LUND UNIVERSITY
School of Economics and Management

Master's Programme in Economic Growth, Population and Development

The Impact of Government Subsidies on Innovation in China's Solar Photovoltaic Industry:

Evidence from Firms in the A-share Market

by

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Energy transition is crucial to mitigate the impacts of climate change globally. Solar energy, particularly through photovoltaic (PV) technology, plays a critical role in this transition. Innovation within the solar PV industry is essential, and policy support, especially government subsidies, is crucial for its technological advancement. This study focuses on China's solar PV industry given its leading position in the global energy transition and solar PV supply chain. It investigates the impact of government subsidies on innovation across different sectors of the industry: upstream, midstream, and downstream. The findings show that government subsidies positively influence innovation in upstream and midstream firms, with upstream firms showing a more significant increase in R&D intensity. Scale efficiency (SE) contributes more to overall innovation efficiency (OE) than pure technological efficiency (PTE), and the relationship between government subsidies and innovation efficiency is complex and non-linear. These results highlight the need for targeted subsidy policies to enhance innovation performance in the future.

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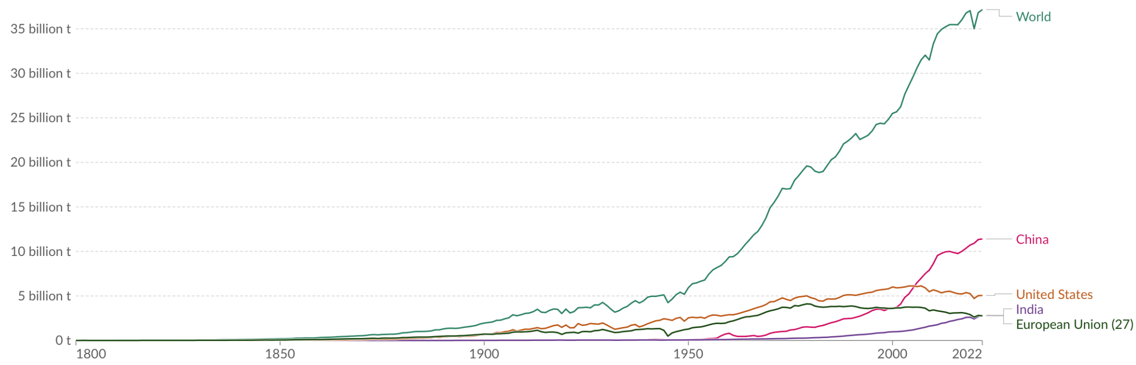
1 Introduction

Climate change is one of the biggest threats that humans face today. Human emissions of greenhouse gases, which have increased rapidly by twelve times in the last century (from 3 billion to 37 billion tons, shown in Figure 1), are the principal causes of contemporary climate change, resulting in profound changes in various environmental parameters such as sea level, precipitation, and frequency of extreme temperatures. These changes affect various facets of human well-being, including public health, agriculture, societal stability, biodiversity, etc. An increasing number of countries have implemented carbon reduction programs to tackle this challenge (Ritchie et al., 2024).

Figure 1 Annual CO_2 Emissions, by region



***Note:** the figure is cited from Global Carbon Budget (2023) with major processing by Our World in Data.*

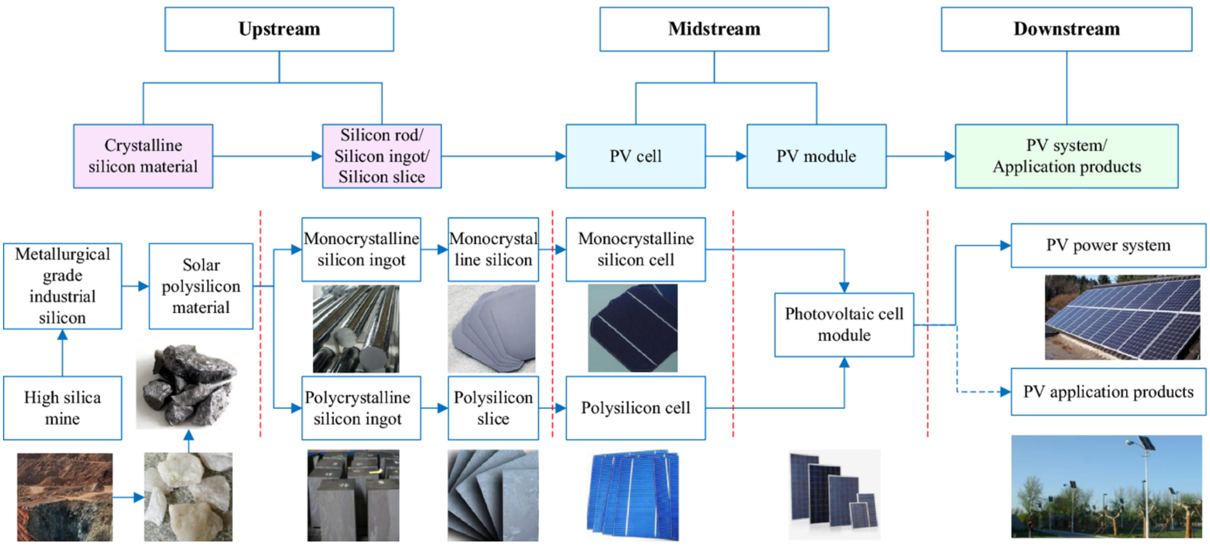
The energy transition from fossil fuels to renewable energy sources is crucial for reducing carbon emissions as the combustion of fossil fuels for energy accounts for about three-quarters of global greenhouse gas emissions. Renewable energy, including solar, wind, hydropower, and biofuels, are central to the transition towards less carbon-intensive and more sustainable energy systems. It provides an alternative to investing in newly built fossil fuel power plants and reduces reliance on existing ones both in end-use sectors like industry and transport and in other sectors like the heating sector (IEA, 2024a).

Solar photovoltaic (PV) is crucial in renewable energy for its rapid growth, cost-effectiveness, and flexibility. It has undergone exponential growth in recent years, becoming one of the fastest-growing renewable energy technologies and the only renewable energy technology on track with the Net Zero Emissions by 2050 (NZE) Scenario. It has also become one of the least costly choices for electricity generation worldwide. Moreover, it can be deployed in various situations from large plants to small residential roof-top systems (IEA, 2024a).

Policy support continues to be a key driver of global solar PV deployment with various instruments such as auctions, feed-in tariffs, net-metering, and contracts for difference contributing to capacity growth. The most important policies in different regions include China's 14th Five-Year Plan for Renewable Energy, the US's Inflation Reduction Act, the EU's REPowerEU Plan, and India's announcement of net zero emissions by 2070 (IEA, 2024a).

Nowadays, the advancement of solar PV technology increasingly relies on the global innovation system, leading to the development of standardized products tailored for the global market. The PV value chain undergoes a gradual disassembled and modularized process worldwide, characterized by differences in knowledge base, market structures, and innovation networks (Yuan et al., 2022). The whole value chain (Figure 2) encompasses a spectrum of stages, spanning from the extraction and processing of silicon raw materials (upstream) to the manufacturing of PV components, assembly of solar panels, distribution channels (midstream), and ultimately the installation and operation of solar energy systems (downstream). Each stage of the PV value chain contributes to the overall efficiency, cost-effectiveness, and sustainability of solar energy generation. Notably, the upstream sector of the value chain possesses greater potential for technological advancements and innovation owing to their high-tech intensity, whereas the middle and downstream sectors are characterized by a more labor-intensive feature (Zou et al., 2017).

Figure 2 The Flow Diagram of the PV Industry Chain



Note: *the figure is cited from Song et al. (2020).*

Over the past two decades, global solar PV manufacturing capacity has significantly shifted from traditional hubs such as Europe, Japan, and the United States to China. China currently dominates all stages of solar panel manufacturing with an overall share exceeding 80% worldwide. Additionally, China hosts the world's top 10 suppliers of solar PV manufacturing equipment (IEA, 2022). Nonetheless, China produces the largest global increase in carbon emissions while global emissions undergo a structural slowdown in 2023, reflecting China's continuation of emissions-intensive economic growth in the post-pandemic era (IEA, 2024a).

This study chooses China's solar PV industry as a case study due to its leading place in the energy transition. China will continuously play a crucial role in achieving the global goal of tripling renewable energy capacity in the future, as it is forecasted to account for nearly 60% of new global renewable capacity by 2028. Despite the gradual withdrawal of government subsidies in recent years, the rapid deployment of solar PV in China persists due to their economic attractiveness and supportive policy environments (IEA, 2024a).

1.1 Research Question

The research question of the thesis is: *do government subsidies affect innovation in China's solar PV industry?* The general hypothesis is that government subsidies have an overall positive effect on innovation in China's solar PV industry. Furthermore, this thesis explores whether government subsidies have different effects on innovation among upstream, middle, and downstream firms.

This study employs R&D intensity as a proxy for measuring willingness to innovate. R&D intensity is measured by the ratio of the R&D expenditures to its net fixed assets. The hypothesis is:

H_{a0}: Government subsidies affect firms' willingness to innovate.
H_{a1}: Government subsidies do not affect firms' willingness to innovate.

It employs innovation efficiency as a proxy for measuring the outcomes of innovation. Innovation efficiency score is calculated with the Data Envelopment Analysis (DEA) model. The hypothesis is:

H_{b0}: Government subsidies affect firms' outcomes of innovation.
H_{b1}: Government subsidies do not affect firms' outcomes of innovation.

1.2 Aim and Scope

This study aims to examine the effects of government subsidies on innovation in China's solar PV industry. By identifying strategic opportunities for government subsidies allocation, policymakers can maximize innovation outcomes in the solar PV industry. Moreover, it might suggest the implementation of more effective subsidy policies tailored to the specific sectors within the solar PV value chain.

This study selects 97 firms listed in China's A-share market as the sample. The number of observations is 730. Data of all indicators are from the China Stock Market & Accounting Research Database, a comprehensive database focusing on China's finance and economy (CSMAR, 2024). Based on the firms' main products, this study divides them into three groups – upstream, midstream, and downstream, to explore whether the effects of subsidies on innovation are different within the value chain. The period is from 2007 to 2022. Given the solar PV industry as a strategic emerging industry in China since 2010 (SC, 2010), the number of firms listed in the A-share market has steadily increased each year. Consequently, later years contribute a greater abundance of data points. It uses simple OLS regression model as any subsidy policies in a given year are uniformly adopted by all firms, suggesting that year-specific effects are negligible.

The contribution of this study is to divide the whole solar PV industry chain into upstream, midstream, and downstream sectors. Policymakers might provide financial support more precisely according to the innovation performance within the industry chain, to avoid wasting fiscal resources.

1.3 Outline of the Thesis

This study contains five sections except introduction. **Section 2** introduces the context of the study, including an overview of China's renewable energy policy system, the current development of China's solar PV industry, and the necessity of more accurate subsidies to foster innovation. **Section 3** discusses theory and previous research. Its theoretical framework builds upon the relationship between industrial policy, innovation, and economic growth. Subsequently, it discusses the difficulties and solutions in measuring innovation and previous empirical analysis covering different countries and different types of renewable energy. **Section 4** exhibits data and quantitative methodology, including DEA model, OLS regression model, indicators, and hypotheses. **Section 5** analyzes the relationship between government subsidies and innovation in China's solar PV industry. The findings are: 1) Government subsidies have a positive effect on the upstream and midstream firms' willingness to innovate. Furthermore, upstream firms have a higher increase in R&D intensity than midstream firms do when subsidies increase by the same proportion. 2) scale efficiency (SE) contributes more to overall innovation efficiency (OE) than pure technological efficiency (PTE). 3) There is a non-linear relationship between PTE and government subsidies; a non-linear relationship between SE and government subsidies; and no significant relationship between OE and government subsidies. It also discusses the limitations of this study and further exploration. **Section 6** is the conclusion.

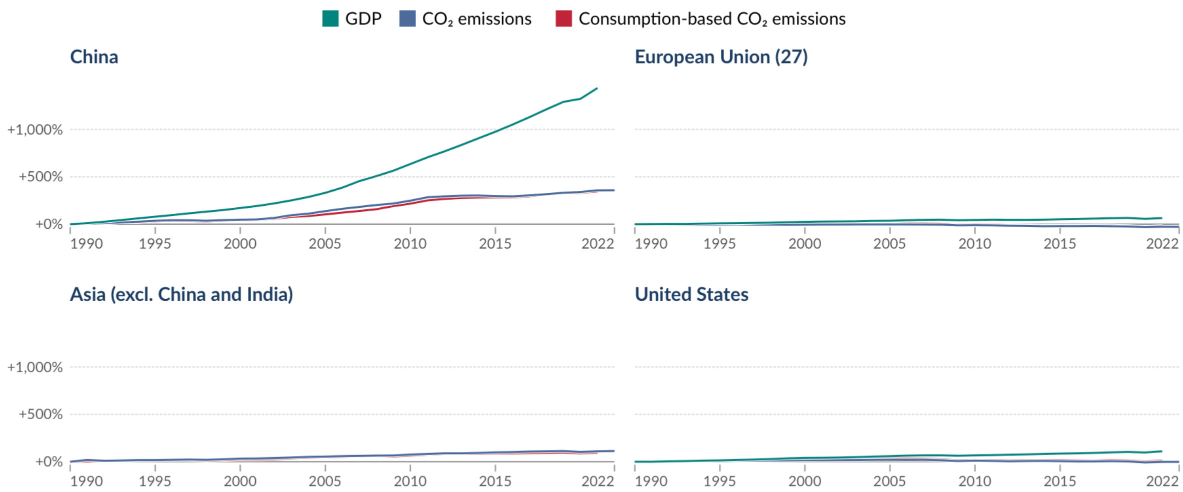
2 Context

China is the second-largest economy globally after the United States and the second-largest country by territory after Russia. With a population of over 1.4 billion, China stands as the world's second most populous nation. China's economy has begun to take off since the introduction of the Reform and Opening policy in 1978. Its gross domestic product (GDP) has reached an average annual growth rate of around 10%, resulting in an approximately 100-fold increase over the past four decades (Liu et al., 2023).

2.1 Overview of China's Energy Consumption

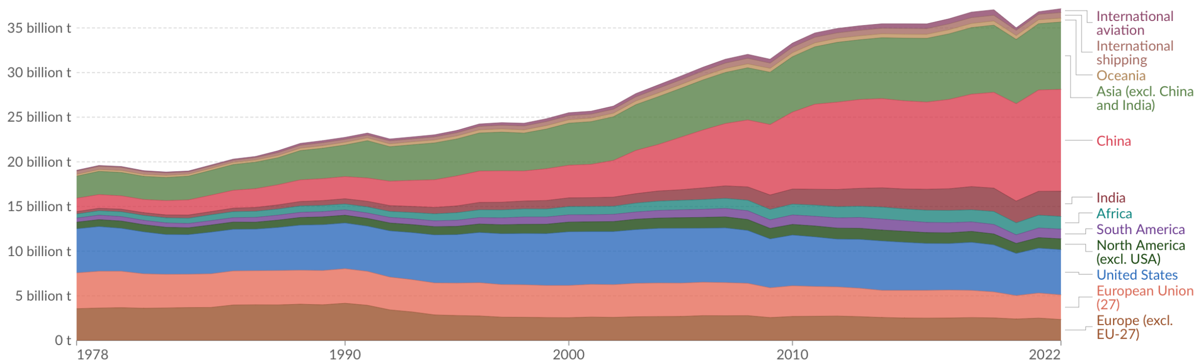
China's CO_2 emission has rocketed concurrent with its economic growth due to its reliance on coal and energy-intensive industries. However, the growth rate of its GDP has been four times that of the CO_2 emission at the aggregate level since 1990, and this kind of gap cannot be found in advanced economies such as the US and EU (Figure 3). China has become the world's biggest emitter of CO_2 at the aggregate level since 2006 and accounts for nearly 31% of the global total in 2022 (Global Carbon Budget, 2023), which is nearly equivalent to the whole North America and Europe (Figure 4). Therefore, the rate of China's carbon reduction will play a crucial role in preventing global warming. To address the climate change issue, in September 2020, Chinese President Xi Jinping announced the "Dual Carbon" Goals – China aims to peak CO_2 emissions before 2030 and achieve carbon neutrality before 2060 (Liu et al., 2023).

Figure 3 Change in CO_2 Emissions and GDP, by region



Note: *the figure is cited from Global Carbon Budget (2023) with major processing by Our World in Data .*

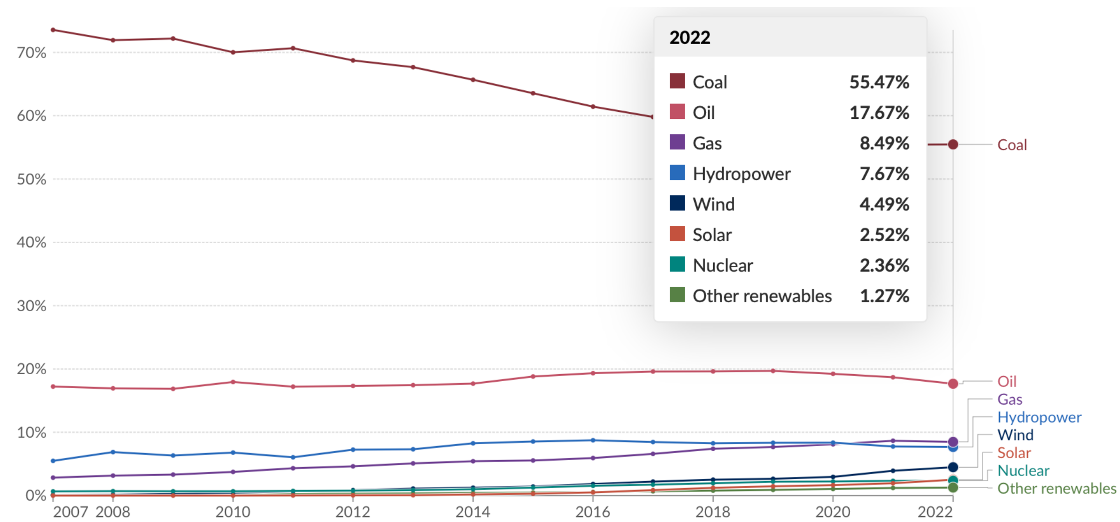
Figure 4 Annual CO_2 Emissions from Fossil Fuels and Industry, by region



Note: *the figure is cited from Global Carbon Budget (2023) with major processing by Our World in Data.*

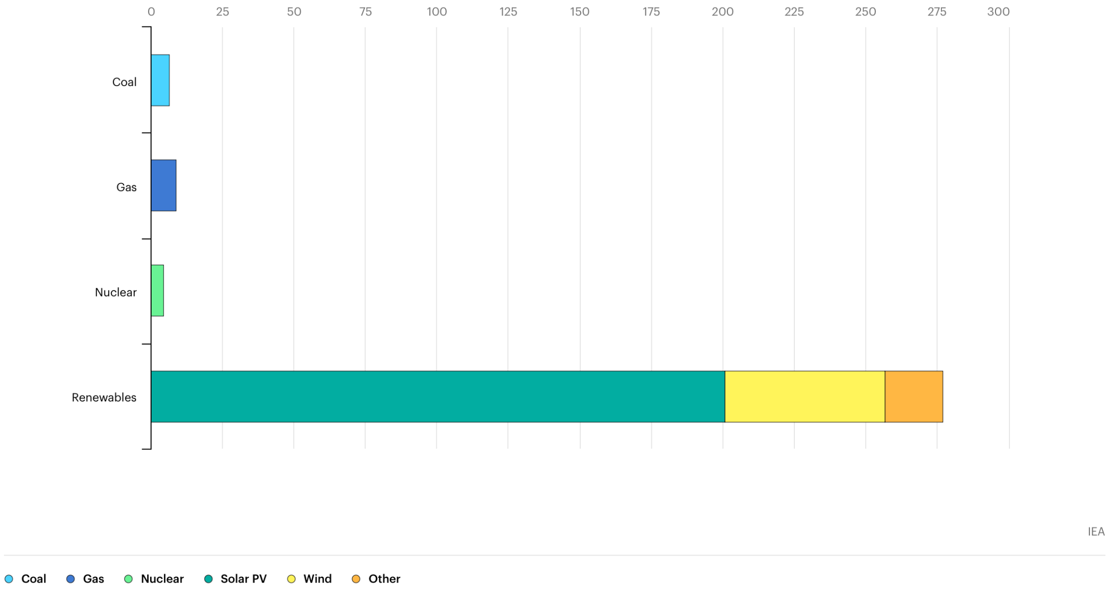
As the energy sector accounts for nearly 90% of China's greenhouse gas emissions, the transition from depending on fossil fuels towards renewable resources in power generation is critical to reaching the goals (IEA, 2021). The share of fossil fuels in final energy consumption in China is more than 80% in 2022 (Figure 5: coal 55.47%; oil 17.67%; gas 8.49%). The development of renewable energy has become the key to China's energy transformation and climate change mitigation. The Announced Pledges Scenario (APS 2020-2060) given by China announces that the average annual power capacity addition is around 300 GW, among which the renewables sector will take a share of over 90% (275 GW). Moreover, solar PV alone in the renewables will generate more than 200 GW, accounting for two-thirds of the total (Figure 6). In China's 14th Five-year Plan, the proportion of non-fossil energy in total energy consumption will increase to about 20% in 2025, among which PV power generation accounts for about 40% (NDRC, 2022).

Figure 5 Share of Energy Consumption by Source, China



Note: *the figure is cited from Energy Institute (2023) with major processing by Our World in Data.*

Figure 6 Average Annual Power Capacity Additions in the APS 2020-2060, China



Note: *the figure is cited from IEA (2021). The unit is GW.*

Innovation is recognized by the Chinese government as the main driver of economic growth in the next few decades and renewable energy is a crucial component of its strategic emerging industries (SC, 2010). China's technological development is predominantly attributed to its industrial policies due to its top-down policy formulation and implementation (Jiang & Raza, 2023). The government has introduced various kinds of policies to facilitate development and innovation in the solar PV industry, including granting government subsidies, mobilizing government-led industrial fundings, setting KPIs in innovation for state-owned enterprises, encouraging regional competition, tax incentives, etc. (IEA, 2021). Government subsidies have had a positive influence on the growth and thriving of the solar PV industry, fostering several competitive firms. However, a meticulous subsidy scheme is necessary to enable firms to gradually reduce their reliance on governmental support, thereby promoting greater financial self-sufficiency (Xiong & Yang, 2016). Moreover, such a policy approach might promise a more efficient fiscal allocation to investing in innovation rather than merely expanding capacity.

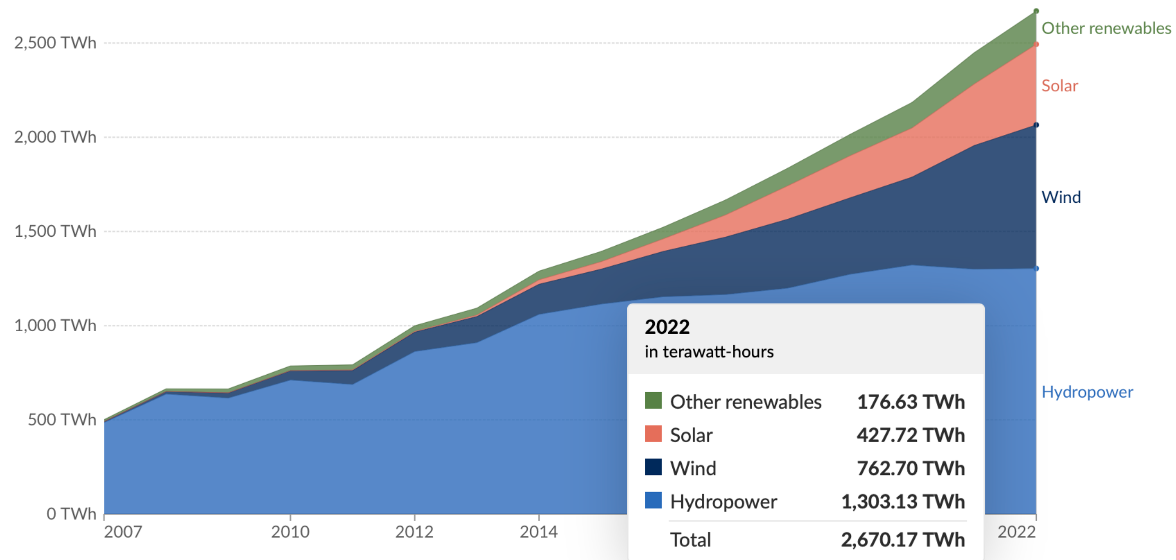
2.2 Overview of China's Renewable Energy Policy

2.2.1 Development of China's Renewable Policy System

The Renewable Energy Law (2005) came into force in 2006 and has become the foundation for the development and utilization of renewable energy in China since then. It contains renewable energy development plan, industry guidance, technical support measures, price and cost sharing, regulation, legal liability, etc.

Since 2009, China has successively introduced the Solar Roofs Program, the Golden Sun Demonstration Program, other feed-in tariff subsidy policies, and adjusted benchmark prices for wind power, solar PV power, and biomass power generation to promote investment in its renewable energy power generation projects. Meanwhile, the government ensures investment returns from renewable energy power generation by standardizing the renewable energy electricity price surcharge system (Ye et al., 2017). During this period, China's renewable energy has developed rapidly, with non-hydro renewable energy electricity generation rising from 15 TWh in 2007 to 1363 TWh in 2022 (Figure 7).

Figure 7 Renewable Electricity Generation by Source, China



Note: *the figure is cited from Energy Institute (2023) with major processing by Our World in Data.*

However, China's renewable energy development once relied heavily on government subsidies, resulting in a large subsidy funding gap and an insufficient consumption capacity. The problem of wind and solar energy curtailment emerged. China has gradually increased the renewable energy surcharge standards for investment and maintenance costs to encourage the electricity connection to the state grid. Meanwhile, it begins to explore the renewable portfolio standard (RPS) and tradable green certificates (TGC) to gradually replace the direct feed-in tariff (Auffhammer et al., 2021). Since 2021, the central government will no longer subsidize newly registered centralized PV power stations, industrial and commercial distributed PV projects, and newly approved onshore wind power projects (NRDC, 2021).

2.2.2 Types of China's Renewable Energy Policy

China's renewable energy policy system mainly includes four types of policies based on different parts of energy generation and consumption: 1) Renewable portfolio standard (RPS) and tradable green certificates (TGC); 2) Feed-in tariff subsidies (FIT); 3) Policies to promote technological research and development (R&D); 4) Policies to promote renewable energy consumption.

Renewable portfolio standard (RPS) is the proportion of renewable energy that should be achieved according to the provincial electricity consumption regulations, including the total renewable energy power quota and the non-hydro renewable energy power quota. Each province has a minimum proportion as binding indicators and the proportion exceeding 10% as incentive indicators (NEA, 2016; NRDC, 2019). **Tradable green certificates (TGC)** is a policy tool for implementing the RPS. Fossil fuel power generation firms can achieve RPS by purchasing green certificates from renewable energy power generation firms. TGC is in its initial stage in China and the detailed trading standards still need to be clarified (NRDC, 2017a).

Feed-in tariff (FIT) is to purposely set higher on-grid electricity prices for renewable energy than for traditional fossil fuel power to maintain the daily operation of renewable energy power generation firms. This subsidy comes primarily from the price surcharge levied on fossil fuel power and aims to mitigate the high cost faced by renewable energy generation. China first set benchmark on-grid electricity price for onshore wind power in 2009, and successively set benchmark prices for solar PV, offshore wind power, biomass energy, etc. (NRDC, 2009; 2010; 2011). China has begun to gradually cancel preferential FIT subsidies for renewable energy in recent years to reduce the dependence on subsidies while promoting self-driven technological advancement (NRDC, 2016; 2018).

Policies to promote technological research and development (R&D) refers primarily to R&D investment subsidies from both national and local governments to reduce the firms' financial pressure when developing technologies, including direct R&D subsidies, patent rewards, tax benefits for extra deduction of R&D expenses, etc. (NRDC, 2016; 2022). China has also revised the Patent Law (2020) to protect technology patents and accelerate advancement.

Policies to promote renewable energy consumption include establishing grid connection and consumption systems, peak shaving compensation mechanism, energy storage systems, and promoting market-oriented renewable energy power trading system (CPC Central Committee, 2015; NRDC, 2017b; 2019). They are designed to cope with the wind and solar curtailment caused by the rapid expansion of renewable energy production capacity and its volatility.

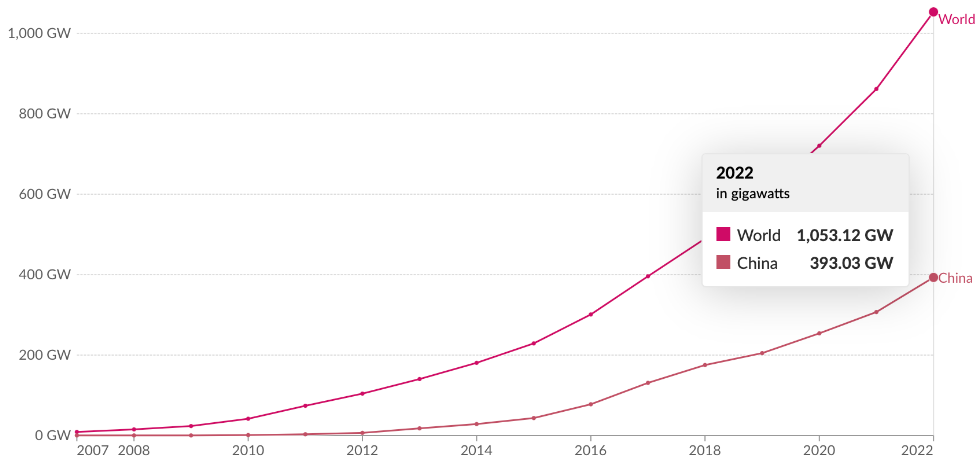
2.3 Overview of China's Solar PV Industry

Solar PV technology offers a clean and sustainable method of generating electric power directly from solar radiation. Its applications, ranging from small-scale isolated systems to large grid-connected installations, have become increasingly prevalent across the world. Solar PV technology has reached commercial acceptance and technological maturity, positioning it as a pivotal player in the ongoing energy transition aimed at mitigating the climate challenges associated with fossil fuel power generation. (Allouhi et al., 2022).

Expected technological innovation in global solar PV industry include improving solar energy conversion efficiency, reducing raw material use and costs, and enhancing recycling capabilities (IEA, 2022). A PV panel's efficiency measures the proportion of incident solar energy converted into electricity. Current PV technologies achieve less than 23% conversion efficiency, highlighting the need for further improvements to ensure greater competitiveness (Alami et al., 2022). In the upstream sector, new solar cell designs, such as tandem and perovskite technologies, are crucial for achieving higher efficiency (Allouhi et al., 2022; IEA, 2022). Deposition of dust particles on PV modules and effective thermal management of PV panels also enhance efficiency and reduces operational and maintenance costs (Allouhi et al., 2022). In the midstream sector, innovations in manufacturing processes to reduce material intensity, particularly for critical minerals like silver and copper, are essential to strengthen supply chain stability (IEA, 2022). Moreover, PV recycling remains technically challenging across the entire industry chain, requiring further research to improve recovery rates and material value retention (IEA, 2022).

China's solar PV industry, as a crucial part of generating solar power electricity, has employed all the renewable energy policies mentioned above to develop itself rapidly. From 2007 to 2022, China witnessed a remarkable increase in solar PV installed capacity, soaring from 0.2GW to 393GW and taking the share of nearly 40% in the world (Figure 8), representing a dramatic growth rate of 166% annually. Over the same period, the global weighted average levelized cost of electricity of utility-scale PVs decreases by 89% between 2010 and 2022, having reached USD 0.049/kWh, even lower than the most economical fossil fuel-fired electricity generation globally. This achievement marks the era of "Grid Parity" for solar power generation, signifying a milestone in the transition towards renewable energy (IRENA, 2023: 89-113). Despite the investment announcements and the anticipated impact of industrial policies in the United States, India, and the European Union, China is expected to sustain its predominant 80-95% share of the global solar PV manufacturing capacity in the next five years (IEA, 2024b).

Figure 8 Installed Solar Energy Capacity, China & World



Note: *the figure is cited from Energy Institute (2023) with major processing by Our World in Data.*

The upstream sector of the solar PV industry requires high technological complexity and substantial capital investment, which poses barriers to firms seeking to enter it. Although China's solar PV industry has undergone rapid expansion in the past ten years and the generation cost has reduced dramatically, it still lacks some core technologies due to the technical barriers from western countries and weak domestic independent R&D capabilities. Some of the core technologies in the upstream are dominated by the United States, Japan, and Germany. For instance, Germany remains a prominent supplier of polysilicon to the crystalline silicon photovoltaic (c-Si PV) modules industry, whereas the United States and Japan, while possessing considerable capacity, predominantly concentrate on producing semiconductor-grade products. Over the past five years, China has also been the main importer of PV-grade polysilicon, primarily from Germany, Malaysia, and Japan, as its domestic production cannot meet the demand for wafer production (IEA, 2022). The midstream sector is more labor-intensive than the upstream and faces a barrier to scale economies. Leading firms within this sector can leverage scale economies effectively, thereby significantly decreasing production costs (Zou, et al., 2017). In accordance with China's industrial policies for the solar PV industry, local governments encourage numerous firms to enter this sector by granting subsidies. However, this pattern contributes to intense price competition, overcapacity, and receives the accusation of dumping and vailing from western countries. It also faces challenges in fostering technological innovations and enhancing technological efficiency (Liu et al., 2023). The downstream sector includes the installation, utilization, and operation of solar energy systems. It needs to obtain necessary permits and approvals to construct electricity plants and connect electricity to the state grid (Zou, et al., 2017).

China's exponential expansion in the solar PV industry can be attributed primarily to the implementation of targeted industrial policies aimed at promoting renewable energy development (IEA, 2022). Government subsidies to the solar PV industry bring positive externalities in achieving green energy transformation. The ex-ante subsidies in initial investment have the advantages of direct fund allocation and a quick return period, bringing unprecedented financial support to the PV industry in its embryonic stage, effectively solving the problem of high initial investment costs and accelerating the scale economies in the midstream. Nonetheless, large-scale subsidies cannot guarantee effective incentives for PV product quality and technology upgrading (Auffhammer et al., 2021). The shift from ex-ante to ex-post subsidies in 2013 not only mitigates the over-investment caused by initial subsidies, but also fundamentally eliminates the subsidy fraud, avoiding the loss of economic efficiency to a certain extent. While it has contributed to a more prudent allocation of financial resources and reduced malpractice, it still lacks accurate stimulation in technological innovation (Tu et al., 2020).

Consequently, there remains a pressing need for a more nuanced and strategic approach to government subsidy schemes. Policymakers are urged to pivot towards a refined subsidy model characterized by quality enhancement, cost-effectiveness, and targeted support for technological innovation. By aligning subsidy schemes with the incentives of technological advancement and market competitiveness, China might achieve substantial energy transformation while simultaneously fostering economic growth and profitability within its solar PV industry. This refined approach needs to shift from blanket subsidies towards targeted encouraging cutting-edge technology research and development.

3 Theory and Previous Research

3.1 Theoretical Framework

The theoretical framework of this study lies in the relationship between industrial policy, innovation, and economic growth.

Conventional neoliberal scholars argue that extensive government interventions in industrial policy can distort market mechanisms, leading to inefficiencies and misallocation of resources. Industries heavily supported by industrial policy may lack the incentive to innovate (Krugman, 1993). Nonetheless, both developed and developing economies employ industry policy to foster innovation and growth nowadays. The United States employs a mixed industrial policy approach, combining government intervention with free-market principles. For instance, the Inflation Reduction Act issued in 2022 aims to boost renewable energy and reduce carbon emissions, which is expected to generate significant economic benefits and job vacancies in green technologies (Bistline et al., 2023). The two-way fixed contract for difference is common in Europe and makes up over one-third of the region's growth in large-scale renewable energy projects (IEA, 2024a). Industrial policy in Latin American countries has mixed results. Some sectors like Brazilian aircraft manufacturing have thrived, while others have not succeeded due to issues like corruption and poor implementation (Schneider, 2009). Industrial policy in Sub-Saharan Africa often fails due to weak institutions and lack of coherence (Page, 2012). The experience of high-performing East Asian economies proves that strategic government interventions can be crucial for growth. The conventional strategy employed by East Asian economies for developing emerging industries often adopts an import-substitution approach to nurturing infant industries that initially focuses on serving the domestic market under the shelter of government protection. Subsequently, as these firms attain competitiveness compatible with international standards, they gradually shift towards exporting their products to global markets at lower prices (Rodrik, 1995; Wade, 2005).

Industrial policy fosters growth in developing countries through at least two channels. One is to ensure the increasing returns to scale by absorbing the large sunk cost and making the spill-over effects. The other is to help different firms overcome coordination failure and build a cluster of industries (Quibria, 2002). Some studies emphasize the need for developing dynamic capabilities, where industrial policy should focus on fostering innovation and adaptability within industries to sustain long-term growth (Pisano & Shih, 2009). In the case of newly industrialized countries in East Asia, the development of "national systems of innovation" was a key aspect of industrial policy, and successful industrial upgrading contributed significantly to joining higher-income economies (Weiss, 2005). It is still controversial whether more proactive government policies should be applied to diversify and upgrade economies in both advanced and developing economies today. China, like its East Asian predecessors, serves undoubtedly as a compelling example of how coordinated government interventions can drive rapid diversification and innovation (Aiginger & Rodrik, 2020). The "Made in China 2025" initiative launched in 2015 is transforming China from a manufacturing giant into a world leader in high-tech industries, such as robotics, aerospace, and clean energy (Kennedy, 2015). However, China's industrial policy currently leads to trade tensions, particularly with the United States, over issues of unfair trade practices and intellectual property plagiarism (Brown & Singh, 2018).

3.2 Measurements

3.2.1 Measuring Government Subsidies

Industrial policy commonly refers to a set of government interventions and strategies and is difficult to measure. Government subsidies are a tool within industrial policy to provide direct financial support to targeted industries. This study narrows down to government subsidies because the Chinese government, like many other countries, has pledged to reduce carbon emissions within timeframes. Subsidies as direct financial support can enhance the innovative efforts targeted at meeting these time-bound objectives while other indirect instruments might not, making them particularly conducive to assessing the impact on firms' innovative endeavors (Warwick & Nolan, 2014). Additionally, it is a directly measurable indicator in the firms' financial statements with the detail of each payment, which helps to trace subsidy type, specific project, or policy document.

3.2.2 Measuring Innovation

Innovation is sometimes considered to have its inherent difficulties in measuring and quantifying due to its novelty and the diverse forms it can take. Smith (2006) explores various approaches and indicators used to measure innovation, emphasizing the need for careful conceptualization and the challenges posed by trying to measure something inherently qualitative and dynamic. The basic conceptual challenges in measuring innovation are to define what constitutes "new" and the degree of novelty required for something to be considered an innovation. Traditional indicators like R&D and patents are employed but Smith (2006) points out their limitations, particularly in capturing the full spectrum of innovation activities. For instance, measuring innovation in service sectors or low-tech industries should capture changes through customer interactions, service delivery enhancements, or operational efficiency. Therefore, the author emphasizes the importance of broadening the scope of indicators to include non-R&D activities such as design, market research, and organizational changes. Some researchers often combine multiple indicators to provide a more comprehensive picture of innovation performance. Dewangan and Godse (2014) offer several guidelines for creating an innovation measurement system, including being process-based, multi-dimensional, easy to use, and proposing casual relationships between measures.

Innovation can be measured from various perspectives. R&D intensity is the ratio of a firm's investment in R&D relative to its other economic outputs. It represents a firm's willingness and emphasis on innovation in comparison to its overall operations (Hughes, 1988). R&D intensity is commonly calculated as the ratio of a firm's R&D expenditure to its total sales revenue or profit (Galindo & Verger, 2016). However, considering that the total revenue of the solar PV industry may be inflated due to large amounts of subsidies, some studies employ an alternative approach by using the ratio of R&D expenditure to the fixed assets to measure R&D intensity (Jiang et al., 2021). Basically, it supposes that the R&D intensity has a distribution and is not fairly dispersed among firms within an industry (Hughes, 1988).

Innovation efficiency, another common indicator, is more comprehensive to calculate. It measures how well a firm can convert inputs into valuable innovations. Researchers have increasingly improved and employed a frontier analysis approach, such as stochastic frontier analysis (SFA) and Data Envelopment Analysis (DEA). SFA is a parametric analysis methodology that presupposes a defined functional form for the relationship between input and output functions and utilizes econometric methods to estimate unknown parameters, while DEA is more flexible without setting a functional form a priori. These methods have currently emerged as predominant techniques for evaluating innovation efficiency (Wang et al., 2016).

3.3 Previous Research

Existing studies investigate the relationship between government policies and innovation in the renewable energy industry in different regions and countries. Hille & Diederich (2020) finds that intensive portfolios of policies supporting renewable energy are associated with an increase in patenting activities using a large sample covering 194 countries from 1990 to 2016. R&D support programs exert the most significant positive influence on patenting. Other important instruments include targets, fiscal incentives, and certificate trading. Some research shows that targeted subsidies are necessary to stimulate innovation in costly technologies such as the solar PV industry (Johnstone et al. 2010). On the contrary, Pitelis et al. (2020) find that policy instruments play an important role in technological innovation, but the effectiveness of different types of policies differs among subsectors with samples covering 21 countries and over 24 years. Demand-pull policies, such as tax refunds for consumers of new technologies, generally have more potential to foster innovation than technology-push ones such as government-sponsored R&D, especially in the case of solar energy technologies.

Some other factors affect innovative activities in the renewable energy industry. Firm size has a positive effect in general because of scale economies (OECD, 2013). Larger firms can leverage their scale to reduce costs and increase efficiency in their innovation activities, and allows them to reciprocally invest more in R&D, access a broader range of technological resources, and implement more ambitious innovation strategies compared to smaller firms. The effects of financial leverage and age are more controversial. Established models under free competition show that appropriate loaning scale and interest rate are essential to green innovation (Huang et al. 2019). Older firms generally benefit from learning effects while younger firms are more likely to invest in R&D to gain rapid growth (Coad et al. 2016). Plank and Doblinger (2018) use data from 1448 German firms and find that the overall financial situation has a positive effect while age is negative.

There is also empirical research specific to the development and innovation of China’s solar PV industry. Huang et al. (2016) analyze how China obtained its worldwide leading position in the solar PV industry under the framework of the Technological Innovation System (TIS) and other external conditions. It highlights the proactive role of Chinese government policies in creating favorable conditions for the industry’s development, including financial support, subsidies, and stringent renewable energy targets. It also notes the importance of a robust domestic market that facilitates scale economies and reduces costs. Ye et al. (2017) find that feed-in tariff policies from 2011 to 2016 fostered China's solar PV industry but also brought overcapacity as a side effect. Xiong & Yang (2016) suggest that government subsidies should be granted during the industry's growing period and exit gradually to foster a matured market. Zhao et al. (2023) finds that substantial government subsidies played a crucial role in the initial phase of solar PV industry development. As the industry matured, the government gradually reduced subsidies to encourage competition and firms increased innovation investment for cost reduction. Lin & Luan (2020) uses the two-stage DEA-Tobit model to estimate the innovation performance of China's solar PV industry based on a sample consisting of 44 firms from 2012 to 2016. They find that government subsidies have an overall positive effect on the technological innovation efficiency of China's solar PV industry. Moreover, pure technical efficiency (PTE) contributes more than scale efficiency (SE), which means that technology is the main reason for the high innovation efficiency. Notably, this study also shows that firm size negatively affects innovation efficiency. On the contrary, Zhang et al. (2016) use the DEA model to evaluate the operating performance and spatial characteristics of 58 listed solar PV firms. The result shows that most firms lack pure technical efficiency (PTE). It suggests that firms should enhance their PTE to improve their operational performance by increasing investment in R&D and strengthening the capacity for independent innovation. Government policies should lead to more rational and balanced subsidies.

The contribution of this study lies in its approach to dividing the whole solar PV industry chain into upstream, middle, and downstream sectors. It allows for a more detailed analysis of the relationship between government subsidies and innovation within the industry. It is suggested that different sectors of the industry chain require varying levels of innovation due to differences in technology intensity, market structures, and regulations. By distinguishing different effects across these sectors, policymakers can grant financial support more accurately, aligning subsidies with the specific needs to foster innovation. This targeted approach not only enhances the effectiveness of policy instruments but also helps minimize fiscal waste.

4 Data and Methods

4.1 Data

This research employs a dataset comprising 97 firms drawn from China's A-share market. The A-share market refers to the stock market in mainland China where shares of Chinese companies are traded in Chinese yuan. It is one of the largest stock markets in the world by market capitalization and is included in major global equity indices such as MSCI. Data for firms listed on the A-share market is relatively transparent and credible due to regulatory requirements. Two criteria for selection are: 1) Solar PV is registered as one of the firm's main business areas; 2) ST / *ST[1] firms are excluded.

This study divides these selected firms into three sectors – upstream, midstream, and downstream. The solar PV industry chain involves the following stages: purifying silicon, making solar wafers and cells, assembling the solar cells into modules, manufacturing other key components, and installing and operating the solar PV systems. The main business of some outstanding firms covers the whole value chain. Based on their strong upstream R&D capabilities, this study classifies them as the upstream sector. The period of data is from 2007 to 2022 for two reasons: 1) China's Renewable Energy Law came into force on January 1, 2006, which signifies a starting point for government-led development of the renewable energy industry; 2) China's Ministry of Finance required listed and proposed listed companies to disclose their R&D expenses since January 1, 2007 (MF, 2006). Data of patents of the firms listed in A-share market are available since then.

Data of all indicators are from the China Stock Market & Accounting Research Database. (CSMAR, 2024). It is a leading provider of China financial market, industries, and economic data. It covers a vast compilation of over 200 databases and is widely used in the study of China's financial market. This study uses two databases of its compilation: CSMAR Financial Statements Database of Chinese Listed Companies and CSMAR Research, Development, and Innovation Database of Chinese Listed Companies. The Financial Statements Database includes historical data of financial statement accounting items since the

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[1] In China's A-share market, firms with the **"ST"** designation means they may face challenges or uncertainties that could impact their stock performance but are not yet at a critically severe level, and investors should carefully consider these factors in their investment decisions; firms with the **"*ST"** designation means they are in more severe financial distress (e.g. having incurred financial losses in three consecutive years) and have the risk of withdrawal from the stock market.

establishment of the A-share market, ensuring complete and accurate financial data. The Research, Development, and Innovation Database includes detailed information on listed firms' R&D investments, R&D expenditures, intangible assets, patent applications and acquisitions since 2007.

Table 2 gives the description of all the indicators employed in this study. This study eliminates data with input factors both being 0 or output factors both being 0 to ensure the calculation is consistent with reality. The number of observations is 730. Table 1 gives information on the three sectors.

Table 1 Description of Sectors

Sector	Primary activities	Number of firms	Number of observations
Up	Purification of silicon Manufacturing silicon wafers	46	344
Middle	Assembling solar cells & modules Manufacturing other key components	24	189
Down	Installing solar PV systems Operating solar PV systems	27	197
Total	/	97	730

4.2 Methodology

The methodology of this study is quantitative and contains two parts. Software Stata 18.0 is used for all the models below.

This study employs both R&D intensity and innovation efficiency as dependent variables as they respectively represent firms' innovation willingness and outcomes. While firms may invest substantial resources in R&D, the actual outcomes might not always meet expectations. R&D intensity is measured by the ratio of R&D expenditure to the net fixed assets annually, aiming to discern the influence of government subsidies on revenue. Data Envelopment Analysis (DEA) is used to evaluate overall innovation efficiency considering several facts. First, the solar PV industry is fundamentally a high-technology industry that necessitates R&D expenditure and patents, thereby leaving traditional indicators still effective (Smith, 2006). Second, DEA model allows for the assessment of the relative efficiency of decision-making units (DMUs) in transforming inputs into outputs, so the efficiency among different years, chain sectors, and firms is comparable (Charnes, Cooper & Rhodes, 1978). Third, DEA can handle multiple inputs and outputs without needing to specify weights a priori, making it ideal for evaluating innovation because multiple factors may contribute differently to the innovative output in practice.

Table 2 Description of Indicators

Indicators	Unit	Role	Description	Model
Researchers	Person	Input - human	Number of researchers	DEA model
R&D Expenditure	million CNY	Input - material	Expenditure on research and development activities annually	
Patent	Number	Output-patent	Number of patent applications annually	
Total Revenue	million CNY	Output-others	Overall income generated from primary business activities annually	
R&D Intensity	/	Dependent variable	Ratio of R&D expenditure to net fixed assets	Regression model
Innovation Efficiency	/	Dependent variable	Overall efficiency (Results of the DEA model above)	
Government Subsidies	million CNY	Independent variable	Received from the government and listed in financial statements (Use logarithm in regression model)	
Financial Leverage	/	Control variables	Asset-liability ratio	
Size	million CNY		Total assets (Use logarithm in regression model)	

4.2.1 DEA Model

This study first measures and evaluates the overall innovation efficiency (OE) of China's solar PV industry with the BCC model in Data Envelopment Analysis (DEA). DEA is a common method used in previous research to evaluate the relative efficiency of decision-making units (DMUs) based on their input-output relationships. The final OE ranges from 0 to 1, where 1 indicates a fully efficient DMU using inputs optimally to produce outputs, and scores less than 1 indicate varying degrees of inefficiency. BCC model in DEA allows for variable returns to scale (VRS), as in practice outputs grow not proportionately with inputs. With BCC model in DEA, OE can be disassembled into pure technological efficiency (PTE) and scale efficiency (SE) under the assumption of VRS. Results will present the trend of OE in China's solar PV industry and investigate whether technological advancement or scale economies contributed more to OE. The calculation is given as follows:

$$OE = PTE * SE$$

The results given by DEA model are used as guidance and the dependent variable in the regression model. First, it calculates OE of the whole solar PV industry. The hypothesis is that scale economies play a more important role than technological advancement in the past, so the primary task for the next phase is to enhance pure technological innovation by allocating financial resources efficiently. Second, it compares OE / PTE / SE among the upstream, midstream, and downstream respectively to see the different contributions made by technological innovation and scale economies.

This study sets the input indicators as the number of researchers and the amount of R&D expenditure; and sets the output indicators as the number of patents and the total revenue (seen in Table 2). Innovation inputs include both human and material investment. It uses the count of R&D persons as a proxy for human investment. Since OECD suggested that R&D expenditure constitutes a pivotal form of material investment in innovation (Sharma & Thomas, 2008), it uses R&D expenditure as a proxy for material investment. Patents are conventionally used as proxies for technological innovation (Smith, 2006). Rather than patent grants, it uses the number of patent applications annually, given the uncertainties inherent in the patent licensing process and the potential application of patents in production prior to their formal granting (Piao et al., 2017). Given the limitations of patent applications in accurately reflecting the transformative capacity and market value of innovation, it also uses total revenue as other outputs.

Table 3 shows the description statistics of indicators employed in the DEA model. It presents relatively large differences among the 97 firms. At the end of 2022, the mean number of R&D persons and expenditure are 629 and 544 million CNY and the standard deviates are 850 and 1109 million CNY respectively, indicating the large gap in innovation inputs. Similarly, the mean number of patents annually applied and revenue are 55 and 14401 million CNY and the standard deviates are 191 and 26555 million CNY respectively, indicating the large gap in innovation outputs among firms.

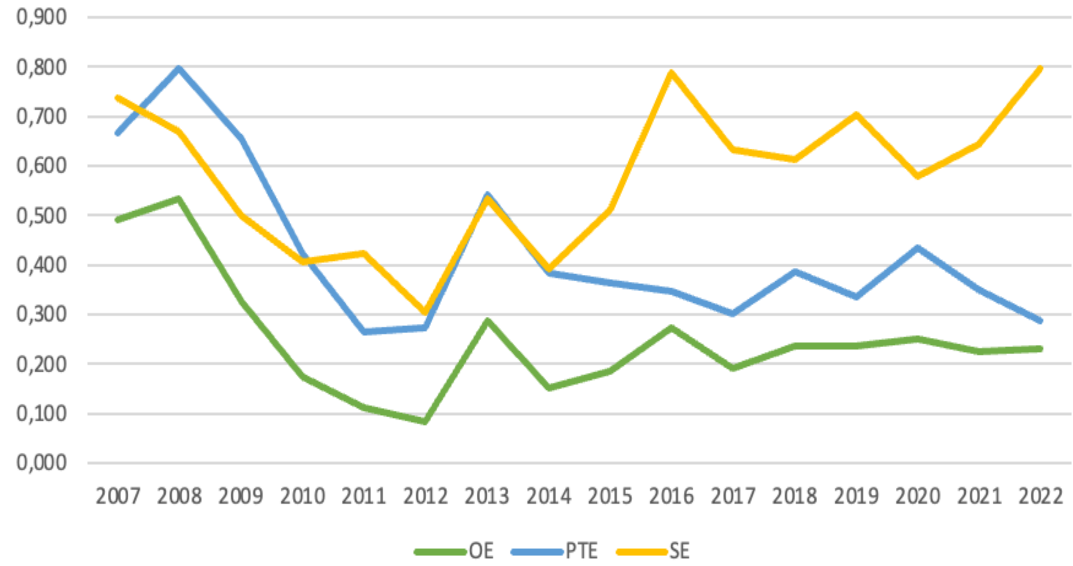
Table 3 Descriptive Statistics of Indicators in DEA Model

Model	Variable	Obs	Mean	Std. dev.	Min	Max
Input	**R&D Person**	97	629,4124	850,7803	0	4507
	R&D Expenditure (m CNY)	97	544,5643	1109,666	0,8934758	5614,615
Output	**Patent**	97	55,56701	191,0295	0	1581
	Revenue (m CNY)	97	14402,34	26555,45	301,3227	142422,5

Figure 9 shows the overall efficiency (OE), The scale efficiency (SE), and the pure technological efficiency (PTE) listed by year. OE is constantly low, indicating that there is still a large space for optimizing the overall innovation capabilities within the solar PV industry. SE has been constantly higher than PTE since 2011, indicating that scale economies contribute more to OE rather than technological advancements in the past decade.

SE declines from 2007 to 2010 and then increases relatively fast from 2012 to 2016. It peaked in 2016 and then slows down and fluctuates slightly. PTE also declines from 2007 to 2010 but then keeps fluctuating without obvious improvement. The decline of both SE and PTE in the initial phase might be attributed to the absence of detailed subsidy policies, therefore firms must rely on their own financial resources to invest and operate. The increase in SE since 2012 may be attributed to the implementation of the subsidy policies for solar energy power generation in Jul 2011 (NRDC, 2011). The Chinese government later classifies three types of solar resource areas and sets benchmark on-grid electricity prices for solar PV power (NRDC, 2013). It then gradually improves its on-grid electricity price subsidy policy for renewable energy power generation and issued additional standards for renewable energy electricity prices, which ensures stable funding sources and encourages the industry's rapid expansion (NRDC, 2015). The turning point appears due to the cost reduction and resource curtailment in this progress. China sets the goal of "grid parity" and the gradual withdrawal of subsidies in the 13th Five-Year Plan for Renewable Energy (NRDC, 2016). It further restricts the expansion, reduces the subsidy intensity, and replaces government pricing with market bidding since 2018 (NRDC, 2018).

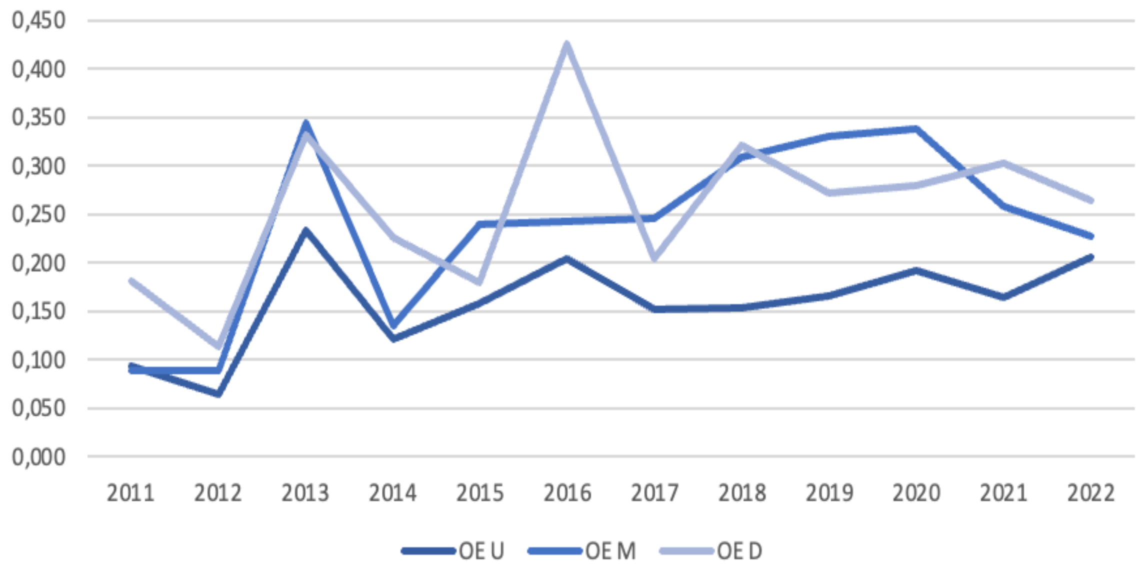
Figure 9 Overall Efficiency Score with DEA Model, by year

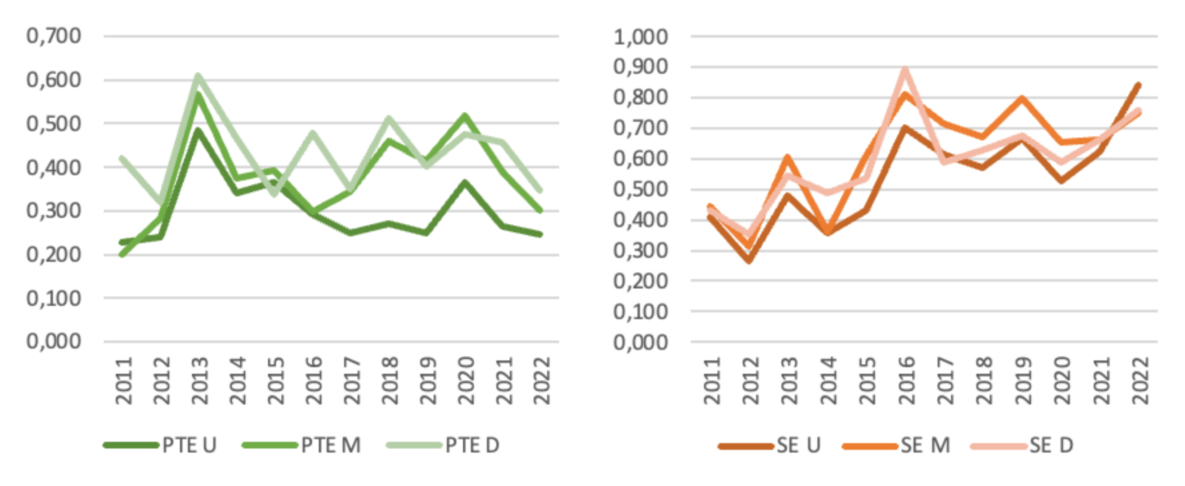


Note: *the figure is illustrated by the author; data is listed in the Appendix.*

Figure 10 shows the innovation efficiency by sectors within the industry chain from 2011 to 2022. OE of upstream is constantly lower than that of middle and downstream. When disassembled into PTE and SE, the score of upstream is also lower than that of middle and downstream in almost all years, indicating that China's solar PV industry has an unbalanced development with both better technological improvement and better scale economies among middle and downstream firms.

Figure 10 Overall Efficiency Score with DEA Model, by sector





Note: *the figure is illustrated by the author; data is listed in the Appendix.*

4.2.2 Regression Model

This study explores the relationship between government subsidies and firms' innovation with the OLS regression model. It study takes firms' scale and leverage as control variables because firms with more resources or fewer financial constraints may invest more in R&D activities. Age is not included as a control variable because the solar PV industry in China has developed rapidly over a relatively short period, spanning less than 20 years.

4.2.2.1 Regression Model for R&D Intensity

To investigate the impact of government subsidies on firms' willingness to innovate, it uses the R&D intensity as the dependent variable. The regression model is given as follows:

$$RDInt_{it} = \beta_0 + \beta_1 * Sub_{it} + C_{it}$$

To further investigate the different effects among upstream, midstream, and downstream, the basic model is expanded as follows:

$$RDInt_{uit} = \beta_{0u} + \beta_{1u} * Sub_{uit} + C_{uit}$$
$$RDInt_{mit} = \beta_{0m} + \beta_{1m} * Sub_{mit} + C_{mit}$$
$$RDInt_{dit} = \beta_{0d} + \beta_{1d} * Sub_{dit} + C_{dit}$$

RDIn**$_{it}$* is the ratio of each firm's R&D expenditure to its net fixed assets, referring to a firm's willingness to innovate. ***Sub**$_{it}$* is the logarithm of government subsidies that each firm receives annually. ***C**$_{it}$* is other important control variables that may affect R&D investment. The control variables used here are firm size measured by the logarithm of total assets and financial leverage measured by the ratio of assets to liabilities. ***u, m, d represent upstream, midstream, and downstream respectively.

The hypothesis is government subsidies can stimulate their willingness to innovate and form intangible assets. Therefore, the coefficient $\boldsymbol{\beta_1}$ is positive and statistically significant.

4.2.2.2 Regression Model for Innovation Efficiency

To investigate the impact of government subsidies on firms' innovation efficiency, it uses the scores of the DEA model mentioned above, including OE / PTE / SE, as dependent variable respectively. The regression model is given as follows:

$$Eff_{it} = \beta_0 + \beta_1 * Sub_{it} + C_{it}$$

To further investigate the different effects among upstream, midstream, and downstream, the basic model is expanded as follows:

$$Eff_{uit} = \beta_{0u} + \beta_{1u} * Sub_{uit} + C_{uit}$$
$$Eff_{mit} = \beta_{0m} + \beta_{1m} * Sub_{mit} + C_{mit}$$
$$Eff_{dit} = \beta_{0d} + \beta_{1d} * Sub_{dit} + C_{dit}$$

$\boldsymbol{Eff_{it}}$ is the score of each DMU. OE, PTE, and SE are used respectively here. $\boldsymbol{Sub_{it}}$ is the logarithm of government subsidies that each firm receives annually. $\boldsymbol{C_{it}}$ is other important control variables that may affect R&D investment. The control variables used here are firm size measured by the logarithm of total assets and financial leverage measured by the ratio of assets to liabilities. ***u, m, d*** represent upstream, midstream, and downstream respectively.

The hypothesis is government subsidies have positive effects on overall innovation efficiency. Therefore, the coefficient $\boldsymbol{\beta_1}$ is positive and statistically significant.

5 Empirical Analysis

5.1 Results

5.1.1 Relationship between Innovation Willingness and Subsidies

Table 4 shows the description statistics of R&D intensity among upstream, middle, and downstream. ***SUB-REV*** is the ratio of the annual government subsidies to the firm's total revenue. It is similar among the three sectors, indicating that no sector gets especially higher subsidies than others. ***RDInt*** is the ratio of the annual R&D expenditure to net fixed assets. The average RDInt of upstream firms is significantly higher than that of middle and downstream, indicating that upstream firms emphasize more on R&D investment, technological advancement, and intangible assets formation as their strategy.

Table 4 Descriptive Statistics of R&D Intensity

Sector	SUB-REV	RDInt
U	1,23%	28,82%
M	1,03%	16,34%
D	1,11%	17,42%

Table 5 and Table 6 show the descriptive statistics and correlation coefficients of the explanatory variables respectively. Government subsidies and total assets are calculated by the logarithm. The amounts of subsidies, firm size, and financial leverage vary widely among firms and years. The correlation coefficients of the explanatory variables are all less than 0.6, indicating that this study will not be affected significantly by a severe multicollinearity.

Table 5 Descriptive Statistics of the Explanatory Variables

Variable	Obs	Mean	Std.dev.	Min	Max
Sub	730	44.68576	93.31069	0	1088.674
Size	730	13020.13	24851.14	223.8886	262127.2
Leverage	730	2.919972	2.257246	.3495229	19.3825

Table 6 Correlation Coefficients of the Explanatory Variables

Variable	Sub	TotalAssets	Leverage
Sub	1		
Size	0,5662	1	
Leverage	-0,2083	-0,4193	1

Table 7 shows the results of the regression model for R&D intensity. The relationship between R&D intensity and government subsidies is statistically significant for the whole industry at a 99% level. It is also statistically significant for the up and midstream at 95% level, while it is not significant for the downstream.

The positive coefficients of the up and midstream indicate that government subsidies have a positive effect on the firm's willingness to innovate. Furthermore, upstream firms have a higher increase in R&D intensity than midstream firms do when subsidies increase by the same proportion. The result provides evidence for policymakers about the impact of subsidies on encouraging firms to invest in R&D. If the goal of subsidies in the next phase is to stimulate firms to invest in innovation rather than merely capacity expansion, a positive coefficient of the up and midstream would suggest that subsidies might achieve their intended goal.

Table 7 Results of Regression Model for R&D Intensity

	Total	**U**	**M**	**D**
	RDInt	**RDInt**	**RDInt**	**RDInt**
Sub	0.0570***	0.0937**	0.0324**	0.0105
	(3.00)	(2.36)	(1.99)	(0.58)
Size	-0.106***	-0.139***	-0.0456*	-0.0701***
	(-4.43)	(-2.64)	(-1.93)	(-3.43)
Leverage	-0.00652	-0.0196	0.0138	0.0295*
	(-0.58)	(-1.03)	(1.28)	(1.71)
Constant	0.998***	1.262***	0.431**	0.693***
	(4.99)	(3.01)	(2.15)	(3.68)
Observations	730	344	189	197

Note: *t statistics in parentheses; * p<0,10, ** p<0,05, *** p<0,01.* ***Total*** *is the regression for the whole chain;* ***U*** *is upstream;* ***M*** *is midstream;* ***D*** *is downstream.*

5.1.2 Relationship between Innovation Outcomes and Subsidies

Table 8 shows the results of the regression model for SE. When employing government subsidies as the sole independent variable, its relationship with SE is not significant. However, the inclusion of the squared term for government subsidies in the model presents a statistically significant relationship for the entire industry as well as for all three sectors. This finding suggests a non-linear relationship between SE and government subsidies.

Specifically, SE increases with the introduction and initial growth of subsidies but begins to decline once subsidies surpass a certain threshold.

The process of granting government subsidies to any sector of the solar PV industry can increase firms' scale efficiency until the optimal production scale is reached. Beyond this point, further increases in government subsidies will cause scale efficiency to decline. This is consistent with the findings of previous research, indicating that while subsidies can initially help the industry grow rapidly, excessive subsidies lead to overcapacity and inefficiency (Ye et al., 2017).

Table 8 Results of Regression Model for Innovation Efficiency, SE

	Total	**Total2**	**U**	**M**	**D**
	SE	**SE**	**SE**	**SE**	**SE**
Sub	0,00973	0,129***	0,101***	0,108**	0,195***
	-1,1	-5,51	-2,65	-2,59	-4,62
Size	0,107***	0,133***	0,149***	0,128***	0,128***
	-9,58	-11,15	-7,33	-5,31	-6,35
Leverage	-0,00514	-0,00475	-0,00287	-0,00506	-0,0122
	(-0,98)	(-0,92)	(-0,44)	(-0,49)	(-0,78)
Sub2		-0,0233***	-0,0213***	-0,0161**	-0,0349***
		(-5,48)	(-3,00)	(-2,14)	(-4,66)
Constant	-0,320***	-0,648***	-0,729***	-0,583***	-0,697***
	(-3,44)	(-5,95)	(-4,06)	(-2,69)	(-3,40)
Observations	730	730	344	189	197

***Note**: t statistics in parentheses; * p<0,10, ** p<0,05, *** p<0,01. **Sub2** is the squared term of the logarithm of subsidies; **Total** is the regression for the whole chain without adding squared term; **Total2** is the regression for the whole chain after adding squared term; **U** is upstream; **M** is midstream; **D** is downstream.*

Table 9 shows the results of the regression model for PTE. When employing government subsidies as the sole independent variable, its relationship with PTE is not significant. However, the inclusion of the squared term for government subsidies in the model presents a statistically significant relationship for the entire industry, up and downstream. The coefficient of subsidies is nearly significant for midstream. This finding suggests a non-linear relationship between PTE and government subsidies. In contrast to SE, PTE declines with the introduction and initial growth of subsidies but begins to increase once subsidies surpass a certain threshold.

A possible explanation for this result is the existence of a learning curve (Cantono & Silverberg, 2009). When government subsidies are first introduced, firms might experience a period of adjustment. Temporary inefficiencies appear as firms figure out how to best utilize the additional resources, which can result in a short-term decline in PTE. As firms learn how to integrate the subsidies into their technological development effectively over time, they can allocate these funds efficiently, leading to improved PTE.

Table 9 Results of Regression Model for Innovation Efficiency, PTE

	Total	**Total2**	**U**	**M**	**D**
	PTE	**PTE**	**PTE**	**PTE**	**PTE**
Sub	-0,0121	-0,109***	-0,0987***	-0,0786	-0,160***
	(-1,21)	(-4,07)	(-2,61)	(-1,51)	(-3,31)
Size	0,0267**	0,00538	-0,0736***	-0,0463	0,0672***
	-2,12	-0,4	(-3,65)	(-1,54)	-2,9
Leverage	-0,00584	-0,00616	-0,00684	-0,0157	-0,0175
	(-0,99)	(-1,05)	(-1,06)	(-1,21)	(-0,98)
Sub2		0,0189***	0,0192***	0,0159*	0,0294***
		-3,89	-2,72	-1,7	-3,43
Constant	0,189*	0,455***	1,043***	0,890***	0,0377
	-1,81	-3,66	-5,86	-3,28	-0,16
Observations	730	730	344	189	197

***Note**: t statistics in parentheses; * p<0,10, ** p<0,05, *** p<0,01. **Sub2** is the squared term of the logarithm of subsidies; **Total** is the regression for the whole chain without adding squared term; **Total2** is the regression for the whole chain after adding squared term; **U** is upstream; **M** is midstream; **D** is downstream.*

Table 10 shows the results of the regression model for OE. None of the results are significant here. Since OE is the product of SE and PTE, its trend of change may be offset by the opposing trends of these two factors.

Table 10 Results of Regression Model for Innovation Efficiency, OE

	Total OE	Total2 OE	U OE	M OE	D OE
Sub	-0,00384	0,00217	-0,00561	0,0252	-0,0136
	(-0,47)	-0,1	(-0,17)	-0,59	(-0,31)
Size	0,0502***	0,0515***	0,00481	0,00112	0,0940***
	-4,82	-4,52	-0,28	-0,05	-4,56
Leverage	-0,00215	-0,00213	-0,000329	-0,0124	-0,0171
	(-0,44)	(-0,43)	(-0,06)	(-1,17)	(-1,08)
Sub2		-0,00117	0,00037	-0,00174	0,00275
		(-0,29)	-0,06	(-0,23)	-0,36
Constant	-0,187**	-0,203*	0,16	0,22	-0,503**
	(-2,15)	(-1,95)	-1,06	-0,99	(-2,41)
Observations	730	730	344	189	197

***Note**: t statistics in parentheses; * p<0,10, ** p<0,05, *** p<0,01. **Sub2** is the squared term of the logarithm of subsidies; **Total** is the regression for the whole chain without adding squared term; **Total2** is the regression for the whole chain after adding squared term; **U** is upstream; **M** is midstream; **D** is downstream.*

5.2 Discussion

In summary, these findings support the crucial role of government subsidies in fostering innovation within China's solar PV industry.

First, Government subsidies significantly enhance the willingness to innovate among upstream and midstream firms. Upstream firms exhibit a higher responsiveness to subsidies in R&D investment. Second, SE contributes more substantially to OE than PTE. This indicates the importance of scale economies in fostering the solar PV industry. Third, the relationship between government subsidies and innovation efficiency is complex and non-linear. There exists a non-linear relationship between SE and government subsidies as well as between PTE and government subsidies across up, middle, and downstream sectors. Moreover, the trends of these two relationships are opposing. The reversed U-shaped relationship between SE and subsidies has been discussed in previous research (Xiong &

Yang, 2016; Ye et al., 2017; Zhao et al., 2023). The U-shaped relationship between PTE and subsidies might be explained by the existence of a learning curve.

This study exclusively draws its sample from China's A-share market, introducing a limitation to it. Opposed to the conventional registration system in advanced economies, China's A-share market is characterized by a stringent auditing system requiring meticulous scrutiny of a firm's historical financial statements. Consequently, the successful issuance of shares is predominantly decided by a firm's relatively robust financial performance (Qian et al., 2024). Several small and medium-sized enterprises (SMEs), despite receiving government subsidies, fail to enter the A-share market due to shortcomings in sustained growth. As a result, the sample used in this study may not fully represent the broader scope of firms within the solar PV industry, particularly those at different stages of development and with varying capacities for innovation. Therefore, the study's findings may primarily reflect the effects of government subsidies on relatively well-established firms, potentially overlooking the nuanced impacts on emerging companies that are also crucial to the industry's overall innovation efficiency. Further research may incorporate data from those excluded SMEs once it becomes available and credible. By expanding the sample to include a broader range of firms, future studies can provide a more comprehensive analysis of the relationship between subsidies and innovation.

6 Conclusion

Climate change is a global issue that humans are facing nowadays. The release of CO_2 and other greenhouse gases from human activities, such as burning fossil fuels and deforestation, has led to an increase in global temperatures, altered weather patterns, and more frequent and severe natural disasters. These impacts call for the urgent need for a comprehensive approach to mitigate climate change. One critical strategy in addressing climate change is the energy transition to reduce carbon emissions. It involves shifting from reliance on fossil fuels to renewable energy sources, such as wind, solar, and biomass power. This transition is essential not only to reduce greenhouse gas emissions but also to decrease air pollution and enhance energy security by diversifying energy supplies and reducing dependence on imported fuels.

Solar energy, particularly utilized through photovoltaic (PV) technology, plays a pivotal role in this energy transition. Solar PV systems can convert sunlight directly into electricity, offering a clean and abundant energy source that can significantly reduce carbon emissions. The solar PV industry has witnessed rapid growth and technological advancements, making solar power more cost-effective and accessible globally nowadays. Its development is crucial for achieving large-scale deployment of renewable energy.

Innovation is a key driver in fostering the growth and efficiency of the solar PV industry, especially technological advancements in the upstream sector have improved the performance and reduced the costs of solar PV systems. Continuous R&D efforts are essential to overcoming current technological limitations, thereby making solar energy more competitive with traditional energy sources.

Policy support is vital for the thriving of the solar PV industry and its ongoing innovation. Financial incentives, such as subsidies, tax credits, and feed-in tariffs, lower the economic barriers to adopting solar technology and encourage investment in R&D activities. These policies create a favorable market environment that accelerates the deployment of solar PV systems and stimulates technological advancements.

China has become the biggest carbon emitter at the aggravate level with its rapid economic growth. Meanwhile, it has also emerged as a global leader in the energy transition, especially in the solar PV supply chain. Its substantial investments led by the government in renewable energy infrastructure and manufacturing capabilities in the past two decades have made it at the forefront of solar PV production. China's dominance in the global solar PV market is supported by strong policy support and a robust domestic market.

This study focuses on China as a case study as the country is proven to be a success story and is forecasted to remain the leader in the global solar PV industry in the next few years. China's dominance in this industry makes it an ideal subject for examining the impacts of government policies on the industry's expansion and innovation. Understanding the dynamics within China's solar PV industry may provide valuable insights for policymakers to enhance renewable energy capabilities. The aim of this study is to investigate how government subsidies affect innovation in China's solar PV industry. The findings come from empirical analysis covering data from 97 firms listed in China's A-share market.

First, government subsidies positively influence the willingness to innovate among upstream and midstream firms. Notably, upstream firms demonstrate a greater increase in R&D intensity compared to midstream firms when subsidies are increased by the same proportion. This suggests that upstream sectors may have a higher responsiveness to subsidies in terms of boosting R&D investment. Second, the study finds that scale efficiency (SE) contributes more significantly to overall innovation efficiency (OE) than pure technological efficiency (PTE). This indicates that scale economies play a crucial role in fostering the development of the solar PV industry. Third, the relationship between government subsidies and innovation efficiency is complex and non-linear. There is a non-linear relationship between SE and government subsidies, as well as between PTE and government subsidies. Moreover, they exhibit opposing trends, which may result in no significant relationship found between OE and government subsidies. These nuanced relationships suggest that while subsidies can stimulate expansion or innovation, their impact varies across different dimensions of efficiency and may not directly transfer into overall innovation efficiency.

In summary, this study confirms the critical role of government subsidies in promoting innovation within China's solar PV industry. By examining the different sectors of the industry chain and identifying the specific impacts of financial support, the findings provide implications for policymakers seeking to allocate fiscal resources more effectively.

First, government subsidies should be preferentially allocated to upstream and midstream firms within the solar PV industry. These firms exhibit a higher willingness to invest in R&D when they receive financial support. In contrast, downstream firms, which are generally more labor-intensive, do not exhibit the same level of responsiveness to subsidies in terms of innovation. Second, while scale economies have historically contributed substantially to overall innovation efficiency, there is a risk associated with excessive subsidies leading to overexpansion and overcapacity, which ultimately may result in economic inefficiencies and market distortions. Third, as the solar PV industry matures, the focus of government subsidies should shift towards improving PTE, which is essential for driving the next phase of innovation and may require substantial and long-term financial support. Finally, while financial support is crucial for technological advancements, it must be complemented by a comprehensive suite of other policies such as regulatory frameworks, intellectual property rights protection, and international cooperation.

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Appendix

Overall efficiency score with DEA model, by year

Year	OE	PTE	SE
2007	0,492	0,667	0,738
2008	0,532	0,796	0,668
2009	0,328	0,656	0,500
2010	0,172	0,424	0,407
2011	0,111	0,264	0,422
2012	0,083	0,274	0,304
2013	0,288	0,541	0,532
2014	0,151	0,384	0,393
2015	0,186	0,365	0,510
2016	0,274	0,347	0,789
2017	0,191	0,302	0,633
2018	0,236	0,385	0,612
2019	0,235	0,334	0,704
2020	0,250	0,433	0,578
2021	0,225	0,350	0,643
2022	0,229	0,288	0,796

Overall efficiency score with DEA model, by sector

Year	OE			PTE			SE		
	U	M	D	U	M	D	U	M	D
2011	0,093	0,089	0,181	0,229	0,200	0,420	0,407	0,442	0,431
2012	0,064	0,089	0,113	0,240	0,282	0,320	0,267	0,315	0,354
2013	0,233	0,344	0,332	0,485	0,568	0,609	0,481	0,606	0,545
2014	0,121	0,135	0,227	0,341	0,374	0,465	0,356	0,360	0,488
2015	0,158	0,240	0,180	0,365	0,394	0,338	0,432	0,609	0,534
2016	0,205	0,243	0,426	0,292	0,299	0,477	0,702	0,813	0,892
2017	0,152	0,246	0,205	0,248	0,344	0,349	0,613	0,717	0,587
2018	0,154	0,308	0,321	0,271	0,460	0,511	0,569	0,670	0,628
2019	0,167	0,331	0,272	0,250	0,414	0,403	0,666	0,800	0,674
2020	0,193	0,338	0,280	0,364	0,517	0,475	0,529	0,654	0,590
2021	0,164	0,259	0,302	0,264	0,391	0,458	0,622	0,662	0,661
2022	0,206	0,227	0,264	0,245	0,302	0,348	0,839	0,751	0,760