a result of the policy. In other words, there are not only more solar firms, they have substantially grown in size.

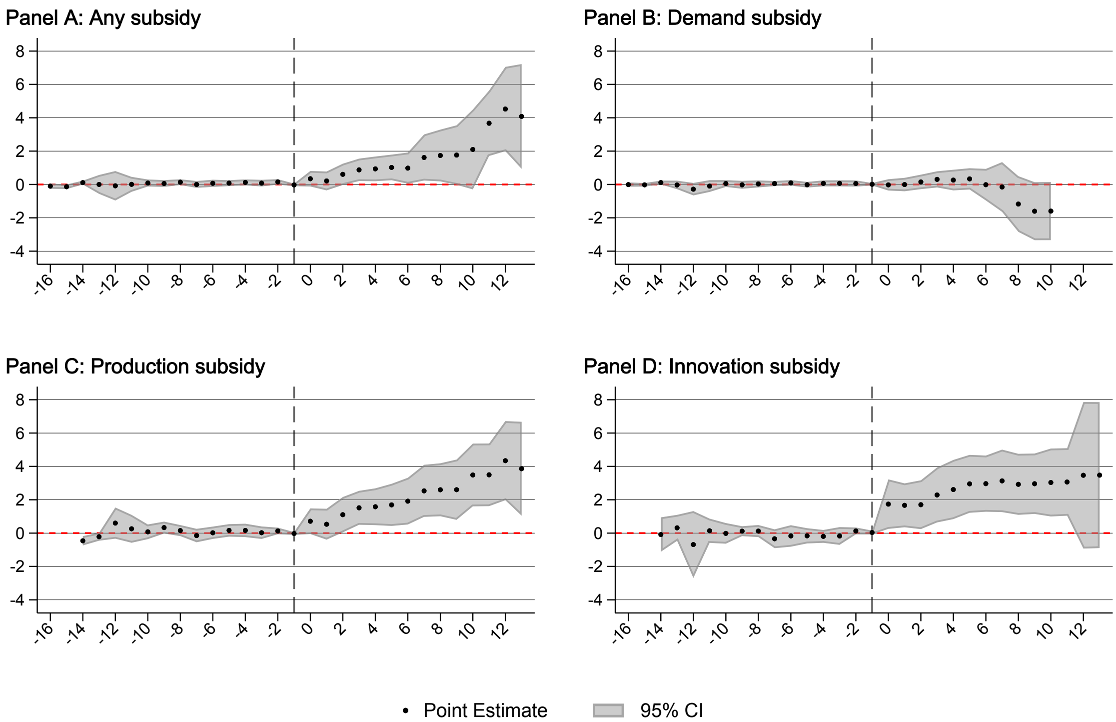
The difference in treatment effects with respect to the type of subsidy in Table 5 goes in the same direction as our previous results. Demand policy coefficients remain the smallest, innovation subsidies the largest and production subsidies are in between.

Although most of our solar firms are "pure plays", some are multi-product and produce more than just solar panels and solar cells. Hence underlying Figure 9 and Table 5 there is an adjustment which should bring the revenue numbers more in line with just the solar activity[24].

[23] Capacity is defined as the maximum 12-month output that could be achieved based on the company's end of the year factory conditions. Production is defined as the likely output that will be achieved in the year based on expected orders

[24] The adjustment leverages yearly firm level data on exports to calculate the revenue share that is likely driven by solar PV sales. Our results are robust to using the non-adjusted revenue measure and to a number of different possible specifications of the adjustment algorithm. See Appendix B.8 for a discussion of the adjustment mechanism and Figure **??** and Table F.7 for the raw revenue numbers.

Figure 9: Revenue



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. The outcome variable in all panels is the total revenue of solar firms (with arcsinh 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.

Table 5: Revenue

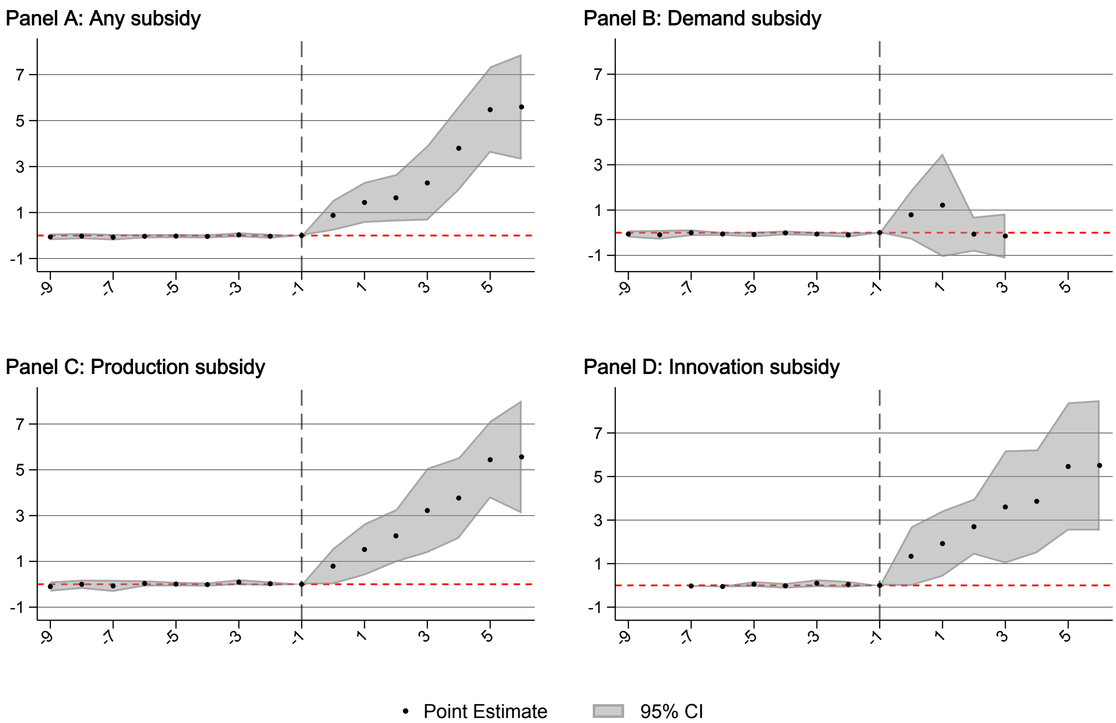
	(1)	(2)	(3)	(4)
	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	1.015**	0.069	1.802***	2.563***
	(0.455)	(0.277)	(0.629)	(0.844)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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 with the revenue adjustment procedure summarized in Section B.8 and without controls

In addition, revenue contains a mark-up, which means we are not just measuring the quantity of solar output, but any increase in post-policy prices. We turn next, to a more precise volume measure of output in Figure 10 and Table 6 using *ENF production* data, in which we can measure directly the MWh that could be generated with the solar panel output of each manufacturer.

The data reveals that treated cities experienced a faster increase in panel capacity after policy shocks than the selected control cities did. The event-study analysis indicates that treatment effects become statistically significantly different from zero two years after policy implementation. Table 6 again shows statistically significant and positive effects of production and innovation subsidies on production capacity.

Figure 10: 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 5. The outcome variable in all panels is the total panel capacity MWh of solar firms (with arcsinh 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

According to Table 6, the ATT of any subsidy on production capacity is roughly twice as large as its effect on revenue. However, when we examine the revenue results in Table F.14 in the Appendix, limiting the revenue outcomes to end in 2013 as per the ENF production dataset, the ATT for revenue is much closer to that for panel capacity. This suggests that our revenue data is a reasonably accurate measure of production activities. The smaller overall ATT for revenue implies that some multi-product firms may be shifting output from non-solar

Table 6: Panel Production Capacity

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Observations	3,580	3,580	3,580	3,580

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 18 regions are treated by any subsidy. Time: 2004-2013. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

activities to solar ones to capitalize on subsidies, or that solar companies may be using some of the solar subsidies to increase their price-cost margins.

The richness of the ENF data allows us to look at many other measures of solar output. In the Appendix Figure F.6 we show results for solar PV module production (an adjusted measure of capacity based on expected orders) as well as solar cell production and capacity. The results are qualitatively similar to what we have documented in the main text.

5.4 Exports

The final set of results we consider are related to international trade. We use Chinese official customs data from 2004 to 2016 (the last year available). We match all export records with the names of ENF firms, and aggregate the data at the city level according to the location of each firm.

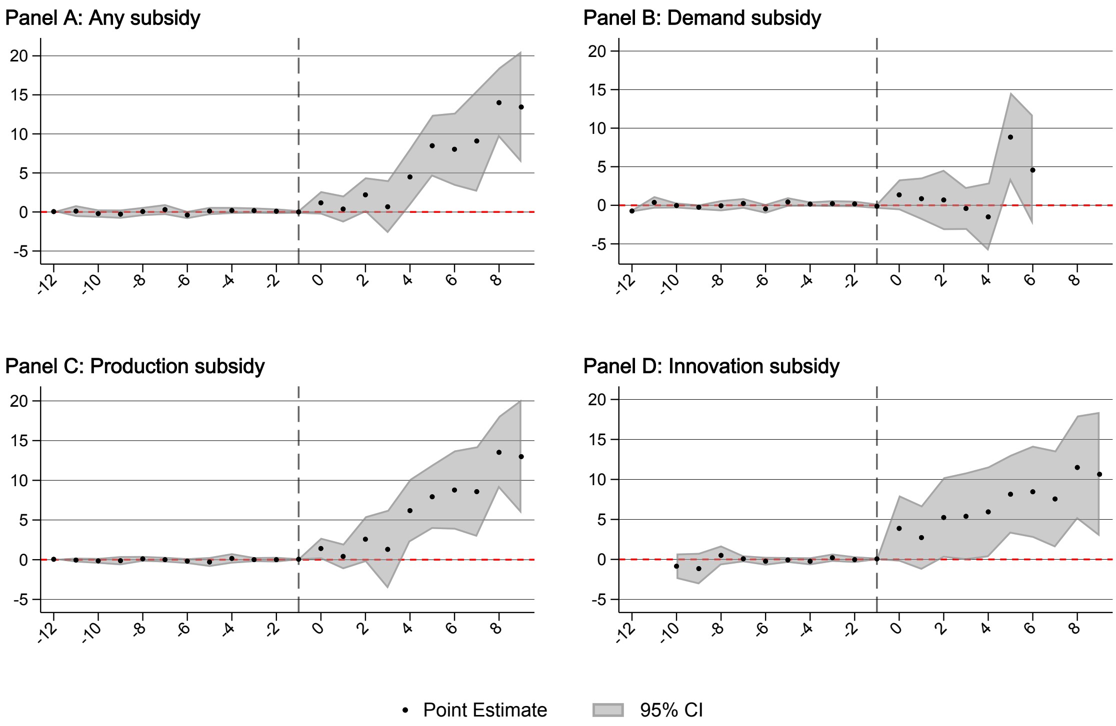
As noted above, some of our solar firms are multi-product, so they will be exporting non-solar products. Since we would expect the effects of the subsidy to be larger for solar exports, we differentiate between solar and non-solar exports using HS code "854140", which includes solar panels and cells.[25]

Figure 11 illustrates the difference in solar export value of solar manufacturers in treated and control cities. As with the other outcomes, we observe an increase in solar exports if a city introduces a pro-solar policy.

The aggregate results of our export analysis are presented in Table 7. The two rows represent estimates for solar exports and all exports from solar firms, respectively, and show a famil-

[25] In addition to solar products, the "854140" HS6 include some non-solar-related semi-conductor devices as well, such as LED. Our results are highly similar if we use the more detailed "85414020" HS8 code, but we prefer the HS6 code as the HS8 was introduced only in 2009.

Figure 11: 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 5. The outcome variable in all panels is the total value of solar exports from solar firms (with arcsinh 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.

iar pattern, with positive effects in column (1) which are small and insignificant for demand subsidies in column (2) but larger and positive for production and innovation policies (last two columns). Comparing the two rows, we see that, although the qualitative patterns are identical, the ATT effects are about 1.5 times as large when focusing on solar exports instead of all exports. This is consistent with our expectations. Table F.8 in the appendix also shows non-solar exports. The magnitude for the non-solar exports is much smaller than the solar exports in Table 7, which is consistent with our argument.[26] Lastly, we observe a significant, albeit small, increase in the number of exporting firms in treated vs control cities.

[26]There can be effects of solar subsidies on non-solar exports for a number of reasons. First, if the firm faces financial constraints, the solar subsidy can help relieve this and enable greater production and exporting of all goods. Second, if there is a fixed cost to exporting, the greater size of the subsidised firm will help spread this cost over a large number of units.

Table 7: Exports

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Solar export value	3.192***	1.153	4.298***	6.092**
	(1.231)	(1.145)	(1.498)	(2.366)
Export value	2.451**	0.658	3.217**	4.160**
	(1.178)	(1.130)	(1.443)	(2.143)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. Time period for estimation: 2004-2016. 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.

5.5 Impact of Solar Subsidies: Summary

We have documented a set of results that appear consistent with our theoretical model. City-level solar industrial policies do appear to have important effects on the development of the solar industry. First, we find positive effects on all the solar outcomes we have examined: innovation, firm numbers, revenue, production, and exports.

Second, we find that the impact of different types of subsidies also lines up with our model predictions. Demand subsidies have positive although small and statistically insignificant effects. We interpret this as other city-regions in China being able to supply any city with solar panels in response to a policy-driven demand increase. Hence, demand policies have a muted effect on the local industry.

In contrast, production subsidies have larger and significant effects on output (higher capacity, exports, revenues and firm numbers), because they are only given to firms located in the city. Their effect on innovation is consistent with larger firms being able to cover the fixed costs of R&D and also learning-by-doing.

The largest effects come from innovation subsidies. This is unsurprising for innovation outcomes, but it may appear less obvious for variables like production, revenues, or exports. The reason, as noted above, is that in our data the cities who introduce innovation subsidies also introduce production subsidies. Hence, the innovation policy is actually a bundled production and innovation policy. The larger effects imply that this bundle is more effective than a single production subsidy, indicating an additional effect driven by the innovation subsidy.

6 Extensions and Further Robustness Tests

Our data allows us to extend the previous analysis in a number of ways. In this section, we briefly summarise some of these.

6.1 Business Stealing? Cross-city spillovers

To what extent do the positive treatment effects we identify arise from cross-city business stealing? A plausible concern is that the introduction of a solar policy in one city may simply re-allocate activity from non-targeted to the targeted city. These still represent positive effects from the perspective of the local city. However, from the national perspective, if all subsidies do is alter the distribution of solar activity within China achieving no increase in aggregate solar activity, then these are simply beggar-thy-neighbor policies.

On the other hand, there may be positive spillovers. For example, if firms can learn from their neighbors in other cities, then policy-induced innovation or expanded production in one city may increase solar activity in a neighbor.

To investigate these potential effects we have, as usual, to identify who are the cities most "at risk" of business stealing effects. The most obvious group of cities are those who are contiguous to the cities who introduce solar policies. We set up a new set of SDID estimates which use contiguous cities as the treatment group and search for the best synthetic controls amongst the rest of the never-treated cities.

We summarize the results in Appendix Table F.9. Contrary to the business stealing concern, all the ATT effects are positive, rather than negative, rejecting business stealing. As would expect, these indirect effects are all much smaller in magnitude than the direct effects. For example, the ATT for revenue is only a bit more than half (0.62), compared to our main result (an ATT of 1.0). Moreover, the effects are weaker than the direct effect for many outcomes. For example, not only is the production capacity impact only 0.385 compared to 2.098, it is statistically insignificant.

Rather than business stealing, positive spillover effects will magnify the city-level policy impact from a national perspective.

6.2 Pollution

One important outcome is the degree to which industrial policy has helped tackle climate change. Ultimately, the major effect on reducing emissions comes from the aggregate effect on reducing solar prices which helps electricity grids around the world decarbonize. We can look more narrowly, however, at whether industrial subsidies have reduced local pollution in China. Our model suggests that there should be some local impact, as the grid planner switches away from dirty sources of electricity such as coal and into solar power.

To look at this empirically we implement our SDID approach using the amount of particulate matter (PM2.5) in the city's atmosphere as an outcome (see Appendix Table F.10). The results show that there is a negative effect in each column, but this is larger and only statistically significant for demand subsidies. This is the opposite from the other outcomes where production and innovation subsidies dominated but it makes sense, as the demand subsidies work directly to switch the grid planner away from using fossil fuels (like coal) for energy and so reduce local pollution.

6.3 Patent Quality

A concern with patents in the Chinese patent office (SIPO) is that they may be of very low value. We have argued that this is in some ways a strength as it enables us to pick up many of the more minor process innovations that would be missed in say, the US or EU patent offices. Nonetheless, to examine whether our results are driven solely by low value patents we implement several tests.

First, we construct measures of cite-weighted patents, i.e. we weight each patent by the number of patents it receives in the future from all other patents in every patent office in the world. To do this we use the concept of patent families, so we do not double count an invention that is taken out in multiple patent offices (although we weight the single patent family by all citations to every member of that family as is standard in the literature). The results in Table F.17 show that using citation-weighted patents as an outcome gives very similar results to using patent counts as an outcome. The coefficients are very similar in magnitude to the main results exhibit the same qualitative pattern, being uniformly positive, but insignificant for demand policies.

As a second approach to tackling the quality issue, note that SIPO classifies patents into three types: design, utility model and invention. Design patents are considered low value and would not receive protection in the USPTO or EPO. Hence, we would want to see that solar policies stimulated valuable innovations of the invention or utility type. Table 8 implements this test. We first reproduce the results from Table 3 in the first row. Then in the next row, we confine the results to the Design patents. As expected, the policy effects in all columns are small and statistically insignificant for these low value patents. The next row looks at the complement - invention/utility patents. Here we find the usual pattern of results with much larger and significant effects (except for demand, which remains small and insignificant).

The last two rows split the invention/utility patents into solar vs. non-solar patents using technology class codes. We find larger effects on solar patents than on non-solar patents. For example, in column (1) the ATT effect for solar is twice as large as non-solar, and the solar ATT is statistically significant, whereas the effect on the non-solar patent outcome is not.

Table 8: Results by Patent 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	0.515***	0.189	0.857***	1.090**
	(0.168)	(0.210)	(0.216)	(0.358)
• Non-solar patents	0.247	−0.034	0.732***	0.809**
	(0.168)	(0.196)	(0.203)	(0.320)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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.

These results are not only reassuring as an econometric check. They also help to rule out alternative mechanisms. Subsidies create enhanced cash flows for firms, so one concern is that the innovation effects are driven simply from relieving such financial frictions, which are believed to be large for innovation (Arrow, 1972), and a major issue in China (e.g. Song et al. 2011). The fact that we only observe effects for non-trivial, solar innovation and not for more trivial, non-solar innovation suggests financial constrains are not what primarily drives our findings.

6.4 Learning-by-doing Patents

As a further investigation of innovation mechanisms, we used the text of patent abstracts to identify those that were more closely related to learning-by-doing, as opposed to those representing new products or basic science research. We leverage the pioneering work of Liu (2023) who manually read the text of 3,299 Chinese solar patents and classified them into different types. We follow standard text cleaning procedures and train a random forest algorithm on 85% of his data. We use our model to classify the universe of patents filed by ENF solar manufacturers during the full time period of our analysis into patents associated with learning-by-doing and patents that correspond to new products or basic science research. The 15% hold-out sample had a high rate of validation (over 90%).

As illustrated above, our hypothesis is that solar manufacturers will patent certain efficiency improvements that result from learning-by-doing. Thus, we can shed light on the importance of learning-by-doing in driving our results by examining treatment effects for those patents that reflect process improvements.

In Appendix Table F.13, we replicate our results using patents that have learning by doing characteristics. The results follow the same pattern observed for all patents in Table 3. Again, we find no effects for demand subsidies and a clear hierarchy of positive effects where innovation subsidies achieve the greater impact followed by production subsidies. This suggests that learning by doing may have some role in the pattern of results we observe which is something we will investigate further.

6.5 Productivity Analysis

As a further cross-check on using patents as an innovation measure, we turn to an entirely different source of information. Our accounting data from Orbis enables us to construct the inputs to production such as labor and capital. These have many of the concerns that are well discussed in the production function literature (see De Loecker & Syverson 2021, for a survey). We are fortunate, however, to have a direct quantity based measure of output from ENF which means that we can, in principle separate TFPQ from TFPR. Panel A of Table F.14 focuses on the Orbis derived measures which are available through 2020 and Panel B repeats these for the data through 2013 where we also have ENF production. Panel A shows that the treatment effects are smaller for labor and capital than they are for revenues. For example, the ATT for production subsidies is 1.78 for revenues and only 1.45 for labor and 1.25 for capital.

Since the larger impact on revenues could in principle be due to increasing prices as well as increasing quantity of output, Panel B of Table F.14 shows the analogous results over the shorter period. We see that the coefficient on Solar production is actually slightly larger than for revenues (e.g. 2.5 vs. 2.17 in column (3)), suggesting if anything, a small fall in solar prices. Consistent with the longer period results of Panel A, policy effects on inputs are smaller than for outputs, suggesting positive productivity effects.

Overall, Table F.14 suggests that solar subsidies appear to increase not only total activity in a city, but also productivity. This is independent evidence over and above the earlier results from patenting, that the policies stimulated innovation.

6.6 Placebo Tests: Using Non-Solar Patents and GDP per capita as Outcomes

A concern is that there may be other policies (or events) that are introduced at the same time as the solar policies we focus on. For example, maybe a dynamic city government has a raft of policies that raise performance, so are treatment effects are biased upwards. For example, Wei et al. (2023) and Z. Chen et al. (2021) focus on the InnoCom policy that subsidizes all high-tech firms and was expanded after 2008. Although there did not seem to be a bunching of lcoal policies concurrent with solar from the PKULaw data, we can test for these concerns more formally by running a series of placebo tests. In particular, we can examine whether or not the solar policies were associated with an increase in GDP, population, non-solar patenting, etc. If they were, this might reflect other 'hidden policies', driving our results.

Fortunately, when we apply the same synthetic DID method using city-level total patents and GDP per capita, it seems that this is not the case. In theory, solar-specific industrial policies should have minimal impact on the total number of patents, as non-solar patents make up the vast majority. Additionally, these policies are unlikely to significantly affect GDP per capita since the solar industry represents a relatively small portion of the city-level total GDP. Indeed, Tables F.16 and F.18 reveal that there is no significant effect on either total patents or GDP per capita.

6.7 Adding Controls

Our baseline SDID analysis does not control for additional variables, since the city fixed effects should effectively absorb most of the relevant confounders. As a complementary strategy to the previous subsection, we 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 they 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

F.15 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.

6.8 Compositional Changes and Dynamic Effects

In Section 5, we used aggregate event studies to discuss our policies' dynamic effects. While these event studies summarise 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 Appendix Section F.11, 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.[27] 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.[28] Based on this, aggregate event studies using cohorts treated between 2007 and 2013 are reported in Appendix Figures F.1, F.2, F.3, F.4, and F.5. They should be interpreted as the event studies presented in Section 5, 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.[29]

A second approach is to examine an event studies for each individual cohort. These cohort-

[27]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.

[28]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.

[29]The one difference is that the long-term effects of the policy start to stabilise 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.

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 figures are shown in Appendix Section F.11.2. 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, at the end of Appendix Section F.11.2, we also inspect cohort-specific dynamic effects using the 2013 cohort, which was at the end of our previously selected study window. The results, here, are consistent with what we have seen for the 2007 cohort.

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

6.9 Solar Patents Taken out by Non-solar Firms

As noted in Section 3, our city-level measures of the Chinese solar industry's activity are derived by aggregating the outcomes of solar producer firms listed in the ENF register. For some variables, however - specifically, patents and exports - we could also identify city-level activity directly using 'solar'-related classification codes or patent and product descriptions. This strategy has the advantage that it relies less on the ENF data set, but it comes with the cost that these alternative measures may be coarse measures of the relevant industrial activity.

There are a substantial number of solar patents that are taken out by entities outside our dataset such as by 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.

Table F.12 provides a robustness check utilising this alternative strategy by applying the SDID method to city-level total solar patents.[30] 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 Table 8. A possible explanation for this is that the keyword-based identification strategy may capture a host of technologies which support solar technology but are not among the core technologies affected by solar subsidies.

[30]City-level solar patents here are captured 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.

6.10 Magnitudes

We can use the structure of our model to do a more rigorous quantification, but we first present some simple exercises to get an idea of the order of magnitude of benefits compared to the costs of the policies. The ASIE data has information on the total amount of subsidy received by our solar firms. We do not know whether these are all solar related local subsidies, but we can use the amount of subsidies as an outcome variable using the same SDID strategy employed in the rest of the paper.

Table F.19 shows the results. Although they are imprecise, column (1) suggests a significant positive treatment effect of local policies on subsidies received by solar firms, as we would expect. On face value, it implies that that the average subsidy per city per year was around RMB 13.6 million (about US \$2 million). This is almost the same as the average difference in subsidy between all treated and all non-treated cities at the end of the sample period, which is reassuring. If we include an estimate of administrative costs and conservatively apply a heavy 100 % additional deadweight cost for the distortions induced by the policy, this comes to about US\$4.3 million. We estimate that revenue increases on average by RMB 135 million (about US \$19 million). So the benefits seem about 4.4 times the costs.

Of course, this calculations may be missing out on other 'hidden subsidies' that are not captured by the ASIE data which would reduce this benefit-cost ratio. Still, it would take quite a large increase in costs for the policy to have been deemed a failure.

7 Conclusions

In this paper, we have shown how city-level solar supply subsidies (both of production and innovation) increased innovation (as measured by patenting) and production (as measured by number of firms, revenue, panel production capacity and exporting) in treated cities relative to those who do not implement such policies. By contrast, the local effect of demand side subsidies were small and statistically insignificant.

We interpret these effects through the lens of a model whereby production subsidies increase firm size which incentivises them to cover the fixed cost of exporting and R&D. Innovation subsidies which in Chinese cities are always layered on top of production subsidies add to this impact by directly subsidising R&D.

Demand subsidies targeted at encouraging *generation* of solar electricity do not have a sizeable effect on solar production or innovation. We argue this is because the demand stimulus can be met with production supplied from anywhere in China (solar parks and other solar generators were not required to use locally produced solar panels).

We are therefore able to document a link between government support at the early stages of an industry and persistent growth and innovation. This is the central tenet of industrial policy. The fact that we observe this in an industry that is displacing dirty energy generation worldwide magnifies the importance of our finding.

Our results indicate that city-level solar policies helped to drive up not just entry and production but also innovation and exporting. This helped to drive down solar generation costs not just in China but across the world which, in turn, may have helped to encourage global diffusion of solar energy.

What Chinese cities have achieved in the last 20 years using these policies is staggering. Our results represent a “ray of hope” for countries worldwide who are trying to balance the need for more energy to drive economic growth with the the need to drop emissions in order to avoid catastrophic climate change. There is hope not only because citizens everywhere will benefit via diffusion from cheaper solar energy built on the back of Chinese solar policies but also because what China has done can serve as a guide to what might be achieved elsewhere.

The industrial policies pursued in China, in effect, offer a route to renewable energy that is cheap enough to displace dirty sources of energy. This is a route that the US and EU (and many other countries) are also pursuing offering additional hope that we will reach net zero whilst continuing to raise living standards around the world.

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ONLINE APPENDICES

A Institutional Background on China's Industrial Policy towards Solar

In this Appendix we expand on the summary in the main text regarding China's policy support towards solar manufacturing and R&D. This borrows from Ball et al. (2017)'s rich account of China's photovoltaic industry as well as other sources such as T. J. Chen (2016) and Nemet (2019). We outline several features of solar policy support in China. The 5-Year Plans provided national guideline and sectoral industrial policy focus. However, the funding and implementation of these guidelines was mostly carried out at the local level, which generates considerable heterogeneity in policy support towards the solar industry across cities. Measuring industrial policy support is challenging and the Chinese solar industry is no exception. We close this background section by illustrating our novel approach to obtain micro-level measures of policy support towards both solar manufacturing and solar innovation. Our approach is based on the analysis and classification of the policy text of the universe of laws and regulations covering the solar industry during the 2004-2022 period using the PKULaw database.

A.1 Solar PV in the Government's Five-Year Plans

The Chinese government outlines its vision for sectoral industrial policies in its five-year plans. These documents provide national guidance for stakeholders and local implementation what ultimately determines the intensity of policy support. 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, together with other renewable energy sources. 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 feed-in-tariffs and legalized the provision of interest subsidies and tax incentives 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 guided the industry towards more sophisticated R&D spanning the whole solar value chain in later periods.

In 2001, at the start of the Tenth Five-Year Plan for New-and Renewable-Energy-Industry Development, China had no domestic solar photovoltaic industry. This plan was China's first serious attempt to launch renewable energy industries. With the aim of developing a solar supply chain, the State Economic and Trade Commission, encouraged the production of solar cells and modules, with specific targets to be met by the end of the Plan. While innovation appeared as a long-term objective to increase the competitiveness of the national solar industry, the Plan did not specify policy support towards R&D. The Tenth Five-Year Plan period brought considerable growth to the solar industry, exceeding government's expectations.

The Eleventh Five-Year Plan (2006-2010), for the first time, saw the solar industry as an opportunity to attain technological leadership. It 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 panels across the country. This was with the broad objective of strengthening the PV manufacturing supply chain. The Plan included funding for R&D and manufacturing development for the first time, to be generated by renewable energy from local manufacturing by 2010 and technological self-reliance by 2020. The solar industry witnessed exceptional growth during this period. Figure 2, which we construct with our data on the universe of solar manufacturers in China, displays a clear increase in industrial activity, along both production and patenting outcomes. On top of this, in 2006, the Chinese government kick-started its Renewable-Energy Law to sustain and speed the incipient growth of its solar industry. Of course, the 2004-08 period was one of big increases in demand for solar panels 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 Great Recession through many stimulus policies including solar energy through (i) investment in domestic power stations through feed-in-tariffs, (ii) the "Golden Roof" program subsidising home installation of solar panels and (iii) the "Golden Sun" demonstration stations.

With the Twelfth Five-Year Plan (2011-2015), the government kept pushing for solar adoption, supply-chain expansion and indigenous R&D. The 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. There was realisation of over-capacity in NDRC ordinances and pressure for consolidation from 2012, with Suntech and LDK both going bankrupt.

China's Thirteenth Five-Year Plan (2016-2020) again mentions solar as a sector to prioritise through industrial policy support, 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.

A.2 Policy Support Towards Solar Manufacturing

China's national, provincial, and local governments, all provided an array of subsidies to the solar industry. However, the extent and nature of this policy support in China remains a disputed issue, which has reached the international courts.[31] 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 and a rough estimate of its size.

Subsidies to solar manufacturing were managed and allocated by local governments, despite following the national guidance embedded in the Five-Year Plans. The timing, size, and targeting of policy support thus varied significantly depending on the city or region. Local governments often 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 (2015) 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, 2020). Examples include Suntech (PV producer) founded in 2001 and sponsored by the city of Wuji, or LDK (wafer producer) founded in 2005 and sponsored by the city of Xinju.

Subsidies followed a similar structure to that of other sectoral industrial policies in China. At first, they were mostly targeted towards manufacturing. Since 2006, many local governments took advantage of the national legal framework easing policy support for renewable energies and provided generous tax incentives to solar manufacturers. Many city-level governments also offered discounts for land acquisitions and cash investments for struggling solar manufacturers. Moreover, city governments hosting solar-manufacturing clusters within their administrative boundaries, offered additional mechanisms for financial assistance to resident firms. 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 this paper.

[31] 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.

A.3 Policy Support Towards Solar R&D

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, the 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), all contribute, to varying degrees, to crafting energy-policy, and designing industrial and R&D policies targeting the solar industry.

The structure of the Chinese government policy support towards R&D is much more complex than that of policies targeting manufacturing. Government funding for solar innovation encompasses a variety of programs at a range of firms, universities and research institutions, which fund both basic and applied research. As it is the case for manufacturing subsidies, there is a lot of opaqueness around the nature and quantity of public solar R&D expenditure in China. However, Ball et al. (2017) provide some clarity on the government's solar-R&D efforts, constructed from the analysis of public information and interviews with key actors in the Chinese solar industry. [32] The authors estimate a lower bound of $74 million spending in solar R&D during the 2000-2005 period by both the national and local governments. Over the same period, they estimate that total solar R&D (public and private) was around $223 million, implying that about a third of solar R&D was government funded. As it is the case with manufacturing subsidies, there is considerable regional heterogeneity in solar R&D funding, as cities and provinces support local laboratories and research centres dedicated to engineering and technology innovation. The next section explains our approach to measuring local industrial policy support for both solar manufacturing and solar innovation.

[32] In section 2.3 we explain how we provide novel city-level measurement of the government's support towards both solar manufacturing and solar R&D.

B Data

We summarized the rich and original data we have compiled in the main text in 3. Here, we go into more details on the various datasets that we have matched and compiled.

B.1 Solar industrial policy

The main data on industrial policy towards solar manufacturing and installation comes from PKULaw's Laws & Regulations dataset. The Laws & Regulations database 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 pertaining to the solar photovoltaics industry, which start in 2006. 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 inspect the full text of each policy and classify them into subsidies, announcements, poverty alleviation policies, and records. We further classify subsidy policies according to whether they target solar installation, production, or innovation.

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 the remaining new solar companies. Additionally, ENF relies on government organizations and a variety of web-scraping techniques to complete the full list of solar companies. ENF uses automatic scanning to detect company updates, which triggers careful checks from ENF database experts to update manufacturers' information. Finally, ENF automatically scans for signs of companies ceasing their activities. Hence, ENF is able to reasonably capture a snapshot of all 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 gained access to the last edition of 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 and address the remainder of the mismatches. We are left with a sample of 1,718 Chinese solar panel manufacturers, operating at some point between 2004 and 2020, which includes production and capacity data for each manufacturer during the 2004-2013 period.

ENF includes projections of production and capacity in 2014, but we chose not to use this. 2013 is a transition year with some actual and some projected data, so we felt comfortable with using this year. We also checked robustness of the results to ending the sample in 2012.

B.3 Firm counts, entry and exit

The Qichacha platform[33] 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 Hongkong 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.

We still face one limitation when using this approach. The 2013 and 2014 ENF solar manufacturing registers only record firms' English names, which cannot be uniquely matched to the Qichacha platform. We use Google and Baidu to obtain the corresponding Chinese name for the English-name-only firms, allowing us to further identify 462 firms (out of a total of 673 firms without Chinese name in the ENF register).

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

[33] https://www.qcc.com/

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. To understand the nature of the underlying innovation, we classify the patents filed by our sample of manufacturers into several categories. 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, we further classify invention and utility model patents into solar and non-solar patents. Finally, we use text mining techniques to detect "learning-by-doing" (LBD) patents based on the information in the patent abstracts (see next section).

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.[34]

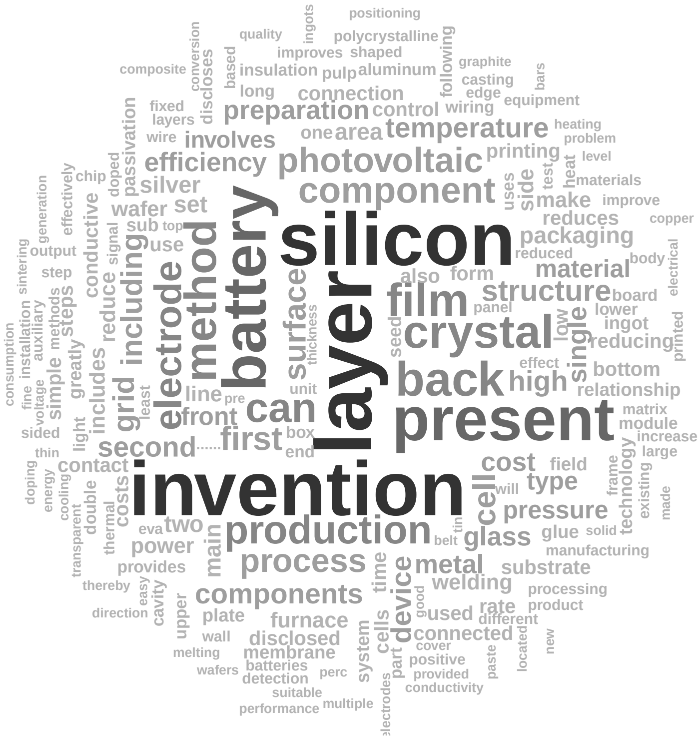
We follow standard text cleaning procedures and train a random forest algorithm on 85% of Liu (2023)'s data. The model classifies the remaining patent abstracts in the hold-out sample with an accuracy of 85-90%, which seems a high rate of validation. We then use our model to classify the universe of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

B.6 Examples of Learning by doing (LBD) patents

Figures B.2 and B.3 offer two additional instances of learning-by-doing patents. Their abstracts highlight the benefits of the current patent for production processes, product quality, and

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

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



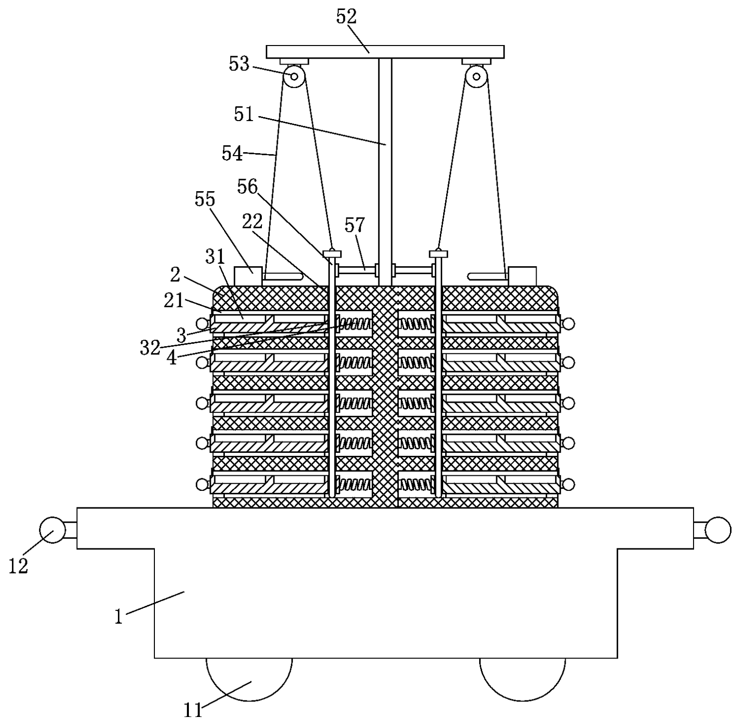
industrial development.

Figure B.4 and B.5 offer two non-learning-by-doing patents. The first non-learning-by-doing patent is a solar-related new product. This type of patent does not refer to firm productivity or process improvement. Therefore, we do not count it as a learning-by-doing patent. The second non-learning-by-doing patent improves the quality of solar cells and involves fundamental chemistry and physics. This type of patent is also unlikely to reflect efficiency improvements driven by increase in production.

B.7 Revenue, Employment and Capital: ORBIS and ASIE data

In order to expand the time horizon of our analysis and estimate long-run effects beyond the effects on production that we calculate using ENF production data, we use Bureau Van Dijk's Orbis dataset, which gives us rich financial data, including total and tangible fixed assets, revenue, employees, and cost of goods sold, throughout the 2004-2020 period. We use the

Figure B.2: Learning-by-doing patent example 1



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.*

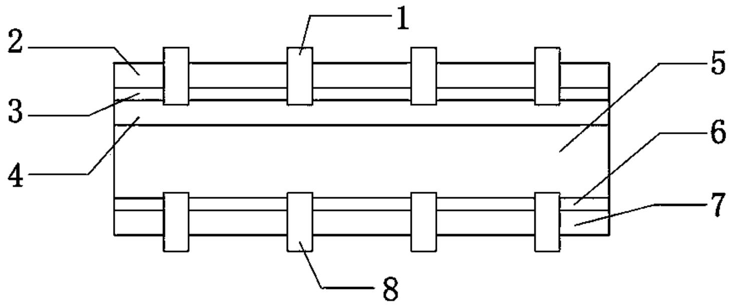
comprehensive firm contact information included in both the Orbis and ENF register datasets to merge the two datasets, and obtain Orbis variables for our sample of solar manufacturers.

We validate the Orbis data making use of the Annual Survey of Industrial Enterprises (ASIE). The Annual Survey of Industrial Enterprises (ASIE), also called as Annual Survey of Industrial Firms (ASIF), is an administrative-level dataset for all large industrial[35] firms in China. The ASIE is only available between 1998 and 2013[36] and the sample of firms included in the survey changes over time. 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

[35]This includes manufacturing, mining, electricity, gas, and water firms

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

Figure B.3: Learning-by-doing patent example 2



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.*

that the Chinese government often uses this dataset to construct official statistics, we use the ASIE to assess the quality of our longer-run Orbis data.

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.[37] 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.6 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. [38]

Broadly, there are three types of missing values for revenues in the Orbis dataset. The first type occurs when we we observe revenue data for the same firm in two different non-consecutive years, but there are missing values for the years in between. In this case, if we were not to interpolate, when aggregating at the city level, we would be assigning a value of 0 for this firm, which would create a false discontinuity in the data. Therefore we use linear imputation

[37] The ASIE and the Qichacha firm registration datasets are of administrative nature, so they share the same standard firm naming system.

[38] 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 and after ASIE became available. This is visible in Figure B.7

to fill these missing values. The second case of missing data occurs when we observe some values for revenue, but we fail to observe data for the first few years in the sample, 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 completely. We checked that the results are robust to just using the non-imputed data and alternative ways of imputation.

B.8 Solar exports volume, value, and prices

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 quantity and unit price, 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 the quantity, value and unit price of exports by ENF solar manufacturers. [39]

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.9 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 total exports and use this to adjust downward the revenues for firms where this is less than 100%. The challenge with this method is that some firms do not export. We make the

[39]Note that for now, we have cleaned and utilise only value information from these.

following three adjustments in these cases. 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, likely because entrants will likely 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 2017-2020.

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 out some of the non-solar activity. Figure B.8, 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.

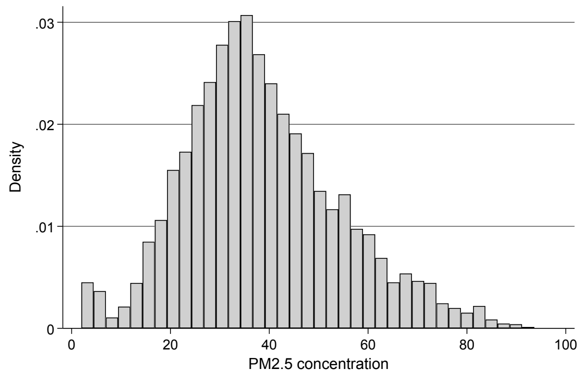
We confirm that our results were robust to various ways of doing these imputations and indeed, even using the unadjusted revenue data (see Table F.7). The main difference is in the precision of the estimates which improves when we deal with these various sources of measurement error.

B.10 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 on this raster 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. These annual city-level observation between 2004 and 2020 are distributed as:

Figure B.9: PM2.5 CONCENTRATION DISTRIBUTION



Notes: The histogram shows the distribution of yearly PM2.5 concentration in 358 Chinese admin2 between 2004 and 2020.

The variable has a less skewed than our other outcome variables which motivates using this variable in levels rather than in an IHS transformed version.

To capture CO_2 emissions, we use the county-level data set of J. 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 CO2 emission for 348 cities from 2004 to 2017. (The data set does not cover cities in the Tibet Autonomous Region.)

B.11 City panel dataset

Out 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. Finally, we calculate a simple average of the price of exports 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.1 reports descriptive statistics for the key variables at the city-level. The full strongly balanced 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.

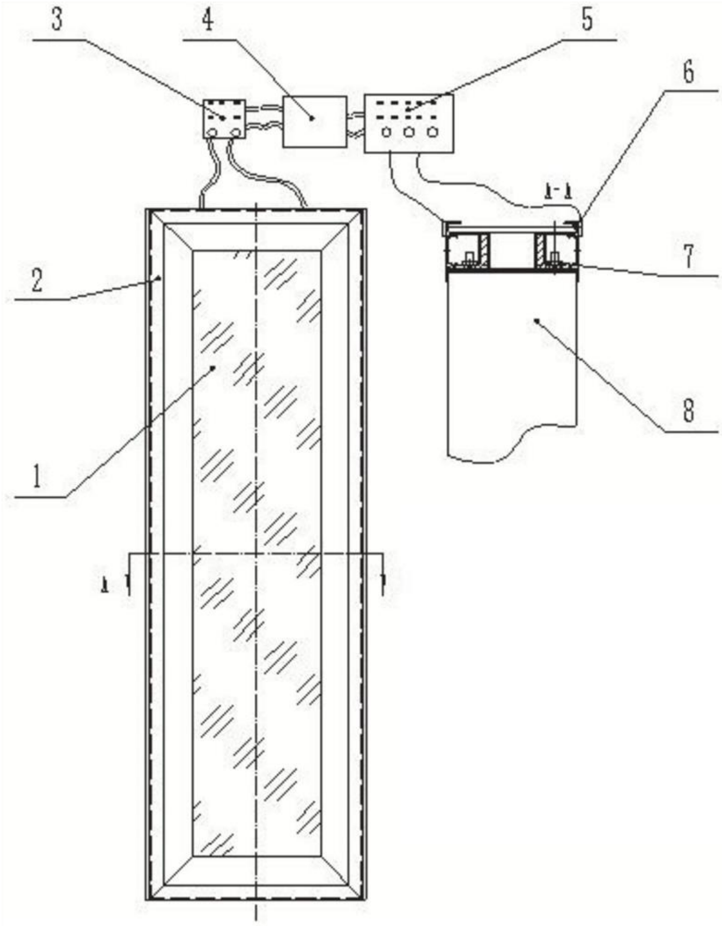
Solar market structure was quite fragmented. For example, in the middle of our sample period in 2012, the top 5 firms had 20.6% of panel production. These were Suntech (5.9%), Yingli (4.5%), Trina (4.2%), Canada Solar (3.7%) and Renesola (2.1%) and

Table B.1: 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
Total export volume of solar firms, millions, 2004-2015	3.18	43.7	4,296
Average export price of solar firms, USD, 2004-2015	9,716	480,762	4,296
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
J. 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.8 for more detail.

Figure B.4: Non-learning-by-doing patent example 1

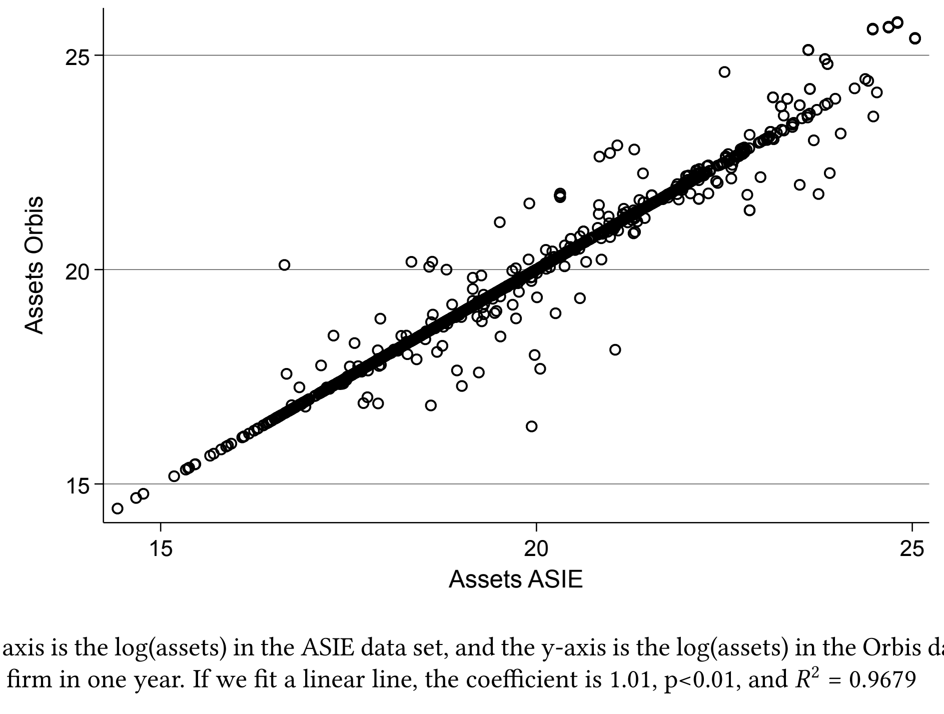


Patent Abstract: This utility model patent relates to a road cliff photovoltaic lighting device, which includes a road cliff stone or road guardrail connected to the outer surface of a photovoltaic component. The photovoltaic component is connected to the inverter and battery through a controller in 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.5: NON-LEARNING-BY-DOING PATENT EXAMPLE 2

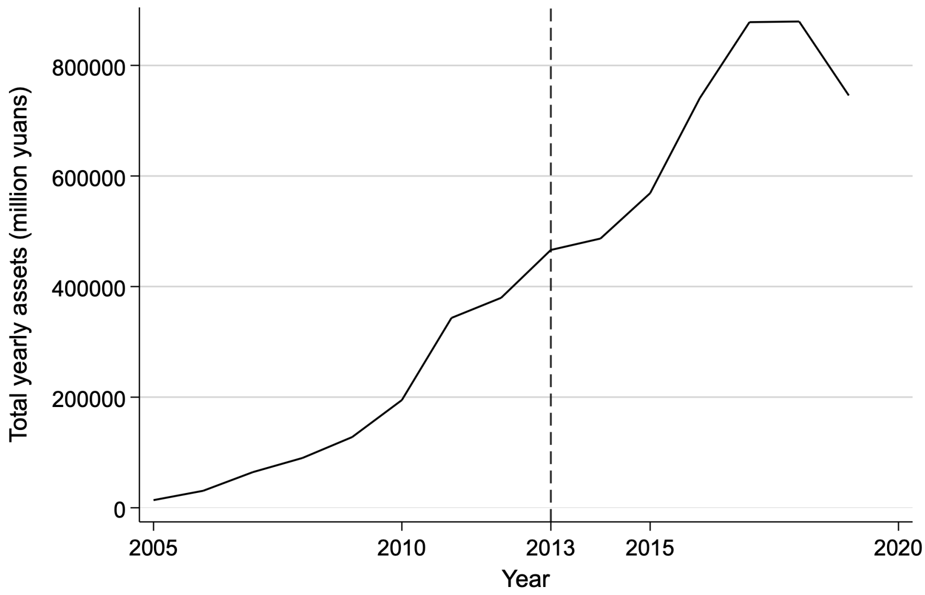
Patent Abstract: The present invention provides a carbon-doped P-type gallium phosphide material, in which carbon is used as the doping element of the P-type gallium phosphide semiconductor material. The preparation method of the material is to use metal organic chemical vapor deposition technology, introduce organic gallium source and phosphorus source into the reaction chamber, let them decompose at high temperature, and react on the surface of the substrate to produce gallium phosphide material. During the generation of gallium phosphide material, carbon impurities are introduced by inputting substances containing carbon elements, or by utilizing carbon atoms generated by the organic gallium source during thermal decomposition. In the present invention, carbon replaces Mg or Zn. Since carbon doping has a small diffusion coefficient and stable properties, highly doped GaP materials can be produced, which are characterized by high efficiency, low diffusion, and high stability.

Figure B.6: VALUE OF FIRM ASSETS IN ORBIS & ASIE



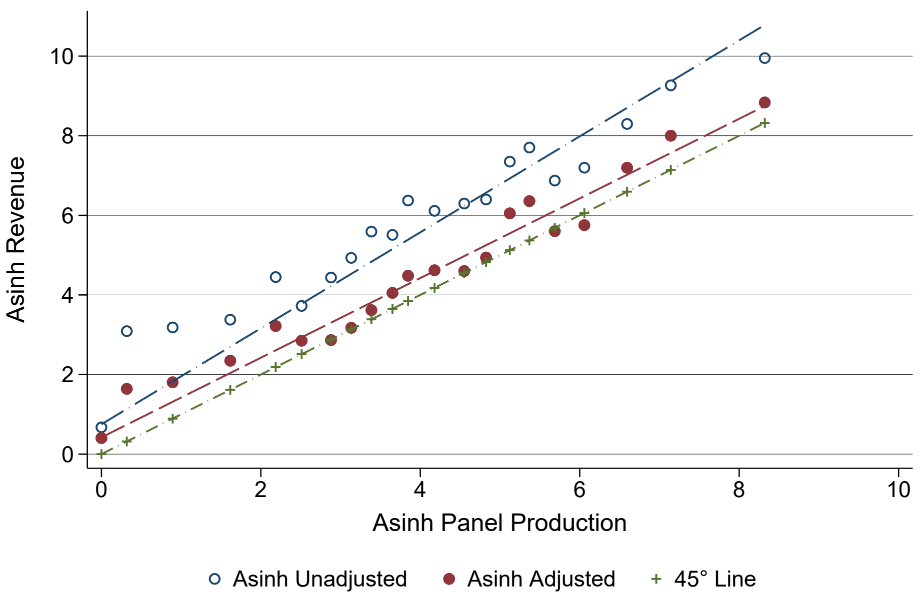
Notes: The axis is the log(assets) in the ASIE data set, and the y-axis is the log(assets) in the Orbis data set. Each point is one firm in one year. If we fit a linear line, the coefficient is 1.01, p<0.01, and R^2 = 0.9679

Figure B.7: Smoothness in Orbis total yearly non-imputed assets



Notes: The time series shows the yearly sum of Chinese solar panel manufacturers' total assets as reported in the Orbis database. The dashed vertical line at 2013 indicates the last year when the ASIE data set is publicly available.

Figure B.8: 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 Theory: Full version of Model

In this Appendix, we provide details of the full model described in the main text. We characterize the determinants of our key endogenous outcomes (innovation, production, revenue, the number of firms and exporting) with respect to exogenous parameters and the three types of solar subsidies (demand, production and innovation) that we analyze. We do not generally have closed form solutions for the endogenous outcomes we wish to model, so to conduct comparative statics we have to calibrate some values and solve the model numerically. We summarize these in subsection 4.4. of the main text. In the next Appendix (D), we consider a simplified closed economy symmetric version of the full model where we can derive closed form analytical solutions. This is what we use in the propositions for subsection 4.5 in the main text.

C.1 The Grid Planner Problem

C.1.1 Demand for Energy Sources

Each region d hosts a representative household that consumes only electricity and a grid planner, who is in charge of installing power plants to provide electricity. One way of expressing this problem, is that the grid planner chooses the electricity mix to maximise the value of the final electricity services that it produces, subject to the prices of final electricity P_d and the price of solar and non-solar electricity P_s and $P_{s'}$ respectively.

$$\max_{e_{d,s},e_{d,s'}} \left(P_d e_d - P_{d,s}e_{d,s} - P_{d,s'}e_{d,s'}\right)$$

$$\text{s.t.} \quad e_d = \left(\kappa_{d,s'}e_{d,s'}^{\rho} + \kappa_{d,s}e_{d,s}^{\rho}\right)^{1/\rho}$$

We can re-express this problem more simply. Because our household consumes electricity only, all of their income will go to the grid planner. Moreover, the production function for electricity services is constant returns to scale. Therefore, the grid planner spends all the income they receive on the production of electricity e_d (zero profits), and the supply of electricity is perfectly elastic, so the price will be pinned down by the production side. The household has a utility function which is strictly increasing in electricity services e_d.

We can therefore rewrite our problem as though the grid-planner uses the full income of households in their area in order to maximise electricity output.

$$\max_{e_{d,s},e_{d,s'}} \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho}\right)^{1/\rho}$$

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

$$\mathcal{L} = \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho}\right)^{\frac{1}{\rho}} - \lambda\left(P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'} - I_d\right)$$

$$\frac{\partial \mathcal{L}}{\partial e_{d,s}} = \frac{1}{\rho} \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho}\right)^{\frac{1}{\rho}-1} \left[\rho k_{d,s} e_{d,s}^{\rho-1}\right] - \lambda P_{d,s} = 0$$

Taking the ratio for $e_{d,s}$ and $e_{d,s'}$ FOCs:

$$\frac{\kappa_{d,s} e_{d,s}^{\rho-1}}{\kappa_{d,s'} e_{d,s'}^{\rho-1}} = \frac{P_{d,s}}{P_{d,s'}}$$

$$e_{d,s} = \left[\frac{P_{d,s}}{P_{d,s'}} \frac{\kappa_{d,s'}}{\kappa_{d,s}}\right]^{\frac{1}{\rho-1}} e_{d,s'}$$

Multiplying by $P_{d,s}$ and adding $P_{d,s'} e_{d,s'}$ on both sides of the equation, we obtain:

$$\underbrace{P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'}}_{= I_d} = \left[P_{d,s}^{\frac{\rho}{\rho-1}} \left(\frac{1}{\kappa_{d,s}}\right)^{\frac{\rho}{\rho-1}} + P_{d,s'}^{\frac{\rho}{\rho-1}} \left(\frac{1}{\kappa_{d,s'}}\right)^{\frac{\rho}{\rho-1}}\right] \left(\frac{\kappa_{d,s'}}{P_{d,s'}}\right)^{\frac{1}{\rho-1}} e_{d,s'}$$

Which simplifies into:

$$I_d = \left[P_{d,s}^{1-\sigma} \kappa_{d,s}^{\sigma} + P_{d,s'}^{1-\sigma} \kappa_{d,s'}^{\sigma}\right] \left[\frac{\kappa_{d,s'}}{p_{d,s'}}\right]^{-\sigma} e_{d,s'}$$

Where $\sigma = \frac{1}{1-\rho}$. Solving for $e_{d,s'}$ and plugging back into the ratio of FOCs for each energy source, we obtain the following expression for $e_{d,s}^*$, our solar installation demand function:

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

C.1.2 Demand for Energy-Sector Manufactured Inputs

In order to meet the optimal demands for energy sources e_s^* and $e_{s'}^*$, the grid-planner has to choose from the available manufactured varieties that aggregate into the final energy output (e.g. the grid planner chooses a set of solar panels to produce a solar park that meets their solar energy output requirements). The choice of manufactured inputs determines the prices P_s and $P_{s'}$. The derivations below are for a planner in any region d. For notational convenience, we omit the d spatial subscript until later in our derivations. A grid-planner can purchase manufactured varieties from any region o, which aggregates using a CES technology:

$$e_s = \left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}}$$

The problem of optimally delivering e_s^* is a new constrained optimisation problem, nested in the above, which we express as follows:

$$\min_{q_o(\omega)} \left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega) p_{o,s}(\omega) \right)$$

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

Note that the manufactured varieties in this problem are only sector s varieties (i.e. to generate solar output the planner only uses solar panels and not manufactured varieties belonging to other energy sectors). Below we detail all solution steps.

$$\mathcal{L} = -\left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega) p_{o,s}(\omega) \right) - \lambda \left[\left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}} - e_s^* \right]$$

The FOCs (as many as solar panel varieties available across regions) are:

$$\frac{\partial \mathcal{L}}{\partial q_{o,s}(\omega)} = -p_{o,s}(\omega) - \lambda \frac{\sigma_s}{\sigma_s - 1} \left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{1}{\sigma_s - 1}} \frac{\sigma_s - 1}{\sigma_s} q_{o,s}(\omega)^{-\frac{1}{\sigma_s}} = 0$$

Which simplify as:

$$p_{o,s}(\omega) = -\lambda \left(\sum_o \int_{\omega \in \Omega_{0,s}} q_{o,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{1}{\sigma_s - 1}} q_{o,s}(\omega)^{-\frac{1}{\sigma_s}}$$

We can take the ratio of two FOC for two different varieties (within the solar sector), denoting the varieties arbitrarily as 1 and 2:

$$\frac{p_{o,s}(\omega_1)}{p_{o,s}(\omega_2)} = \frac{q_{o,s}(\omega_1)^{-\frac{1}{\sigma_s}}}{q_{o,s}(\omega_2)^{-\frac{1}{\sigma_s}}}$$

This can be expressed as:

$$\frac{q_{o,s}(\omega_1)}{q_{o,s}(\omega_2)} = \left(\frac{p_{o,s}(\omega_1)}{p_{o,s}(\omega_2)}\right)^{-\sigma_s}$$

Which is equivalent to:

$$p_{o,s}(\omega_1)\, q_{o,s}(\omega_1) = \left(p_{o,s}(\omega_1)\right)^{1-\sigma_s} \left(p_{o,s}(\omega_2)\right)^{\sigma_s} q_{o,s}(\omega_2)$$

We now take the integral with respect to ω_1 and sum up across all origin regions o :

$$\underbrace{\sum_o \int_{\omega_1} p_{o,s}(\omega_1)\, q_{o,s}(\omega_1)\, d\omega_1}_{=E_s} = \sum_o \int_{\omega_1} \left(p_{o,s}(\omega_1)\right)^{1-\sigma_s} \left(p_{o,s}(\omega_2)\right)^{\sigma_s} q_{o,s}(\omega_2)\, d\omega_1$$

$$E_s = \left(p_{o,s}(\omega_2)\right)^{\sigma_s} q_{o,s}(\omega_2) \sum_o \int_{\omega_1} \left(p_{o,s}(\omega_1)\right)^{1-\sigma_s} d\omega_1$$

Where E_s is the expenditure on the solar sector (in any region d, where the spatial subscript has been omitted). We can generalise for any variety ω and express the demand function as:

$$q_{o,s}(\omega) = \frac{\left(p_{o,s}(\omega)\right)^{-\sigma_s}}{(P_s)^{1-\sigma_s}} E_s$$

Where P_s is the price index for solar that region d faces. Replacing $E_s = e_s^* P_s$, we obtain our expression for the demand for each panel variety:

$$q_{o,s}(\omega) = \frac{\left(p_{o,s}(\omega)\right)^{-\sigma_s}}{(P_s)^{1-\sigma_s}} e_s^* P_s = \left(\frac{p_{o,s}(\omega)}{P_s}\right)^{-\sigma_s} e_s^* = \left(\frac{p_{o,s}(\omega)}{P_s}\right)^{-\sigma_s} \left(\frac{\kappa_s}{P_s}\right)^{\sigma} \frac{I}{\kappa_{s'}^{\sigma} P_{s'}^{1-\sigma} + \kappa_s^{\sigma} P_s^{1-\sigma}}$$

This applies to any region d, so we now generalise notation:

$$q_{od,s}(\omega) = \left(\frac{p_{od,s}(\omega)}{P_{d,s}}\right)^{-\sigma_s} \left(\frac{\kappa_{d,s}}{P_{d,s}}\right)^{\sigma} \frac{I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}}$$

C.2 The Manufacturer Problem

Each region o has a continuum of potential manufacturing firms i in each sector s, which operate under monopolistic competition.

C.2.1 Manufacturing Technology

Firm i, who produces intermediate goods for electricity sector s (e.g. solar panels for the solar electricity sector), uses effective units of labour $L_{o,s,i}$, with unit cost w_o. Firm subscripts i are dropped from now onwards for notational simplicity. To operate, a firm must pay a sunk cost $w_o f^e_{o,s}$, which we express in terms of effective units of labour. This sunk cost could be understood as the cost incurred in initial product definition and development. Upon paying the entry cost, the firm draws an initial level of productivity φ, from a Pareto productivity distribution, whose cumulative distribution function is:

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

That is, once a firm decides which product or variety to produce, it learns about its productivity. To produce $q_{o,s}(\varphi)$ units of a variety, a firm requires an amount of effective labor $l_{o,s} = f_{o,s} + \frac{q_{o,s}}{\varphi}$, where $f_{o,s}$ is the fixed cost of production, expressed in terms of effective units of labour, and $\frac{1}{\varphi}$ is the marginal cost of production.

Technological Upgrading/Innovation:

Upon observing its initial productivity φ, a firm can upgrade its technology (innovate), which increases the fixed cost of production by an additional $f^i_{o,s}$, but reduces its marginal cost to $\frac{1}{\xi_{o,s}\varphi}$, with $\xi_{o,s} > 1$

C.2.2 Firm Profits

A firm can make profits by selling the manufactured intermediate goods to grid planners in d regions. Among these regions there are Chinese second administrative level regions ('cities') and a foreign region $\tilde{d}$. We assume there are no market access fixed cost within China. On the other hand, a firm must pay an international exporting fixed cost $w_o f^x_{o,\tilde{d},s}$ if it wants to serve a representative foreign grid planner, whose demand function for energy sources coincides with that of each of the regional planners within China.

Trade (intra-China and international) is subject to iceberg trade costs such that in order for $q_{od,s}(\varphi)$ to arrive to destination d, a firm in o needs to produce $\tau_{od,s} q_{od,s}(\varphi)$ units of the variety, with $\tau_{od,s} \geq 1$. Trade costs are normalised, such that they are equal to 1 if and only if $d = o$. Firm profits after drawing a productivity φ are therefore:

$$\pi_{o,s}(\varphi) = \sum_{d} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} q_{od,s}(\varphi)}{\xi_{o,s}\varphi} \right\} - \mathbb{1}[d = \tilde{d}] \left(w_o f^x_{o,\tilde{d},s} \right) - w_o f_{o,s}$$

Where $\mathbb{1}[d = \tilde{d}]$ takes the value 1 if a firm decides to serve foreign destination $\tilde{d}$ and 0 otherwise. Note that if a firm decides to export, the summation above is over Chinese regions and the foreign destination $\tilde{d}$, while if a firm chooses not to, it sums over national regions and does not pay the exporting fixed cots. Similarly, $\xi_{o,s}$ is greater than 1 if a firm decides to innovate, and 1 otherwise.

Recall that the demand function for each manufactured variety, with our generalised notation, is:

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

Taking the FOC of firm profits with respect to $p_{od,s}(\varphi)$, and replacing the optimal $q_{od,s}(\omega)$ above, we obtain:

$$\frac{\partial \pi_{o,s}(\varphi)}{\partial p_{od,s}(\varphi)} = (1-\sigma_s) \frac{\left(p_{od,s}(\varphi)\right)^{-\sigma_s}}{\left(P_{d,s}\right)^{1-\sigma_s}} E_{d,s} + \frac{w_o \tau_{od,s}}{\xi_{o,s}\varphi} \sigma_s \frac{\left(p_{od,s}(\varphi)\right)^{-\sigma_s-1}}{\left(P_{d,s}\right)^{1-\sigma_s}} E_{d,s} = 0$$

Which simplifies to:

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

Thus, the optimal price is a constant markup over marginal cost, where the exporting and innovation decisions change the marginal cost of production. 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.

Domestic market only using old technology:

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

Domestic and foreign market using old technology:

$$\pi_{o,s}(\varphi) = \sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s}$$

Domestic market only using new technology:

$$\pi_{o,s}(\varphi) = \sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} - w_o f_{o,s}$$

Domestic and foreign market using new technology:

$$\pi_{o,s}(\varphi) = \sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s}$$

Assuming that the productivity thresholds governing these decisions are such that a firm does not innovate without exporting internationally first, firm optimal profits are:

$$\begin{aligned} \Pi_{o,s}(\varphi) = \max \Bigg\{ & \sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f_{o,s}, \\ & \sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s}, \\ & \sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s} \Bigg\} \end{aligned}$$

C.2.3 Productivity Thresholds

We now calculate the productivity cutoffs that determine firms decisions to i) stay in the market after drawing a productivity, ii) access the international market $\tilde{d}$, and iii) innovate.

Domestic market exit threshold:

We define $\varphi^*_{oo,s}$ as the domestic market exit productivity threshold. This is the productivity that generates zero profits from serving the domestic market only.

$$\sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\varphi^*_{oo,s}} \right)^{1-\sigma_s} \right\} - w_o f_{o,s} = 0$$

That is,

$$\varphi^*_{oo,s} = \left(\sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{w_o f_{o,s}} \left(\frac{w_o \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \right\} \right)^{\frac{1}{1-\sigma_s}}$$

Exporting threshold:

Let $\varphi^*_{o\tilde{d},s}$ describe the productivity level which makes a firm earn zero profits from exporting to foreign country $\tilde{d}$, and therefore indifferent between serving $\tilde{d}$ or limiting its supply to the domestic market. We also assume that the marginal exporting firm is using the old technology. The extra profits from serving $\tilde{d}$ are:

$$\pi_{o\tilde{d},s} = \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \left(\frac{w_o \tau_{o\tilde{d},s}}{\varphi} \right)^{1-\sigma_s} - w_o f^x_{o,\tilde{d},s}$$

$\varphi^*_{o\tilde{d},s}$ is the productivity level φ such that $\pi_{o\tilde{d},s}(\varphi) = 0$. That is:

$$\begin{aligned}
\frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \left(\frac{w_o \tau_{o\tilde{d},s}}{\varphi^*_{o\tilde{d},s}} \right)^{1-\sigma_s} &= w_o f^x_{o,\tilde{d},s} \\
\Rightarrow \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o^{\sigma_s} \sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \left(\frac{\tau_{o\tilde{d},s}}{\varphi^*_{o\tilde{d},s}} \right)^{1-\sigma_s} &= f^x_{o,\tilde{d},s} \\
\Rightarrow \frac{1}{f^x_{o,\tilde{d},s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o^{\sigma_s} \sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \tau^{1-\sigma_s}_{o\tilde{d},s} &= \left(\varphi^*_{o\tilde{d},s} \right)^{1-\sigma_s}
\end{aligned}$$

Therefore:

$$\varphi^*_{o\tilde{d},s} = \frac{\tau_{o\tilde{d},s}}{P_{\tilde{d},s}} \left(\frac{E_{\tilde{d},s}}{f^x_{o,\tilde{d},s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o^{\sigma_s} \sigma_s^{\sigma_s}} \right)^{\frac{1}{1-\sigma_s}}$$

Innovation threshold:

Let $\varphi^i_{od,s}$ be the productivity level which makes a firm indifferent between upgrading its technology or not. We define profits using the old technology as low productivity profits, or $\pi_{o,s,l}$ and profits using the new technology as high productivity profits, or $\pi_{o,s,h}$. We assume that the marginal innovator is already exporting to the international market $\tilde{d}$.

$$\pi_{o,s,l} = \sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\varphi} \right)^{1-\sigma_s} \right\} + \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \left(\frac{w_o \tau_{o\tilde{d},s}}{\varphi} \right)^{1-\sigma_s} - \\
- w_o f^x_{o,\tilde{d},s}$$

$$\pi_{o,s,h} = \sum_{d\neq\tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} + \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{\tilde{d},s}}{(P_{\tilde{d},s})^{1-\sigma_s}} \left(\frac{w_o \tau_{o\tilde{d},s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} -$$
$$- w_o f^x_{o,\tilde{d},s} - w_o f_{o,s}$$

$\varphi^i_{od,s}$ therefore fulfils:

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

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

$$\Rightarrow \sum_d \frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{w_o f_{o,s}} \left(\frac{w_o \tau_{od,s}}{P_{d.s}} \right)^{1-\sigma_s} = \left(\varphi^i_{od,s}\right)^{1-\sigma_s}$$

The innovation threshold is therefore:

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

Where recall, from the grid planner problem, we obtained:

$$E_{d,s} = \frac{I_d P_{d,s}^{1-\sigma}}{\left(\frac{\kappa_{d,s'}}{\kappa_{d,s}}\right)^{\sigma} P_{d,s'}^{1-\sigma} + P_{d,s}^{1-\sigma}}$$

In order to express the exporting and innovation thresholds as a function of the exit threshold, it is useful to regroup terms in each expression as follows (where we have removed the sectoral subscript s to simplify notation):

$$\varphi^*_o = \left(\frac{(\sigma - 1)^{\sigma - 1}}{\sigma^\sigma w_o^\sigma} \right)^{\frac{1}{1-\sigma}} \left(\frac{1}{f_o} \right)^{\frac{1}{1-\sigma}} \left\{ \sum_{d\neq\tilde{d}} E_d \left(\frac{\tau_{od}}{P_d} \right)^{1-\sigma} \right\}^{\frac{1}{1-\sigma}}$$

$$\varphi^*_{o\tilde{d}} = \left(\frac{(\sigma - 1)^{\sigma - 1}}{\sigma^\sigma w_o^\sigma} \right)^{\frac{1}{1-\sigma}} \left(\frac{1}{f^x_{o\tilde{d}}} \right)^{\frac{1}{1-\sigma}} \left\{ E_{\tilde{d}} \left(\frac{\tau_{o\tilde{d}}}{P_{\tilde{d}}} \right)^{1-\sigma} \right\}^{\frac{1}{1-\sigma}}$$

$$\varphi_o^i = \left(\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma w_o^\sigma}\right)^{\frac{1}{1-\sigma}} \left(\frac{1-\xi_o^{1-\sigma}}{\xi_o^{1-\sigma}}\right)^{\frac{1}{1-\sigma}} \left(\frac{1}{\eta_o f_o}\right)^{\frac{1}{1-\sigma}} \left\{\sum_d E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}\right\}^{\frac{1}{1-\sigma}}$$

We can now express the exporting and productivity thresholds as a function of the exit threshold:

$$\varphi_{o\tilde{d}}^* = \varphi_o^* \left(\frac{f_o}{f_{o\tilde{d}}^x}\right)^{\frac{1}{1-\sigma}} \left\{\frac{E_{\tilde{d}}\left(\frac{\tau_{o\tilde{d}}}{P_{\tilde{d}}}\right)^{1-\sigma}}{\sum_{d\neq\tilde{d}} E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}}\right\}^{\frac{1}{1-\sigma}}$$

$$\varphi_o^i = \varphi_o^* \left(\frac{1-\xi_o^{1-\sigma}}{\eta_o \xi_o^{1-\sigma}}\right)^{\frac{1}{1-\sigma}} \left\{\frac{\sum_d E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}}{\sum_{d\neq\tilde{d}} E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}}\right\}^{\frac{1}{1-\sigma}}$$

C.3 Industry Equilibrium

In equilibrium, grid-planners maximise utility from electricity services, manufacturers maximise profits, and labor demand equals labor supply in each region.

To determine the equilibrium price indices, number of firms, aggregate production and revenue, and mass of exporters and innovators in each region, we impose a free entry condition.

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

$$w_o f_{o,s}^e = \left(1 - G\left[\varphi_{oo,s}^*\right]\right) \mathbb{E}\left[\pi \mid \varphi > \varphi_{oo,s}^*\right] \tag{9}$$

We can express the above condition as follows:

$$\begin{aligned} w_o f_{o,s}^e = &\left(G\left[\varphi_{o\tilde{d},s}^*\right] - G\left[\varphi_{oo,s}^*\right]\right) \mathbb{E}\left[\pi_{o,s} \mid \varphi_{o\tilde{d},s}^* > \varphi > \varphi_{oo,s}^*\right] + \\ + \left(G\left[\varphi_{od,s}^i\right] - G\left[\varphi_{o\tilde{d},s}^*\right]\right) \mathbb{E}\left[\pi_{o,s} \mid \varphi_{od,s}^i > \varphi > \varphi_{o\tilde{d},s}^*\right] &+ \left(1 - G\left[\varphi_{od,s}^i\right]\right) \mathbb{E}\left[\pi_{o,s} \mid \varphi > \varphi_{od,s}^i\right] = \\ = &\int_{\varphi_{oo,s}^*}^{\varphi_{od,s}^*} \pi_{o,s}(\varphi) g(\varphi) d\varphi + \int_{\varphi_{od,s}^*}^{\varphi_{od,s}^i} \pi_{o,s}(\varphi) g(\varphi) d\varphi + \int_{\varphi_{od,s}^i}^{\infty} \pi_{o,s}(\varphi) g(\varphi) d\varphi \end{aligned}$$

Replacing the expression for firm profits for reach range of productivities and the expression for the Pareto distribution function we obtain the following:

$$\frac{w_o f^e_{o,s}}{\theta_s b^{\theta_s}_{o,s}} = \int_{\varphi^*_{o,s}}^{\varphi^*_{od,s}} \left(\sum_{d\neq\tilde{d}} \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{\left(P_{d,s}\right)^{1-\sigma_s}} \left(w_o \tau_{od,s}\right)^{1-\sigma_s} \varphi^{\sigma_s-\theta_s-2} \right) d\varphi - \int_{\varphi^*_{oo,s}}^{\varphi^i_{od,s}} \left(w_o f_{o,s} \varphi^{-\theta_s-1}\right) d\varphi$$

$$+ \int_{\varphi^*_{od,s}}^{\varphi^i_{od,s}} \left(\sum_{d} \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{\left(P_{d,s}\right)^{1-\sigma_s}} \left(w_o \tau_{od,s}\right)^{1-\sigma_s} \varphi^{\sigma_s-\theta_s-2} \right) d\varphi - \int_{\varphi^*_{od,s}}^{\infty} \left(w_o f^x_{o,\tilde{d},s} \varphi^{-\theta_s-1}\right) d\varphi$$

$$+ \int_{\varphi^i_{od,s}}^{\infty} \left(\sum_{d} \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{\left(P_{d,s}\right)^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s}}\right)^{1-\sigma_s} \varphi^{\sigma_s-\theta_s-2} \right) d\varphi - \int_{\varphi^i_{od,s}}^{\infty} \left(w_o f_{o,s} \varphi^{-\theta_s-1}\right) d\varphi$$

Notice that the exit, exporting, and innovation productivity thresholds satisfy the following:

$$\left(\varphi^*_{oo,s}\right)^{1-\sigma_s} w_o f_{o,s} = \sum_{d\neq\tilde{d}} \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}} E_{d,s} \left(\frac{w_o \tau_{od,s}}{P_{d,s}}\right)^{1-\sigma_s}$$

$$\left(\varphi^i_{o,s}\right)^{1-\sigma_s} \frac{w_o f_{o,s}}{1-\xi^{1-\sigma_s}_{o,s}} = \sum_{d} \frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}} E_{d,s} \left(\frac{w_o \tau_{od,s}}{\xi_{o,s} P_{d,s}}\right)^{1-\sigma_s}$$

$$\left(\varphi^*_{oo,s}\right)^{1-\sigma_s} - \frac{1\xi^{1-\sigma_s}_{o,s}}{1-\xi^{1-\sigma_s}_{o,s}} \left(\varphi^i_{o,s}\right)^{1-\sigma_s} = -\frac{f^x_{o\tilde{d},s}}{f_{o,s}} \left(\varphi^*_{o\tilde{d},s}\right)^{1-\sigma_s}$$

Replacing these equations into the above expression for the free entry condition, the latter simplifies to:

$$f^e_{o,s} \frac{\sigma_s-\theta_s-1}{\sigma_s-1} = \left(\frac{\sigma_s-\theta_s-1}{\sigma_s-1} - \right) \left(\frac{b_{o,s}}{\varphi^i_{o,s}}\right)^{\theta_s} f_{o,s} - \left(\frac{b_{o,s}}{\varphi^*_{o\tilde{d},s}}\right)^{\theta_s} f^x_{o\tilde{d},s} - \left(\frac{b_{o,s}}{\varphi^*_{oo,s}}\right)^{\theta_s} f_{o,s} \tag{10}$$

Now, replacing the exporting and innovation thresholds with their expression as a function of the exit threshold we obtain the following expression for the exit threshold as a function of fundamentals and price indices:

$$\left(\varphi^*_{o,s}\right)^{\theta} = \frac{f_{o,s}}{f^e_{o,s}} b^{\theta}_{o,s} \frac{\sigma_s-1}{\sigma_s-\theta_s-1} \left\{ \left(\frac{\sigma_s-\theta_s-1}{\sigma_s-1} - \eta_{o,s}\right) \left(\frac{1-\xi^{1-\sigma_s}_{o,s}}{\eta_{o,s}\xi^{1-\sigma_s}_{o,s}}\right)^{\frac{\theta_s}{\sigma_s-1}} \Phi^{-\theta_s}_{o,s} - \left(\frac{f^*_{o\tilde{d},s}}{f_{o,s}}\right)^{\frac{1-\sigma_s+\theta_s}{1-\sigma_s}} \Theta^{-\theta_s}_{o,s} - 1 \right\}$$

Where

$$\Phi_{o,s} = \left\{ \frac{\sum_d E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}}{\sum_{d\neq\tilde{d}} E_d \left(\frac{\tau_{od}}{P_d}\right)^{1-\sigma}} \right\}^{\frac{1}{1-\sigma}} = \left\{ \frac{\sum_d \frac{\kappa^{\sigma}_{d,s} \tau^{1-\sigma_s}_{od,s} I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}}}{\sum_{d\neq\tilde{d}} \frac{\kappa^{\sigma}_{d,s} \tau^{1-\sigma_s}_{od,s} I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}}} \right\}^{\frac{1}{1-\sigma}}$$

$$\Theta_{o,s} = \left\{ \frac{E_{\tilde{d}} \left(\frac{\tau_{o\tilde{d}}}{P_{\tilde{d}}} \right)^{1-\sigma}}{\sum_{d \neq \tilde{d}} E_d \left(\frac{\tau_{od}}{P_d} \right)^{1-\sigma}} \right\}^{\frac{1}{1-\sigma}} = \left\{ \frac{\sum_d E_d \left(\frac{\tau_{od}}{P_d} \right)^{1-\sigma}}{\sum_{d \neq \tilde{d}} E_d \left(\frac{\tau_{od}}{P_d} \right)^{1-\sigma}} - 1 \right\}^{\frac{1}{1-\sigma}} = \left(\Phi^{1-\sigma} - 1 \right)^{\frac{1}{1-\sigma}}$$

Replacing this expression for the exit threshold in the zero-profit condition that defines it, we get a system of equations (one for each domestic region d and sector s), which determines the price indices:

$$\sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{w_o f_{o,s} \sigma_s^{\sigma_s}} \frac{\kappa_{d,s}^{\sigma} I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}} \left(w_o \tau_{od,s} \right)^{1-\sigma_s} \right\} =$$

$$\left(\frac{f_{o,s}}{f_{o,s}^e} b_{o,s}^{\theta_s} \frac{\sigma_s - 1}{\sigma_s - \theta_s - 1} \left\{ \left(\frac{\sigma_s - \theta_s - 1}{\sigma_s - 1} - \eta_{o,s} \right) \left(\frac{1 - \xi_{o,s}^{1-\sigma_s}}{\eta_{o,s} \xi_{o,s}^{1-\sigma_s}} \right)^{\frac{\theta_s}{\sigma_s - 1}} \Phi^{-\theta_s} - \left(\frac{f_{o\tilde{d},s}^*}{f_{o,s}} \right)^{\frac{1-\sigma_s+\theta_s}{1-\sigma_s}} \Theta^{-\theta_s} - 1 \right\} \right)^{\frac{1-\sigma_s}{\theta_s}}$$

Note that if there are no exports the exit threshold simplifies to:

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

C.4 Aggregate variables

In this section we derive expressions for some of our remaining aggregate (city-level) variables of interest.

C.4.1 Mass of firms

The price index in each region d for each sector s satisfies:

$$P_{d,s}^{(1-\sigma_s)} = \sum_{o \neq \tilde{d}} \int_0^{M_{od,s}} p_{od,s}(v)^{1-\sigma_s} dv \tag{11}$$

Note that foreign firms do not serve the domestic market, so the price aggregation is only over domestic suppliers. Also note that firms that are active serve every regional market within China. We can express it as follows:

$$P_{d,s}^{(1-\sigma_s)} = \sum_{o\neq\tilde{d}} M_{od,s} \int_{\varphi^*_{oo,s}}^{\infty} p_{od,s}(\varphi)^{1-\sigma_s} \frac{g(\varphi)}{1-G(\varphi^*_{oo,s})} d\varphi = \sum_{o\neq\tilde{d}} M_{od,s} \int_{\varphi^*_{oo,s}}^{\infty} p_{od,s}(\varphi)^{1-\sigma_s} \theta_s (\varphi^*_{oo,s})^{\theta_s} \varphi^{-\theta_s-1} d\varphi$$

$$= \sum_{o\neq\tilde{d}} M_{od,s}\theta_s(\varphi^*_{oo,s})^{\theta_s} \left(\int_{\varphi^*_{oo,s}}^{\varphi^i_{od,s}} p_{od,s}(\varphi)^{1-\sigma_s} \varphi^{-\theta_s-1} d\varphi + \int_{\varphi^i_{od,s}}^{\infty} p_{od,s}(\varphi)^{1-\sigma_s} \varphi^{-\theta_s-1} d\varphi \right)$$

$$= \sum_{o\neq\tilde{d}} M_{od,s}\theta_s(\varphi^*_{oo,s})^{\theta_s} \left(\int_{\varphi^*_{oo,s}}^{\varphi^i_{od,s}} \left(\frac{\sigma_s}{\sigma_s-1} \frac{w_o\tau_{od,s}}{\varphi} \right)^{1-\sigma_s} \varphi^{-\theta_s-1} d\varphi + \int_{\varphi^i_{od,s}}^{\infty} \left(\frac{\sigma_s}{\sigma_s-1} \frac{w_o\tau_{od,s}}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \varphi^{-\theta_s-1} d\varphi \right)$$

Integrating and simplifying, we obtain:

$$P_{d,s}^{(1-\sigma_s)} = \sum_{o\neq\tilde{d}} \frac{M_{od,s}\theta_s}{\sigma_s-\theta_s-1} \left(\varphi^*_{oo,s}\right)^{\theta_s} \left(\frac{w_o\tau_{od,s}\sigma_s}{\sigma_s-1} \right)^{1-\sigma_s} \left(\frac{\xi_{o,s}^{1-\sigma_s}-1}{\xi_{o,s}^{1-\sigma_s}} \left(\varphi^i_{od,s}\right)^{\sigma_s-\theta_s-1} - \left(\varphi^*_{oo,s}\right)^{\sigma_s-\theta_s-1} \right)$$

The mass of active firms in each region is related to the mass of entrants in each region in the following way:

$$M_{od,s} = \left(1 - G\left(\varphi^*_{oo,s}\right)\right) M^e_{o,s} = \frac{\left(b_{o,s}\right)^{\theta_s}}{\left(\varphi^*_{oo,s}\right)^{\theta_s}} M^e_{o,s} \tag{12}$$

The expression for the price index therefore becomes:

$$P_{d,s}^{(1-\sigma_s)} = \sum_{o\neq\tilde{d}} \frac{b_{o,s}^{\theta_s} M^e_{o,s}\theta_s}{\sigma_s-\theta_s-1} \left(\frac{w_o\tau_{od,s}\sigma_s}{\sigma_s-1} \right)^{1-\sigma_s} \left(\frac{\xi_{o,s}^{1-\sigma_s}-1}{\xi_{o,s}^{1-\sigma_s}} \left(\varphi^i_{od,s}\right)^{\sigma_s-\theta_s-1} - \left(\varphi^*_{oo,s}\right)^{\sigma_s-\theta_s-1} \right)$$

We thus obtain an expression relating the mass of entrants, the price index and the exit threshold:

$$P_{d,s}^{(1-\sigma_s)} = \sum_{o\neq\tilde{d}} \frac{b_{o,s}^{\theta_s} M^e_{o,s}\theta_s}{\sigma_s-\theta_s-1} \left(\frac{w_o\tau_{od,s}\sigma_s}{\sigma_s-1} \right)^{1-\sigma_s} (\varphi^*_o)^{\sigma_s-\theta_s-1} \left(\Phi^{\sigma_s-\theta_s-1} \eta_o^{\frac{\sigma_s-\theta_s-1}{\sigma_s-1}} \left(\frac{\xi_o^{1-\sigma_s}}{\xi_o^{1-\sigma_s}-1} \right)^{\frac{\theta_s}{1-\theta_s}} - 1 \right)$$

C.4.2 Production

We can define aggregate city-level production for city o as:

$$
\begin{aligned}
Q_o &= \sum_d \int_{\omega\in\Omega_{od,s}} q_{od,s}(\omega)d\omega = \sum_d \int_0^{M_{od,s}} q_{od,s}(v)dv \\
&= \sum_{d\neq\tilde d} M_{od,s}\int_{\varphi^*_{oo,s}}^{\infty} q_{od,s}\frac{g(\varphi)}{1-G(\varphi^*_{oo,s})}d\varphi + M_{o\tilde d,s}\int_{\varphi^*_{o\tilde d,s}}^{\infty} q_{o\tilde d,s}\frac{g(\varphi)}{1-G(\varphi^*_{o\tilde d,s})}d\varphi \\
&= \sum_{d\neq\tilde d} M_{od,s}\int_{\varphi^*_{oo,s}}^{\varphi^i_{o,s}} q_{od,s}\theta_s(\varphi^*_{oo,s})^{\theta_s}\varphi^{-\theta_s-1}d\varphi + \sum_{d\neq\tilde d} M_{od,s}\int_{\varphi^i_{o,s}}^{\infty} q_{od,s}\theta_s(\varphi^*_{oo,s})^{\theta_s}\varphi^{-\theta_s-1}d\varphi \\
&\quad + M_{o\tilde d,s}\int_{\varphi^*_{o\tilde d,s}}^{\varphi^i_{o,s}} q_{o\tilde d,s}\theta_s(\varphi^*_{o\tilde d,s})^{\theta_s}\varphi^{-\theta_s-1}d\varphi + M_{o\tilde d,s}\int_{\varphi^i_{o,s}}^{\infty} q_{o\tilde d,s}\theta_s(\varphi^*_{o\tilde d,s})^{\theta_s}\varphi^{-\theta_s-1}d\varphi
\end{aligned}
$$

Which is equivalent to:

$$
\begin{aligned}
B_{o,s}Q_o &= \sum_{d\neq\tilde d} M_{od,s}\frac{E_{d,s}}{P_{d,s}^{1-\sigma_s}}\left(\tau_{od,s}\right)^{-\sigma_s}\left(\varphi^*_{oo,s}\right)^{\sigma_s}\left(\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\sigma_s-\theta_s}{1-\sigma_s}}\Phi_{o,s}^{\sigma_s-\theta_s}-1\right) \\
&- \sum_{d\neq\tilde d} M_{od,s}\frac{E_{d,s}}{P_{d,s}^{1-\sigma_s}}\left(\frac{\tau_{od,s}}{\xi_{o,s}}\right)^{-\sigma_s}\left(\varphi^*_{oo,s}\right)^{\sigma_s}\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\sigma_s-\theta_s}{1-\sigma_s}}\Phi_{o,s}^{\sigma_s-\theta_s} \\
&+ M_{o\tilde d,s}\frac{E_{\tilde d,s}}{P_{\tilde d,s}^{1-\sigma_s}}\left(\tau_{o\tilde d,s}\right)^{-\sigma_s}\left(\varphi^*_{oo,s}\right)^{\sigma_s}\left(\frac{f_{o,s}}{f^x_{o\tilde d,s}}\right)^{\frac{\theta_s}{1-\sigma_s}}\left(\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\sigma_s-\theta_s}{1-\sigma_s}}\Theta_{o,s}^{\theta_s}\Phi_{o,s}^{\sigma_s-\theta_s}-1\right) \\
&- M_{o\tilde d,s}\frac{E_{\tilde d,s}}{P_{\tilde d,s}^{1-\sigma_s}}\left(\frac{\tau_{o\tilde d,s}}{\xi_{o,s}}\right)^{-\sigma_s}\left(\varphi^*_{oo,s}\right)^{\sigma_s}\left(\frac{f_{o,s}}{f^x_{o\tilde d,s}}\right)^{\frac{\theta_s}{1-\sigma_s}}\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\sigma_s-\theta_s}{1-\sigma_s}}\Theta_{o,s}^{\theta_s}\Phi_{o,s}^{\sigma_s-\theta_s}
\end{aligned}
$$

Where $B_{o,s} = (\sigma_s-\theta_s)\left(\frac{\sigma_s}{\sigma_s-1}w_o\right)^{\sigma_s}\frac{1}{\theta_s}$

Without foreign market the expression for aggregate production simplifies to:

$$
\begin{aligned}
\frac{B_{o,s}}{C_{o,s}}Q_o &= \sum_{d\neq\tilde d} M_{od,s}\frac{\kappa^{\sigma}_{d,s}I_d}{\kappa^{\sigma}_{d,s'}P^{1-\sigma}_{d,s'}+\kappa^{\sigma}_{d,s}P^{1-\sigma}_{d,s}}\left(\tau_{od,s}\right)^{-\sigma_s}\left(()^{\frac{\theta_s+1-\sigma_s}{1-\sigma_s}}\left(\frac{\xi_{o,s}^{1-\sigma_s}}{1-\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\theta_s}{1-\sigma_s}}+1\right)^{\frac{\sigma_s}{\theta_s}} \\
&\times\left(\left(\frac{1-\xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}}\right)^{\frac{\sigma_s-\theta_s}{1-\sigma_s}}\left(1-\xi_{o,s}^{1-\sigma_s}\right)-1\right)
\end{aligned}
$$

Where $C_{o,s} = \left(\frac{f_{o,s}}{f^e_{o,s}}\theta_s b_{o,s}^{\theta_s}\left(-\frac{1}{\sigma_s-\theta_s-1}-\frac{1}{\theta_s}\right)\right)^{\frac{\sigma_s}{\theta_s}}$

D Theory: Simplified version of the Full Model

In this simplified version of the model, we remove the export market and we only consider the solar industry. This enables us to prove the four propositions summarized in the main text.

D.1 The Grid Planner Problem: Demand for Solar Energy Sources

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

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

Solve it, we get

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

Where

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

D.2 The Manufacturer Problem: Technology and Profits

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

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

Take the FOC, we can get

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

Productivity threshold

$$\varphi_{o,s}^* = \left(\sum_d \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \left(\frac{w_{o,s} a_{o,s} \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \frac{E_{d,s}}{\chi_{d,s} f_s} \right)^{\frac{1}{1-\sigma_s}} \tag{13}$$

$$\varphi_{o,s}^i = \left(\sum_d \frac{1 - \xi_{o,s}^{1-\sigma_s}}{\xi_{o,s}^{1-\sigma_s}} \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \left(\frac{w_{o,s} a_{o,s} \tau_{od,s}}{P_{d,s}} \right)^{1-\sigma_s} \frac{E_{d,s}}{\chi_{d,s} \phi_{o,s} f_s^i} \right)^{\frac{1}{1-\sigma_s}} \tag{14}$$

D.3 Free entry

$$
\begin{aligned}
w_{o,s} f_s^e &= \left(1 - G\left[\varphi_{o,s}^*\right]\right) \mathbb{E}\left[\pi_s \mid \varphi > \varphi_{o,s}^*\right] \\
= \left(G\left[\varphi_{o,s}^i\right] - G\left[\varphi_{o,s}^*\right]\right) \mathbb{E}\left[\pi_s \mid \varphi_{o,s}^i > \varphi > \varphi_{o,s}^*\right] &+ \left(1 - G\left[\varphi_{o,s}^i\right]\right) \mathbb{E}\left[\pi_s \mid \varphi > \varphi_{o,s}^i\right]
\end{aligned} \tag{15}
$$

Therefore

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

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

From the definition of the price index

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

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

D.4 Solving the model

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

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

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

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

To simplify M_1, we obtain:

$$M_{1,s} = \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{b_s^{\theta_s}(\sigma_s - 1)}{f_s^e \theta_s} \left(\frac{\sigma_s}{\sigma_s - 1} \right)^{\sigma_s - 1}$$

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

D.5 Some Theoretical Conditions

There are a number of regulatory conditions we need for sensible economic outcomes. In particular, $\sigma_s > \sigma > 1$ to obtain non-negative profits. For profit to be bounded, $\sigma_s - \theta_s - 1 < 0$. And, $\sigma_s - \theta_s < 0$ to ensure production is bounded.

D.6 Comparative Statics Proof

PROPOSITION 1 (THRESHOLDS):

We can obtain analytical expressions for the exit threshold as follows:

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

Note that the production subsidy $a_{1,s}$ and demand subsidy $\chi_{1,s}$ do not enter this expression. If we have an innovation subsidy, then 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 because $\frac{\theta_s + 1 - \sigma_s}{1-\sigma_s} < 0$. Consequently, $\varphi_{1,s}^*$ will increase, making it harder for low productivity firms to survive. This is because some firms on the margin of deciding whether to innovate will now innovate, and this will be the relatively more productive firms (those who are already innovating will benefit from a lower cost of their innovation). The additional firms who innovate will now have lower marginal costs, lowering the price index. Therefore, those firms who are just above the zero profit line will lose from this increased market competition and will to exit (i.e. an increase in the exit threshold).

We can write the innovation threshold as:

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

The relative distance between innovation threshold and exit threshold is $\left(\frac{1 - \xi_{1,s}^{1-\sigma_s}}{\xi_{1,s}^{1-\sigma_s}} \frac{f_s}{\phi_{1,s} f_s^i} \right)^{\frac{1}{1-\sigma_s}}$, and it will decrease if we introduce innovation subsidy. Hence, a larger fraction of producing firms will innovate. However, since we showed in the last paragraph that the exit threshold increases with the innovation subsidy, there might be an ambiguity in the effect. To analyze the total effect, write the innovation threshold as:

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

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 and both terms are positive.

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

PROPOSITION 2 (MASS OF FIRMS):

To prove this, we can solve for the equilibrium mass of firms:

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

where $C=\frac{(\sigma_s-1)^{\sigma_s-1}}{\sigma_s^{\sigma_s}}\frac{b_s^{\theta_s}(\sigma_s-1)}{f_s^e\theta_s}\left(\frac{\sigma_s}{\sigma_s-1}\right)^{\sigma_s-1}$. Notice that $\varphi_{1,s}^{*}$ is the only term that contains the innovation subsidy, and $\varphi_{1,s}^{*}$ is not affected by the demand or production subsidy. From the following derivation, it is clear that demand and production subsidies will both increase the mass of firms.[40]

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

Also notice that the demand subsidy will only affect the first term, while the production subsidy will affect both terms. We can write down the derivatives as follows:

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

[40]For the demand subsidy to have an 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. Then if we introduce some small subsidy, the denominator will remain to be positive since the function is continuous.

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

It is less clear which one is larger between $\partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial\chi_{1,s}$ and $\partial\left(\frac{\tau^{\sigma_s-1}\frac{E_{1,s}}{\chi_{1,s}}}{\tau^{\sigma_s-1}\left(\varphi_{1,s}^*\right)^{\theta_s}-\left(a_{1,s}\varphi_{2,s}^*\right)^{1-\sigma_s}(\varphi_{1,s}^*)^{\sigma_s+\theta_s-1}}\right)/\partial a_{1,s}$. However, as long as $E_{2,s}$ is large enough, then we can guarantee that $|\frac{\partial M_{1,s}}{\partial a_{1,s}}| > |\frac{\partial M_{1,s}}{\partial \chi_{1,s}}|$. Intuitively, as long as the untreated region is large enough, or equivalently, as long as there are enough untreated regions, then production subsidy will be more effective because treated firms can sell to more regions and larger market.

The impact of innovation subsidies are more ambiguous. From Proposition 1, we know that innovation subsidy will increase the production threshold $\varphi_{1,s}^*$. However, there is no linear relationship between $\varphi_{1,s}^*$ and $M_{1,s}$. We can prove that 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 the case when we start from no innovation subsidy and then slightly increase the subsidy. When $\phi_{1,s}=1$, the left hand side of the inequality above becomes 1 because we have assumed symmetry between regions. For the right hand side of the inequality, $\frac{\theta_s}{\sigma_s+\theta_s-1} < 1$ because $\sigma_s > 1$. 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 (INNOVATION):

We derive the solution for the mass of innovators:

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

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

With the same conditions that $E_{2,s}$ is large enough, we can also prove 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, production subsidy will be more effective than demand subsidy in terms of bolstering innovation.

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

PROPOSITION 4 (REVENUE AND OUTPUT):

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

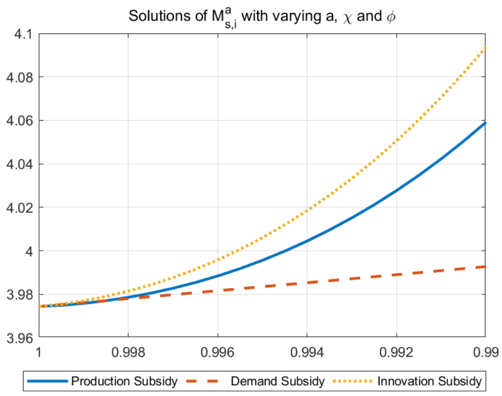
City-level total revenue equals the mass of operating firms multiplied by the average revenue per firm. All subsidies increase the mass of operating firms (Proposition 2), thus raising total revenue. Innovation subsidies encourages more firms to become innovators (Proposition 3), leading to higher average revenues per firm. Hence, revenue rises.

Since prices fall, output will also rise will all subsidies.

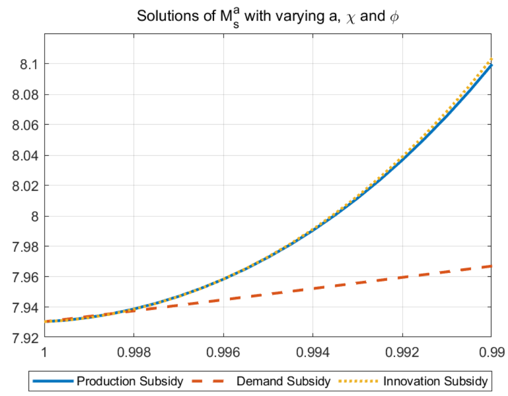
E Further Simulation Results

Figure E.1: Aggregate effects of Policies

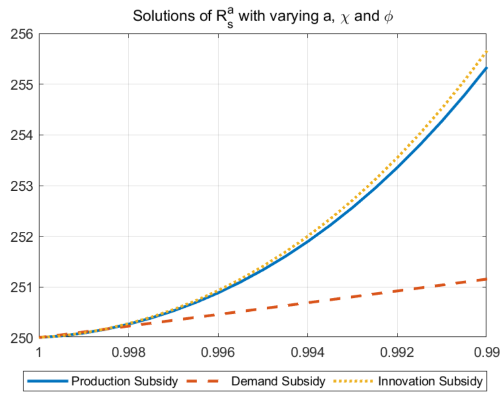
(a) Aggregate Solar Innovation



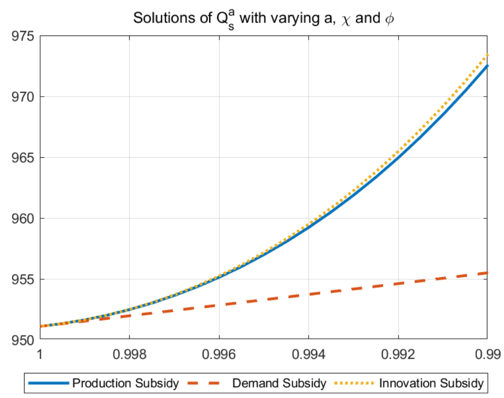
(b) Aggregate Solar Firms



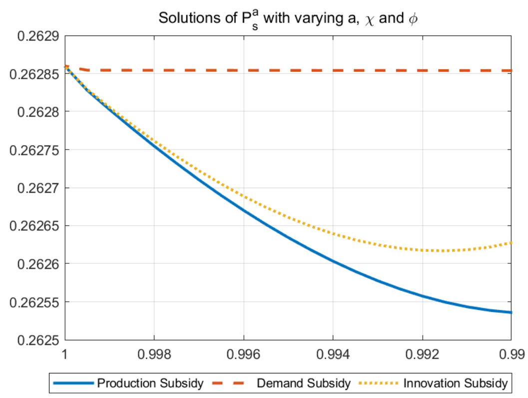
(c) Aggregate Solar Revenue



(d) Aggregate Solar Quantity



(e) Aggregate Solar Price



Note: These are numerically simulated effects of the full model of different city-level subsidies on solar outcomes. Each of the panels looks at a different outcome, with the level on the y-axis. The x-axis changes the level of the subsidy from the no-subsidy economy normalized at 1 up to a 10% subsidy (0.9). The different lines represent different types of subsidy: production (a), demand (χ) and innovation (ϕ). Details in text and Appendix C.

F Further Econometric Results

F.1 Outcome variables in levels

Table F.1: All Patents

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patents	6.310	−7.076	20.046**	25.613*
	(9.949)	(14.578)	(9.569)	(14.873)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	13.128	13.128	13.128	13.128

Notes: *0.1 ** 0.05 *** 0.01. Each observation is a city (admin2 level region) and there are 358 cities in China. 43 regions are treated by any subsidy. The time period is 2004-2020. Outcome variables are winsorised at 1%. 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. All regressions without controls.

Table F.2: Firm Count

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Firm count	1.199	−0.257	2.505*	2.900
	(0.898)	(0.617)	(1.462)	(2.122)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	2.872	2.872	2.872	2.872

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Outcome variables are winsorised at 1%. Each column is one sdid regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls.

Table F.3: Revenue

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Revenue (million RMB)	135	−0.95	329**	397**
	(123)	(109)	(148)	(179)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	157	157	157	157

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 42 regions are treated by any subsidy. Time: 2004-2020. Outcome variables are winsorised at 1%. Each column is one sdid regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions with the revenue adjustment procedure summarized in Section B.8 and without controls.

Table F.4: Panel Production Capacity

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity (MWh)	319.567**	138.574	366.728**	480.764***
	(128.377)	(127.902)	(147.783)	(175.088)
Observations	3,580	3,580	3,580	3,580
Mean of Dep. var.	82.449	82.449	82.449	82.449

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 18 regions are treated by any subsidy. Time: 2004-2013. Outcome variables are winsorised at 1%. Each column is one sdid regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

Table F.5: Exports

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Solar export value (million dollar)	22.1*	4.6	26.9**	31.9*
	(12.4)	(13.7)	(12.7)	(17.3)
Observations	4,654	4,654	4,654	4,654
Mean of Dep. var.	19.27	19.27	19.27	19.27

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. Time period for estimation: 2004-2016 for export value, and 2004-2015 for export volume and price. Outcome variables are winsorised at 1%. 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.

F.2 Solar Panel and Cell results 2004-2013: Production, Capacity and Firm Numbers

Table F.6: Solar production, capacity and firm counts

	(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 admin2 level region and there are 358 admin2 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

F.3 Unadjusted revenue results

Table F.7: Unadjusted Revenue

	(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 admin2 level region and there are 358 admin2 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

F.4 Exports results

Table F.8: Exports: number of exporters and non-solar exports

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Exporters firm count	0.220**	0.046	0.314***	0.400**
	(0.095)	(0.107)	(0.107)	(0.167)
Non solar export value	1.388	−0.736	3.094***	3.560**
	(0.924)	(0.979)	(1.026)	(1.641)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2016. Each column is one sdid regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

F.5 Cross-city spillovers

Table F.9: Cross-city spillovers

	(1) All patents	(2) Firm count	(3) Revenue	(4) Panel capacity	(5) Solar export value
Any subsidy in an adjacent city	0.372***	0.112*	0.617***	0.385	1.099**
	(0.101)	(0.061)	(0.199)	(0.263)	(0.491)
Observations	5,049	5,049	5,049	3,210	3,861

Notes: * 0.1 ** 0.05 *** 0.01. Dependent variables are reported in columns. Each observation is an admin2 level region and there are 358 admin2 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.8. All regressions without controls.

F.6 Pollution and CO_2 emissions

Table F.10: 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 admin2 level region and there are 358 admin2 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 F.11: 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 admin2 level region and there are 348 admin2 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 J. Chen et al. (2020), which we remap to our admin2 regions. All regressions without controls.

F.7 City-level total solar patents

Table F.12: CITY-LEVEL TOTAL SOLAR PATENTS

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.444^{***}	0.114	0.662^{***}	1.029^{***}
	(0.150)	(0.138)	(0.213)	(0.219)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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

F.8 Learning by doing patents

Table F.13: LEARNING-BY-DOING PATENTS

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.365^{**}	0.187	0.604^{***}	0.914^{***}
	(0.149)	(0.186)	(0.235)	(0.377)
Observations	5,728	5,728	5,728	5,728

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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.

F.9 Productivity Analysis

Table F.14: PRODUCTIVITY OUTCOMES

Panel A Period: 2004-2020	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Revenue	1.015^{**}	0.069	1.802^{***}	2.563^{***}
	(0.455)	(0.277)	(0.629)	(0.844)
Labor	0.758^{*}	0.020	1.474^{**}	1.844^{**}
	(0.429)	(0.232)	(0.601)	(0.932)
Capital	0.526	−0.186	1.260^{**}	1.712^{**}
	(0.354)	(0.175)	(0.518)	(0.799)
Observations	6,086	6,086	6,086	6,086
Panel B Period: 2004-2013	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Revenue	1.776^{***}	0.294	2.221^{***}	2.653^{***}
	(0.570)	(0.209)	(0.654)	(1.017)
Panel production capacity	2.098^{***}	0.587	2.496^{***}	2.930^{***}
	(0.532)	(0.467)	(0.575)	(0.773)
Labor	1.460^{**}	0.137	1.825^{**}	2.084^{**}
	(0.598)	(0.246)	(0.710)	(1.017)
Capital	1.177^{**}	0.103	1.494^{**}	1.792^{*}
	(0.524)	(0.246)	(0.611)	(0.923)
Observations	3,580	3,580	3,580	3,580

Notes: *0.1 ** 0.05 *** 0.01. Each observation is a city (admin2 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.8 and all regressions are without controls.

F.10 Controlling for GDP per Capita

Table F.15: Controlling for GDP per capita

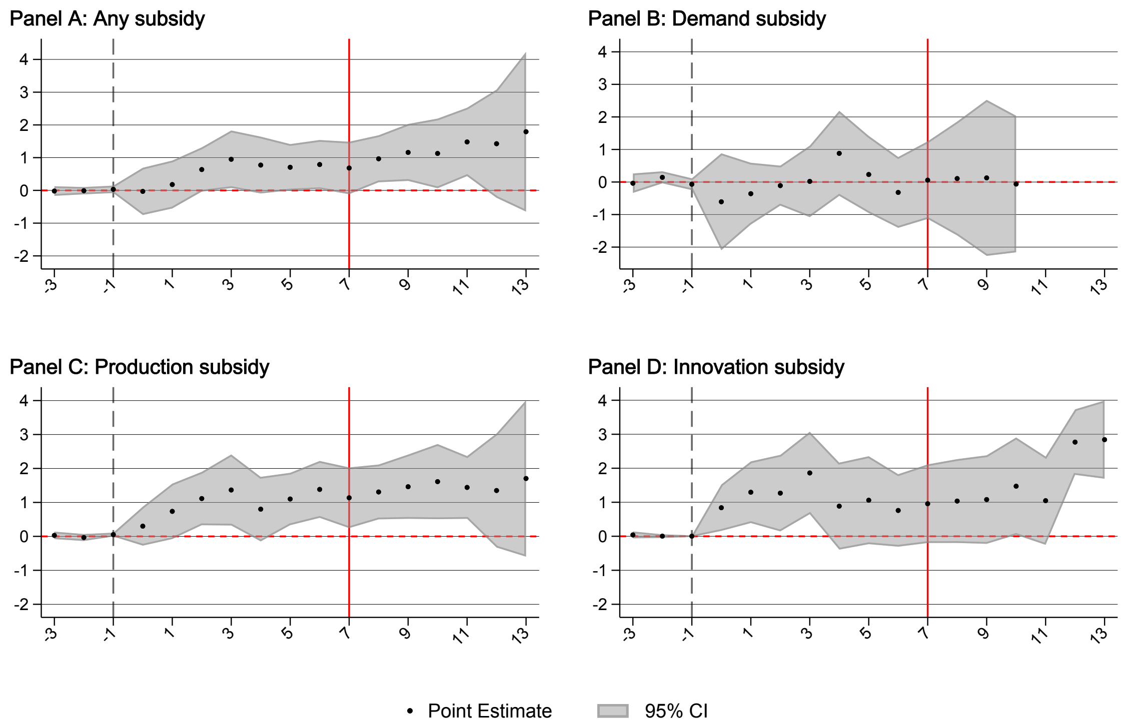
	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patent	0.483**	0.226	0.867***	1.001***
	(0.205)	(0.242)	(0.220)	(0.341)
▫ Design patents	0.187	0.275	0.240	0.141
	(0.132)	(0.190)	(0.167)	(0.254)
▫ Invention/utility model patents	0.527**	0.191	0.960***	1.051***
	(0.213)	(0.241)	(0.232)	(0.361)
• Solar patents	0.523***	0.247	0.802***	0.875***
	(0.191)	(0.230)	(0.204)	(0.339)
• 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	0.380***	0.396***
	(0.081)	(0.031)	(0.125)	(0.138)
Revenue	1.007***	0.083	1.767***	2.496***
	(0.458)	(0.197)	(0.505)	(0.686)
Panel capacity	2.025***	0.531	2.415***	2.848***
	(0.466)	(0.428)	(0.470)	(0.705)
Solar export value	4.515***	1.367*	6.250***	8.967***
	(0.970)	(0.741)	(1.428)	(2.136)
Export value	2.409***	0.577	3.210**	4.041**
	(0.886)	(1.009)	(1.292)	(1.992)

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region. Here we control 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.8.

F.11 Compositional changes and dynamic effects

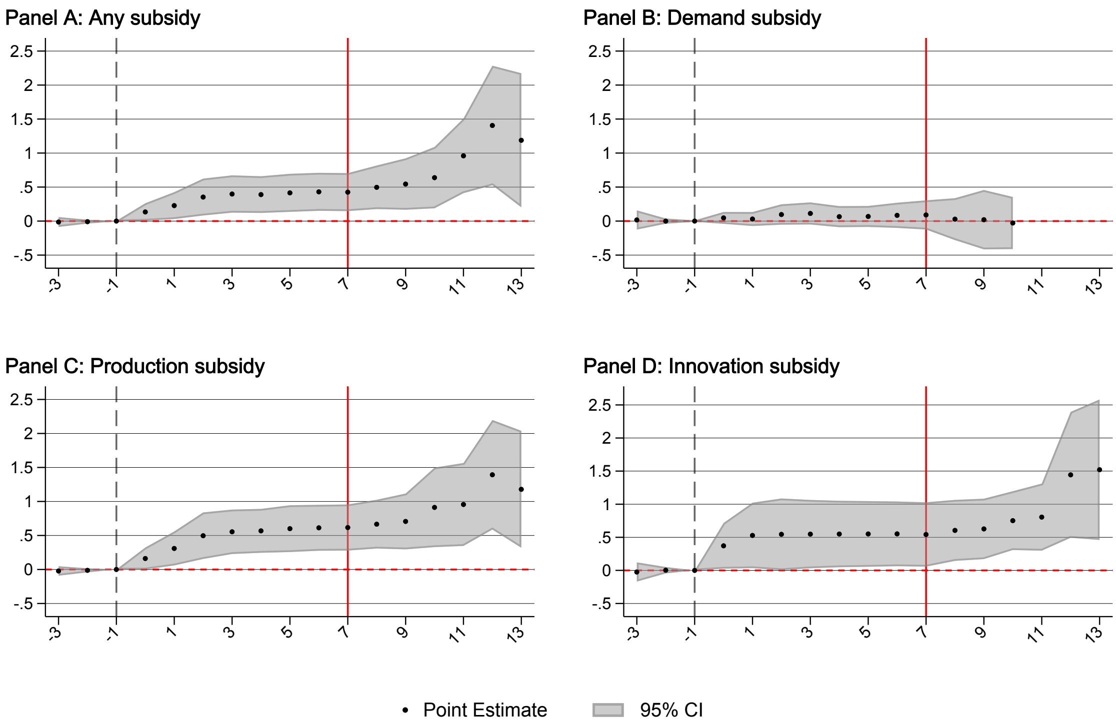
F.11.1 Aggregate event studies for cohorts between 2007 and 2013

Figure F.1: All Patents by Solar Firms - Cohorts between 2007 and 2013



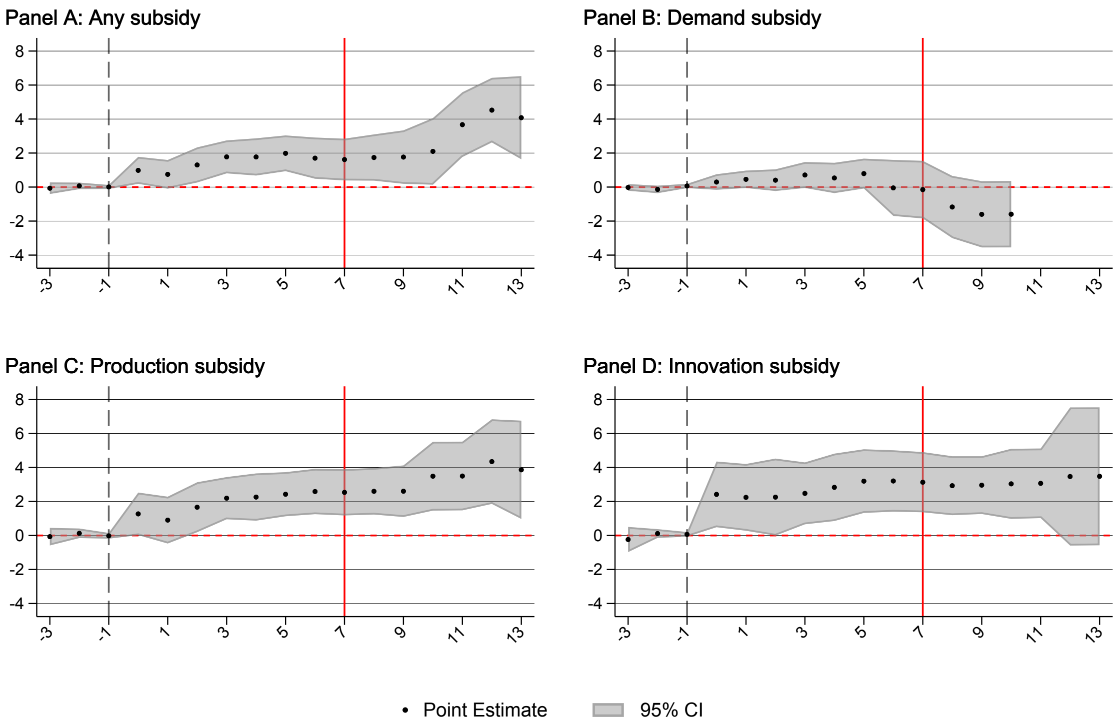
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total number of patents by solar firms (with arcsinh 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 F.2: Firm Count - Cohorts between 2007 and 2013



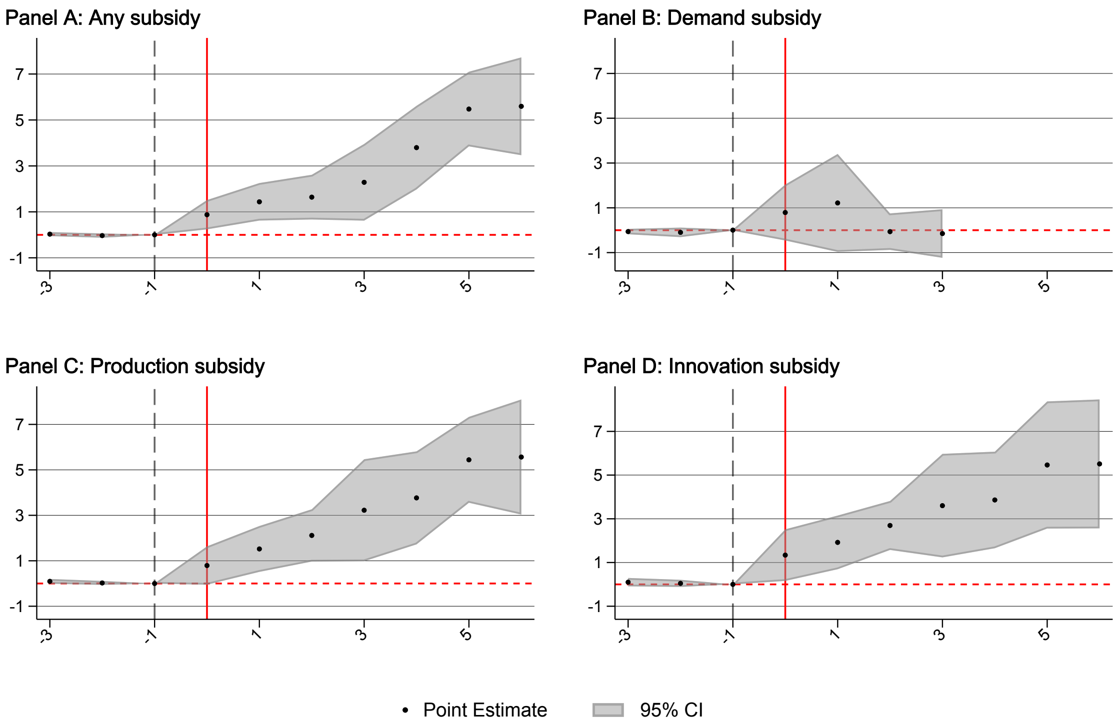
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total number of solar firms (with arcsinh 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 F.3: Revenue - Cohorts between 2007 and 2013



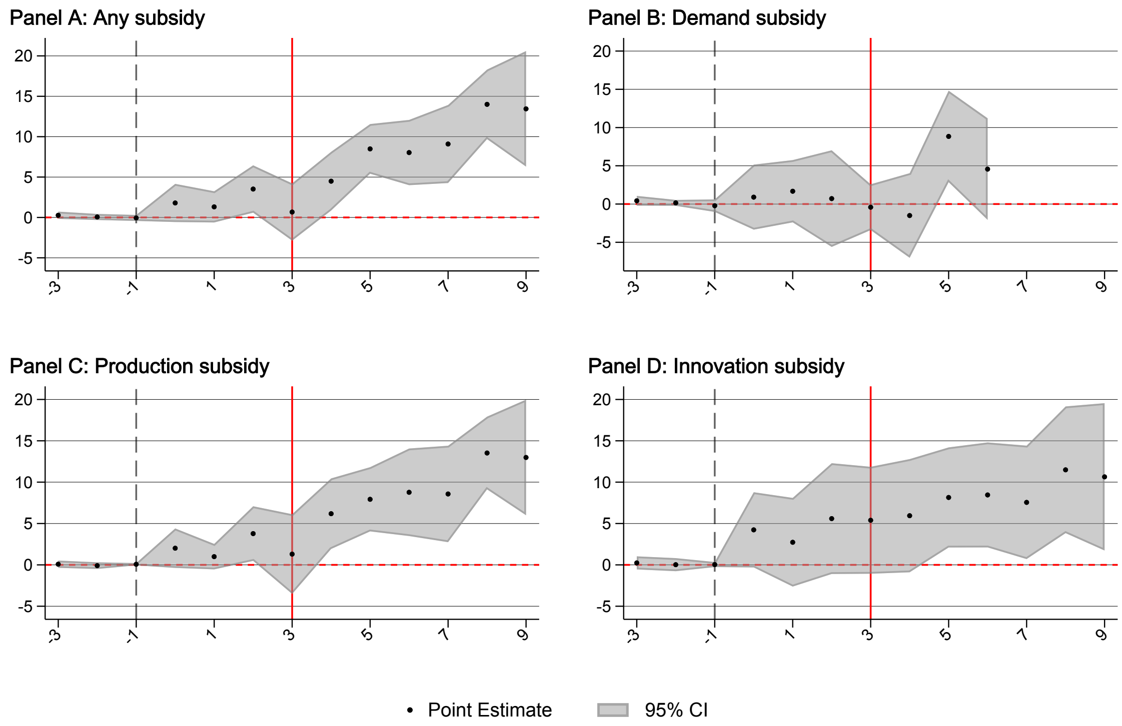
Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. Only estimates from cohorts between 2007 and 2013 are taken into account. The red vertical line indicates the last year for which all cohorts have available estimates. The outcome variable in all panels is the total revenue of solar firms (with arcsinh 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 F.4: 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 5. 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 arcsinh 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.

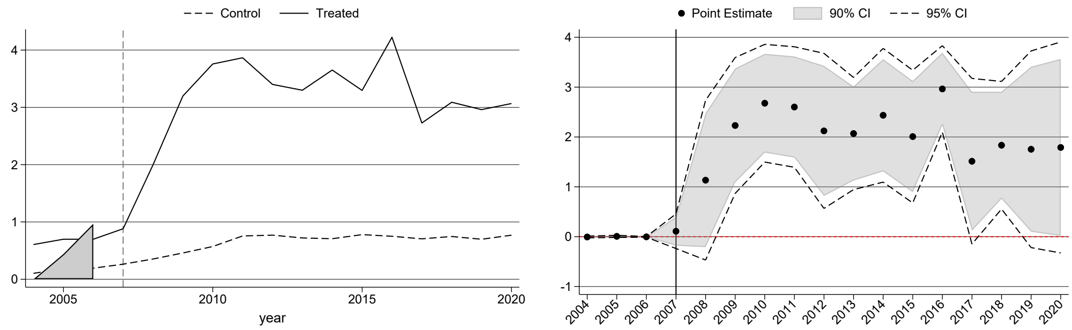
Figure F.5: Solar Export Value



Note: Cohort- and year-specific ATTs are estimated by synthetic DID methods and are aggregated into event studies as described in Section 5. 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 arcsinh 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

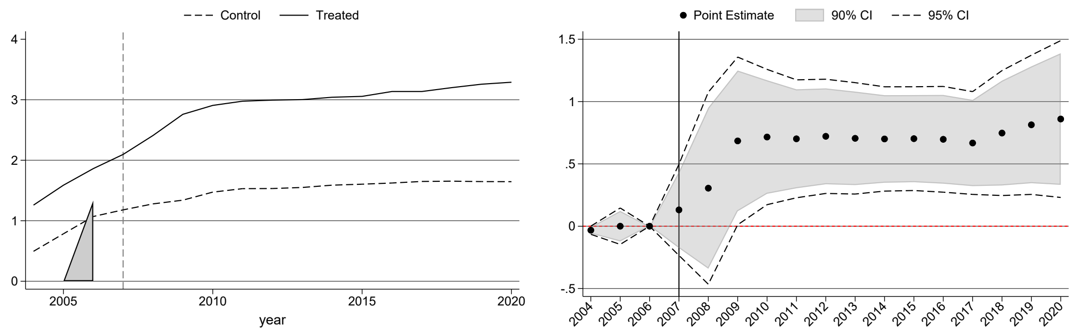
F.11.2 Cohort-specific event studies (2007 and 2013 examples)

Figure F.6: Number of patents by solar firms - Any subsidy (2007 example)



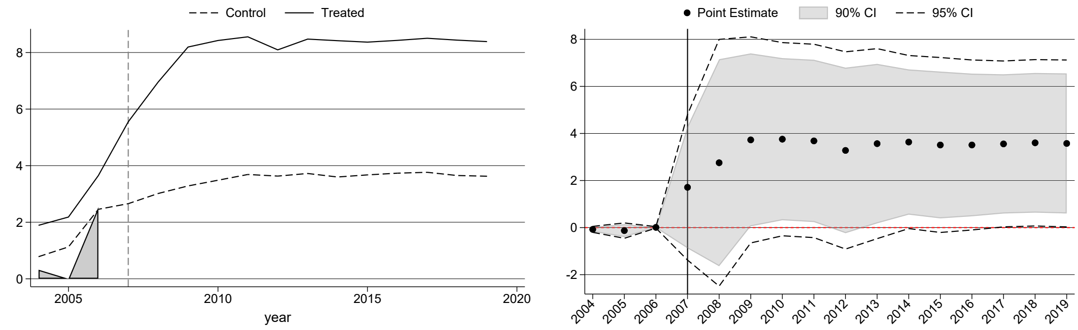
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is firm patents (with arcsinh transformation).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

Figure F.7: Number of solar firms - Any subsidy (2007 example)



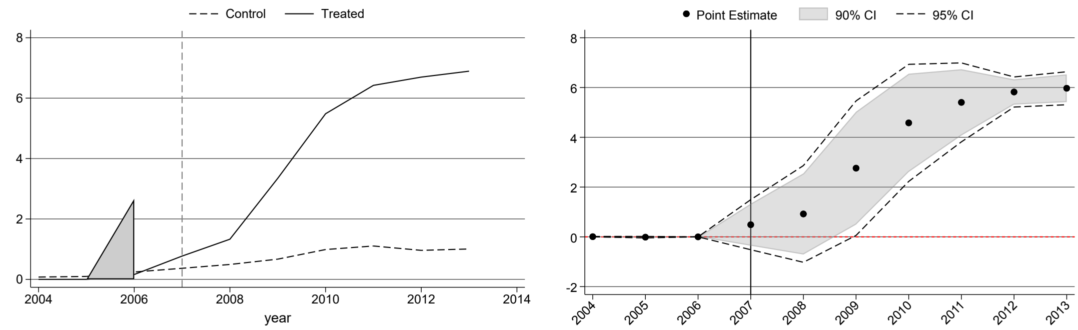
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is number of solar firms (with arcsinh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

Figure F.8: Revenue by solar firms - Any subsidy (2007 example)



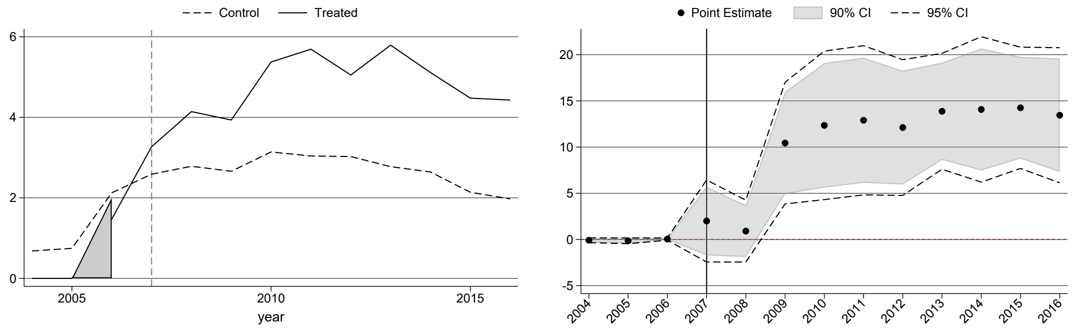
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total revenue of solar firms (with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

Figure F.9: Total panel capacity by solar firms - Any subsidy (2007 example)



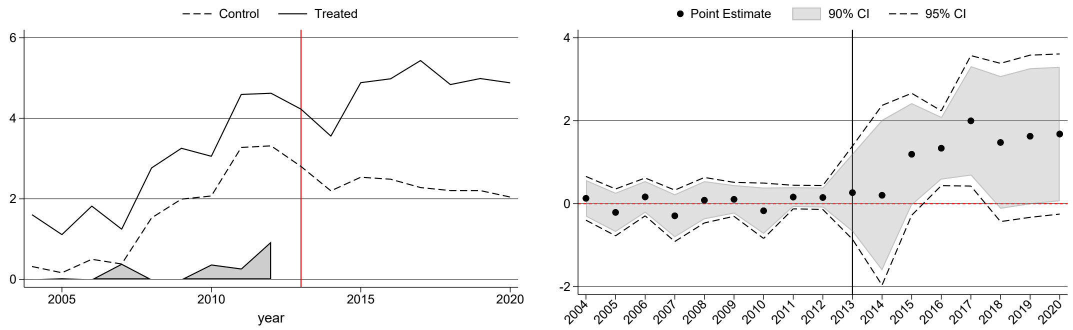
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total panel capacity of solar firms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

Figure F.10: Solar exports by solar firms - Any subsidy (2007 example)



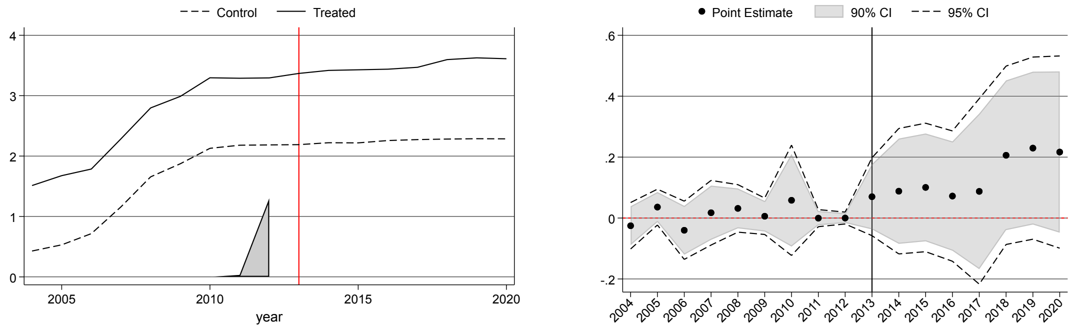
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is total solar exports of solar firms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

Figure F.11: Number of patents by solar firms - Any subsidy (2013 example)



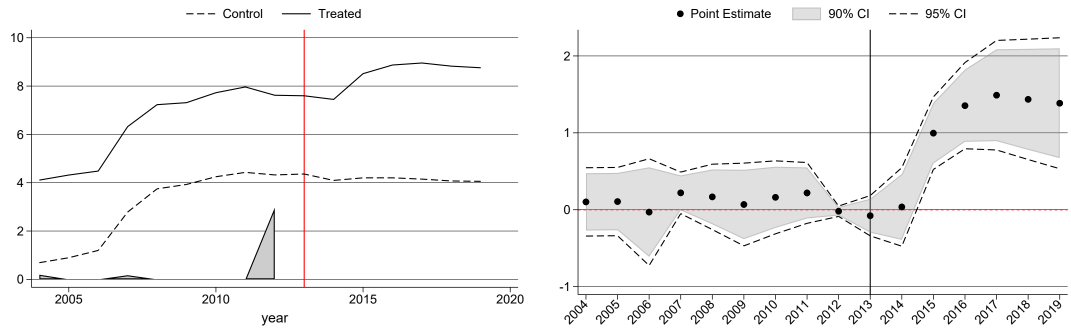
Note: Synthetic DID methods. The left-hand side graph reflects the raw trends of the control group and treated group. The right-hand side graph reflects the difference between the control and treated groups with 95% and 90% confidence interval. The outcome variable is firm patents (with arcsinh transformation).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

Figure F.12: 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 arcsinh transformation). These are estimates for the cohort of cities treated in 2013. There are 358 cities and 3 are treated in 2013.

Figure F.13: 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 arcsinh transformation). These are estimates for the cohort of cities treated in 2013. There are 358 cities and 3 are treated in 2013.

F.12 City-level total patents

Table F.16: Placebo: City-level total patents

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *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 admin2 level region and there are 358 admin2 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

F.13 Quality-adjusted patenting: patent citations

Table F.17: Patent citations

	(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	6,086	6,086	6,086	6,086

Notes: *0.1 ** 0.05 *** 0.01. SDID on 358 cities. Time: 2004-2019. Each column is one sdid regression. Without controls. Outcome is IHS of patent count (weighted by future citations) by solar firms in a city-year pair. Citations are measured as the number of patent families citing a patent's patent family. SE cluster bootstrapped by city.

F.14 GDP per capita

Table F.18: Placebo: GDP per capita

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	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 admin2 level region and there are 358 admin2 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.

F.15 Cost of policies: subsidy

Table F.19: SUBSIDY VALUE

	(1)	(2)	(3)	(4)
	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Subsidy value (million RMB)	13.601*	-0.527	15.993*	24.177
	(7.693)	(1.293)	(9.276)	(17.621)
Observations	2,457	2,457	2,457	2,457
Mean of Dep. var.	1.492	1.492	1.492	1.492

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 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.