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The Impact of Policy Intensity on Overcapacity in Low-Carbon Energy Industry: Evidence From Photovoltaic Firms

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This study evaluates the impact of policy intensity on overcapacity using 55 listed photovoltaic (PV) firms from 2011 to 2019 in China. We divide PV industrial chain into three segments, which are upstream, midstream, and downstream. Results show that China's PV industry is diminishing returns to scale with low level of capacity utilization (20%). The enhancement of policy intensity can significantly promote overcapacity, but its impact varies in different policies and different enterprises. Fiscal subsidy has the largest positive effect in promoting overcapacity, followed by tax preference and land support. For three segments of PV industrial chain, fiscal subsidy, land support, and tax preference play a significant role in promoting overcapacity in each segment; the increase in financial support exacerbates overcapacity in midstream. The present study also tests the effectiveness of an important PV policy posed by the Chinese government in 2013. The results show that the policy is inefficient in the short term. Nevertheless, it promotes the development of PV industry in the long term. It takes a long time to reduce positive effect of policies on overcapacity. This study provides a guide for the government to make comprehensive use of different policies.

Keywords: photovoltaic industrial chain, low-carbon energy, capacity utilization, overcapacity, policy intensity, subsidy

INTRODUCTION

Overcapacity in industrial production has become a huge drag on Chinese economic growth. As the growth rate of economy gradually slows down, its harm has also been increasingly apparent. From a microperspective, overcapacity is reflected in low-capacity utilization of enterprises, which will directly lead to the deterioration of their operation. From a macroperspective, large-scale and sustained overcapacity could lead to economic recession.

Some Chinese scholars believe that, in addition to the cyclical factors of economy, another important cause of overcapacity is the improper intervention of local governments (Zhang et al., 2017; Yang et al., 2019). This improper intervention shows in blindly following central government's instructions to carry out industrial planning while ignoring local development needs (Dai and Cheng, 2016; Wu S. et al., 2016; Zhou et al., 2017). Such tendency often leads to two consequences. First, industries that the government is eager to develop and support are more likely to witness overcapacity in a short time. Second, these industries are large in scale but insufficient in innovation ability and high risk of overcapacity exists.

In China, the National Development and Reform Commission and the National Energy Administration jointly issued *The Strategy for Energy Production and Consumption Revolution* (*2016–2030*). The document pointed out that we should adhere to the production and consumption of renewable energy, vigorously develop low-carbon industries, and reduce environmental damage. It also suggested promoting renewable and low-carbon energy development, for example, focusing on research and development of solar cell materials, photovoltaic conversion, and smart photovoltaic power stations. The renewable energy power generation in China, covering wind power, small hydropower, and solar photovoltaic, has experienced tremendous growth in the last decade (Zhao et al., 2013, 2016; Yi and Liu, 2014; Hu et al., 2015, 2018; Sahu, 2015; Xue, 2017). As a late entrant, the Chinese PV manufacturing sector has managed not only to catch up but also to become the world leader in the PV industry (Huo and Zhang, 2012; Huang et al., 2016; Lin and Chen, 2020). The dominance of photovoltaic among renewable energy technologies is owed mostly to its noiselessness, non-toxic emission, and relatively simple operation and maintenance (Moosavian et al., 2013). One square meter of PV power generation system installation is equivalent to 100 m^2 of afforestation in terms of carbon emission reduction. Photovoltaic power generation is a low-carbon energy and has significant environmental protection and economic benefits (Lei et al., 2019; Ouedraogo and Yamegueu, 2019; Sovacool et al., 2020; Walch et al., 2020).

However, it cannot be ignored that the rapidly developing photovoltaic industry is facing the dual pressure of overcapacity and deteriorating international trade environment (Sun et al., 2014; Wang et al., 2014, 2016, 2018; Shen and Luo, 2015). The industrial overcapacity problem is more prominent in China's solar PV sector than in the wind sector (Zhang et al., 2013). The excess capacity of Chinese photovoltaic enterprises is characterized by concentrated low-end links in the industrial value chain, surplus of various photovoltaic products, low-efficiency capacity cluster in the short run, and staged excess capacity (Zhao et al., 2015; Yang et al., 2017). Overcapacity is seriously affecting healthy development of the industry, resulting in a waste of resources. PV product prices and capacity utilization continued to decline; many companies fell into operating difficulties. Some giant PV enterprises, like SUNTECH and LDK, had been ruled by the local court to bankruptcy.

In this case, the Chinese government issued successive adjustment and transformation policies. In 2013, the State Council issued *Some Suggestions on Promoting the Healthy Development of Photovoltaic Industry* (hereinafter referred to as *Suggestions*). The main contents of *Suggestions* can be summarized as expanding the domestic PV market, controlling total PV capacity, and improving industrial technology level. This policy can improve the capacity utilization rate of PV industry, save materials and energy, and promote the healthy development of PV industry. Furthermore, since local officials in governments paid too much attention to gross domestic product (GDP) in their assessment and promotion, the central government has repeatedly stressed downplaying the GDP assessment. It aims to strengthen the inspection to local economic structure, resource consumption, and environmental protection rather than GDP and the economic growth rate. By 2014, more than 70 counties and cities had abolished the GDP assessment.

However, the effectiveness of *Suggestions* is full of doubt. According to the statistics of Chinese PV Industry Association, in 2015, the average capacity utilization of PV industry was only 77%, which was lower than the international empirical judgment on the normal range of 79–83%. Average capacity utilization of enterprises with an annual output below 200 MW was only about 50% (Wu et al., 2019).

Why does the policy restraining overcapacity of PV industry still play no role in mitigating overcapacity under the tight control? In the literature, the effect of government intervention on overcapacity has been fully studied, but most studies focus on overall industry while they ignore the research on a single industrial chain. Since characteristics vary in terms of different segments of PV industrial chain, government intervention efforts are also varied. Therefore, this study starts from the effect of government intervention on overcapacity of PV enterprises and tries to explore different effects of industrial policy on the three industrial segments. We calculate the capacity utilization rate of China's PV industry in recent years by applying production function. The empirical results show that the enhancement of policy intensity can significantly promote overcapacity, but its impact varies in different policies and different types of enterprises. Furthermore, we tested the effectiveness of *Suggestions* issued by the Chinese government in 2013 by piecewise regression. Hence, this article could provide basis for the reform of government in recent years.

This paper has three contributions. First, it calculates capacity utilization using the production function method, and it estimates the capacity utilization of the PV industry, which provides a clear explanation of the PV industry's overcapacity. Second, we provide new estimation of capacity utilization rate. We find that the capacity utilization rate calculated by the latest data is lower than that in the literature. It means the overcapacity is worsening, which should be attached more importance. Third, it also analyzes the correlation of policy intensity and overcapacity in the low-carbon energy industry and analyzes the different policy instruments' effects. It studies the effect of different policy intensity on overcapacity of different enterprises. The paper provides a basis for the government to make comprehensive use of different policy instruments. Fourth, this paper investigates the effectiveness of an important PV policy in 2013 via piecewise regression. it is the first study to test the effectiveness of *Suggestions* issued by the Chinese government in 2013.

The rest of the study is organized as follows. *Literature Review* lays out a review of relevant literature. *Empirical Model* introduces the methods used in the empirical studies. *Data and Variables* gives an introduction to data source, sample selection, and variable definition. *Empirical Results* reports the measurement of capacity utilization and the empirical regression results. *Extended Regression* tests the effectiveness of *Suggestions*. The final section provides the main conclusions.

LITERATURE REVIEW

Theoretical Causes of Overcapacity in PV Industry

For the sake of coping information asymmetry, preventing potential entrants and conspiring, enterprises have motivation to maintain excess capacity (Kamien and Schwartz, 1972; Zhong and Pan, 2014). Accordingly, a certain degree of overcapacity is normal. Lin et al. (2010) put forward a classic argument that the advantage of backwardness in developing countries makes it easy for enterprises to form correct consensus on the industry with good prospects, causing "Wave Phenomena" of investment and forming overcapacity.

For overcapacity in PV industry, most researchers believe that periodical overcapacity, structural overcapacity, and institutional overcapacity coexist. In China, institutional overcapacity is the main performance. The initial motivation that the government supported PV industry was to adjust industrial structure and stimulate economic growth. But as a policy maker, the central government has a principal–agent relationship with the local government, the policy executor who seeks to maximize its own utility. Under the double principal–agent relationships between the central government, local governments, and enterprises (Holmstrom and Milgrom, 1991), local governments have strong impulsion to help enterprises expand in order to pursue performance in a GDP-centered promotion system. As a strategic emerging industry, PV has naturally become an expansion object favored by local governments (Zhao et al., 2011). This expansion impulsion is most evident in the critical period of promotion after 3–5 years' official tenure (Guo, 2009; Gan et al., 2015). Zhang et al. (2014) found that the massive overcapacity in the solar PV industry has largely been driven by the government's overzealous pursuit of industrial growth.

Meanwhile, local governments in economic transition gradually possess the ability to intervene the economy. After the Tax Sparing System Reform, local governments gained more stable and free power to control local finance. Ambiguous land property right, soft constraint of financial institutions, and serious defects in environmental protection system make it possible for local governments to mobilize funds, sacrifice environment, and blindly assist PV enterprises to expand their capacity (Geng et al., 2011). In spite of the widely accepted fact that the government's improper intervention contributes to overcapacity in PV industry, the strength and mode of government intervention vary in terms of different PV segments. Blonigen and Wilson (2010) proved that the industrial policy that provides protection and subsidy to upstream would increase production cost and reduce technical efficiency of downstream.

Fiscal Subsidy and Overcapacity

Photovoltaic is a strategic industry mainly supported by the country. The central government of China has given huge amount of subsidy to PV investment in a long period, causing a national investment boom in PV industry. In the early stage of the boom, the governmental subsidies can promote the technological innovation and the growth of photovoltaic enterprises and maximize the social and economic effects (Xiong and Yang, 2016; Zhang, 2018; Lin and Luan, 2020). Nevertheless, the government uses the subsidize-in-advance approach and one-size-fits-all approach to subsidize without supervision and neglecting the particularity of different enterprises. Therefore, under another principal–agent relationship between local governments and enterprises, subsidies flow to capacity expansion rather than technical innovation. Many researches indicate that government subsidies and investment contribute to overcapacity (Zeng et al., 2014; Chen, 2015; Lei, 2017). China's investment policy, regarded as subsidy, on PV industry investment should be reduced properly or even canceled, or at least, it should be combined with deployment and R&D (Yuan et al., 2014). However, Qin and Song (2019) believed that the influence of government subsidies on excess capacity is not deep.

Tax Preference and Overcapacity

As a strategic emerging industry, governments also provide PV industry large tax preferences. Most PV enterprises have been recognized as high-tech enterprise and can enjoy 15% corporate income tax reduction every year. For some start-ups, the government even promises their tax exemption in the first three operating year; they only need to pay half tax in the following 3 years. In order to encourage export, the government adopts "exemption, offset, and refund" policy for the export of PV products; tax reimbursement rate is 5–17% (Wu T. et al., 2016; Zhang, 2018). Notice on the added-value tax policy of photovoltaic power generation rules that PV solar products enjoy 50% added-value tax reimbursement rate. These policy rules mean an extremely low tax burden for PV enterprises in comparison with other industries. For a strong green policy, a tax is the dominant instrument to achieve environmental goals (Droge and Schroder, 2005). However, tax preference may cause other problems. Janeba (2000) sets a mathematical model and proves that tax competition that reduces tax rate will result in overcapacity.

Financial Support and Overcapacity

Since 1983, governments providing low-interest loans to state-owned enterprises has become a common phenomenon. Currently, local governments usually guide investment by applying the "loan with interest rate discount" and "financial products." Once a bank credit is obtained at a low interest rate, the proportion of owned capital in total capital would reduce. Jiang et al. (2012) proved that the decrease in owned capital will externalize business risk and increase the probability of overcapacity. In the PV industrial chain, local governments and banks are also more inclined to lend to enterprises in the upstream and midstream, which can help to push GDP forward in the short run.

LAND SUPPORT AND OVERCAPACITY

In China, the local government is usually the main constitutor of local land prices. The ambiguous land property right also provides possibility for the government to allocate land.

Incentives such as low-interest loans and land at reduced cost provided by local governments have largely targeted at enhancing GDP and employment. Indeed, these policies appear to have been successful in assisting Chinese solar PV power manufacturers to rapidly expand over a short period of time (McCarthy, 2014). In addition, once receiving land, PV enterprises can utilize them to obtain mortgage loan from a bank, reducing the proportion of owned capital, thus increasing the probability of overcapacity. Huang et al. (2015) find that the distortion of land price has a significant effect on overinvestment in enterprises, and it has greater effect on enterprises with more new land assets.

EMPIRICAL MODEL

Measurement Model of Capacity Utilization

The common calculation methods of capacity utilization include direct measurement method, peak-to-peak, cost function method, data envelopment analysis, and production function method. These methods have been widely used in previous studies (Klein and Preston, 1967; Charnes et al., 1979; Morrison and Berndt, 1981; Fare et al., 1989; Garcia and Newton, 1997). This study chooses production function method to measure potential output of enterprises. The reasons are as follows: compared with peak-to-peak, this method is not only more accurate but also can analyze the contribution rate of each input factor. Compared with DEA, production function method avoids the problem of weight setting. Compared with cost function method, the production function method does not need to consider factor prices but only need to use capital, labor, and output data, which makes it more direct and objective. Moreover, the production function method is set on the basis of growth theory, so it has a solid theoretical foundation.

It is necessary to set production function form first. In this study, production function is set as the most commonly used Cobb–Douglas production function:

$$Y_{i,t} = f\left(K_{i,t}, L_{i,t}\right) = A_i K_{i,t}^{\alpha} L_{i,t}^{\beta} e^{-\mu},\ \ \mathrm{i} = 1, 2, 3;\ \ \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{1}$$

where i presents three different segments in the PV industry chain, and t is for sample years. Y is the output of an enterprise, and we measure Y using operating receipt. A is the Solow Residual, which represents the level of technology and is generally considered to be a constant in the short run. K the is capital used by the enterprise, and we measure K using annual net fixed assets. L is the corresponding labor use. We use annual headcount as an indicator of labor use. μ is the residual. We assume that it is mutually independent and obeys the standard normal distribution. α and β are the output elasticity of capital and labor, respectively. If $\alpha + \beta = 1$, it is constant returns to scale; if $\alpha + \beta < 1$, it is decreasing returns to scale; if $\alpha + \beta > 1$ with $\alpha, \beta < 1$, it is increasing returns to scale. Take the logarithm to Eq. (1):

$$ln\,Y_{i,t} = lnA + \alpha lnK_{i,t} + \beta lnL_{i,t} - \mu \tag{2}$$

Let $lnA = \delta$, $E(\mu) = \varepsilon$, since $E(\varepsilon - \mu) = 0$, perform OLS on Eq. (2):

$$ln\hat{Y}_{i,t} = \hat{\alpha} lnK_{i,t} + \hat{\beta} lnL_{i,t} + \left(\delta - \hat{\varepsilon}\right) \tag{3}$$

Eq. (3) is the average production function. Adjusting the constant (namely lnA), the estimated value of $\bar{\varepsilon}$ can be obtained by the next equation:

$$\begin{aligned}\hat{\varepsilon} &= \max\left(\ln Y_{i,t} - \ln \hat{Y}_{i,t}\right) \\ &= \max\left\{lnY_{i,t} - \left[\hat{\alpha} lnK_{i,t} + \hat{\beta} lnL_{i,t} + \left(\delta - \hat{\varepsilon}\right)\right]\right\}\end{aligned} \tag{4}$$

Return to Eq. (3) and get the estimated value of $\hat{\delta}$: ()

$$\hat{\delta} = ln\hat{Y} - \hat{\alpha} lnK - \hat{\beta} lnL + \hat{\varepsilon} \tag{5}$$

Then, the estimated boundary production function is:

$$\hat{Y}_{i,t} = e^{\hat{\delta}} K_{i,t}^{\hat{\alpha}} L_{i,t}^{\hat{\beta}} \tag{6}$$

Thus, the capacity utilization is:

$$cu = Y_{i,t} / \ \hat{Y}_{i,t} \tag{7}$$

Regression Model Setting and Variables Measurement

Applying alternative indicators to measure policy is frequently used to measure policy intensity. Yu and Lv (2015) used enterprises' subsidized income to measure government subsidy and used cash inflow in fund-raising activities to represent financial support level. Zhang et al. (2017) used currency investment and tax subsidies to represent government interventions. In this paper, we select alternative indicators to quantify policy intensity. Given the multidimensional feature of policy instruments, we take all the four main policy tools into consideration.

Based on the above analysis, we construct the following regression model to examine the impact of government policy intensity on overcapacity of PV enterprises:

$$\begin{aligned}ovcp_t = \beta_0 + \beta_1 subsidy_{t-1} + \beta_2 tax_{t-1} + \beta_3 gainfund_{t-1} + \\ \beta_4 land_{t-1} + \beta_5 X_{t-1} + \beta_6 \sum year + \sigma_t\end{aligned} \tag{8}$$

where $ovcp_t$ is the enterprise's spare capacity at t, $subsidy_{t-1}$ is the fiscal subsidy obtained by the enterprise at $t-1$, tax_{t-1} is the corresponding tax preference, $gainfund_{t-1}$ is financial support, $land_{t-1}$ is land support, X_{t-1} is a series of control variables, and $\sum year$ is the dummy variable of year.

DATA AND VARIABLES

Data Source and Sample Selection

Photovoltaic is a heavy asset industry, which is categorized as two fields: PV manufacture and PV power generation. We divide

PV industry into three segments: upstream, midstream, and downstream. Upstream includes the extraction and manufacture of crystal silicon materials and related equipment. Midstream consists of the solar cell, solar component manufacture, and related equipment. Downstream contains the installation and establishment of the PV system.

We choose listed companies belonging to the concept of photovoltaic in Shanghai and Shenzhen A-share markets between 2011 and 2019 as the sample. Because a lot of data were missing before 2011, we excluded the enterprises that enter the photovoltaic field later than 2011 or those with serious lack of financial data. Finally, we have 55 PV enterprises altogether. According to the first main business of the listed company, we classify them into upstream, midstream, and downstream of PV industry. Twelve of them belong to the upstream, 22 companies belong to the midstream, and 21 enterprises belong to the downstream. Referring to Yu and Lv (2015) research, this study also adjusts operating receipt and estimated potential output on the basis of Industrial Producer Price Index in 2011; other financial data are also adjusted on the basis of Fixed Asset Investment Price Index in 2011. The list of photovoltaic concept public companies is from the Tonghuashun dataset. Other financial data and annual reports come from Wind database. Price indexes are from the National Bureau of Statistics of China. The statistical work of this study is completed by Excel 2019; graphics and tables are completed by Excel 2019; and regression analysis is completed by Stata16.0.

Variable Definition

(1) Dependent Variables

We use the gap between estimated potential output and actual output, that is, (6) minus the operating receipt, as dependent variable. We define this value as spare capacity, which indicates the gap that enterprises fail to achieve their maximum output due to various reasons. Considering the stability problem of microdata, we take the logarithm to the difference.

(2) Independent Variables

According to the analysis above, this study uses the four main policies (fiscal subsidy, tax preference, financial support, and land support) as independent variables. These four policies can represent the overall policy intensity of government intervention to PV industry. We use government subsidy in non-recurring profit and loss to represent fiscal subsidy, use tax returns in cash flow statements to represent tax preference, use cash inflow in fund-raising activities in cash flow statements to represent financial support, and use land-use right in intangible assets to represent land support. In order to keep the data stable and unify statistical unit, the above variables are taken into the logarithm. Furthermore, considering the time-lag effect of policy on the influence of overcapacity (Hu et al., 2014), the above independent variables are all lagged one period behind.

(3) Control Variables

Enterprise investment decision is not only determined by government policies but also affected by the factors of enterprises themselves. Therefore, these two effects need to be separated. With regard to the enterprise characteristics that affect its investment level, this study refers to the setting of enterprise investment in Richardson (2006) study over the investment model. We use enterprise duration (age), enterprise growth (growth), enterprise asset–liability ratio (lev), enterprise stock yield (ret), and year dummy variables (year) to control the normal investment of enterprises. Since all enterprises belong to the PV industry, the industry dummy variable is omitted. We use accumulated listed year of enterprise, from the listing year to 2019, to represent enterprise duration, and use growth rate of operating receipt to represent enterprise growth. In order to make regression results easier to analyze, enterprise growth opportunity, enterprise asset–liability ratio, and enterprise stock yield are magnified 100 times. The entry of year dummy variable mainly aims to control the impact of economic fluctuations at home and abroad. Referring to the original model, the above control variables are also lagged one period behind except year.

(4) Instrumental Variables

Since there is a positive correlation between subsidy and revenue, considering the possible endogenous problem in the regression model, we use some instrumental variables. The ultimate purpose of government intervention is to achieve its economic, political, and social goals. Compared with private enterprises, state-owned enterprises need to bear a greater "policy burden." Meanwhile, state-owned enterprises can get more government financial support (Yu and Lv, 2015). The size of the firm also affects the subsidy received each year. The enterprise size and type will not directly affect capacity utilization of enterprises. Therefore, we choose enterprise size (size) and enterprise type (state) as instrumental variables. We use the log of total assets to represent enterprise size. As for enterprise type, state-owned enterprises are set at 1 and non-state enterprises are set at 0. **Table 1** shows the definition and calculation method of each variable.

EMPIRICAL RESULTS

Measurement of Capacity Utilization

This study uses a balanced panel data to estimate capacity utilization of PV enterprises. Due to the heterogeneity between enterprises, the direct use of OLS could bring about autocorrelation and heteroskedasticity problems. Thus, we use panel corrected standard error (PCSE) to estimate the potential capacity. The estimated average production function is as follows:

$$lnY = 4.035 + 0.253lnK + 0.678lnL$$
$$(27.33) \quad (21.46) \quad (33.91) \tag{9}$$

Parentheses below Eq. (9) report the z statistical value of three parameters, which are significant at the level of 1%. Furthermore, the frontier production function is:

$$Y = e^{5.953}K^{0.253}L^{0.678} \tag{10}$$

Estimated production function shows that the output elasticity of labor is 0.678, which is higher than the capital's output elasticity of 0.253. It means that the contribution rate of labor to output growth is higher than the capital. One fact that it may indicate is

TABLE 1 | Variable definitions and calculation methods.

	Name	Abbreviation	Measurement method
Dependent Variable	Idle capacity	*ovcp*	Ln[(9)-operating receipt]
Independent variable	Fiscal subsidy	*subsidy*	Non-recurring profit and loss—ln(government subsidy)
Independent variable	Tax preference	*tax*	Cash flow statements—ln(tax returns)
Independent variable	Financial support	*finance*	Cash flow statements—ln(cash inflow in fund-raising activities)
Independent variable	Land support	*land*	Intangible assets—ln(land use right)
Control variable	Enterprise duration	*age*	Total listed years, from listing time to 2019
Control variable	Enterprise growth	*growth*	Growth rate of operating receipt × 100
Control variable	Enterprise asset-liability ratio	*lev*	Asset–liability ratio = total liability/total asset × 100
Control variable	Enterprise stock yield	*ret*	Profit statement—basic earnings per share × 100
Control variable	Year dummy variables	*year*	Set 2011 as reference group; 2012–2019 as the other one
Instrumental variable	Enterprise size	*size*	Balance sheet—total assets
Instrumental variable	Enterprise type	*state*	Set state-owned enterprises as 1 and non-state enterprises as 0

TABLE 2 | Capacity utilization of photovoltaic (PV) from 2011 to 2019.

	Whole industry			Upstream			Midstream			Downstream		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
2011	4.89	68.67	17.31	6.57	42.62	20.59	4.89	51.73	15.23	5.42	68.67	17.63
2012	3.20	40.84	13.94	3.20	40.84	13.77	5.20	37.83	12.03	6.26	25.58	16.04
2013	3.58	40.00	14.84	3.58	36.45	14.53	4.79	36.28	12.86	5.60	40.00	17.09
2014	2.39	100.10	17.52	2.39	36.62	16.03	4.64	100.10	18.03	4.64	52.63	17.83
2015	3.91	68.75	17.68	3.91	37.37	15.02	4.47	39.87	15.82	5.17	68.75	21.15
2016	2.99	59.22	19.27	2.99	38.61	15.98	5.88	54.09	18.03	4.05	59.22	22.44
2017	4.16	56.55	20.63	4.67	34.16	16.70	6.99	56.55	20.01	4.16	52.57	23.53
2018	0.45	70.56	21.64	0.45	44.08	19.50	9.61	70.56	21.02	5.10	56.01	23.53
2019	1.04	58.18	21.68	1.04	34.54	17.95	10.57	58.18	22.07	5.10	56.22	23.40
N		495			108			198			189	

that, in spite of years of development, China's PV industry still relies heavily on labor input; most enterprises assemble at the bottom of the value chain. The sum of two elasticities is 0.931 and is <1, which means that China's PV industry is an industry of diminishing returns to scale, and the only way to improve productivity is innovation.

Table 2 and **Figure 1** list the capacity utilization of China's PV industry between 2011 and 2019. The capacity utilization estimated by the production function method is the relative value rather than the absolute value. Therefore, the capacity utilization calculated in this study is lower than the actual value but can be compared between enterprises. We conclude from the statistics that:

Overall, the capacity utilization of PV industry in China is generally low during the study period; overcapacity exists in every segment. Among the three segments, overcapacity is serious in both midstream and upstream. Downstream has the highest capacity utilization. These all present structural overcapacity, which are also consistent with the economic facts.

For the upstream, although China is huge in silicon chips (which take over more than 90% of the whole world), due to the lack of technical input for purifying polysilicon materials, domestic enterprises are higher in production costs and poorer in product quality. Polysilicon is still heavily dependent on imports, resulting in the coexistence of import and excess. Recently, with the improvement of technical level of domestic enterprises, the cost of production of some advanced enterprises has been lower than that of foreign competitors. This will gradually ease the overcapacity situation in the upstream.

For the midstream, as solar cells and PV modules are mainly for export, the productivity utilization of midstream is kept at a low level in the case of the slump of international market and overlay of trade barriers. Although the situation has gradually improved since 2015, the capacity utilization of midstream is still at a low level.

For the downstream, since it faces customer directly, this part performs better in capacity utilization. But in recent years, there are still more and more enterprises blindly constructing power plants. According to data released by the State Energy Bureau, the average rate of discarding PV power plants among the Northwest five provinces reached 14.1% in 2017, up to 26.5%, which made the overcapacity situation in downstream also aggravated.

Since Europe and the United States launched some antidumping and countervailing actions, China's PV industry suffered a serious shock. The capacity utilization of the industry dropped 3.37%. Among the three segments, capacity utilization

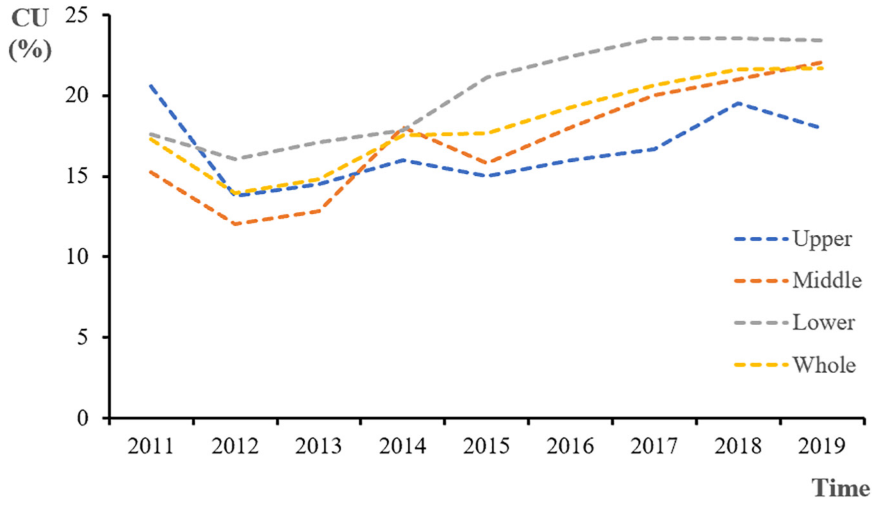

FIGURE 1 | Variation of photovoltaic (PV) capacity utilization through 2011–2019.

of upstream enterprises fell most dramatically, which decreased by 6.82%; while the downstream enterprises are relatively less affected. The utilization rate started to rise slowly from 2015, probably mainly because of rising demand. On the one hand, domestic demand is growing rapidly. On the other hand, the implementation of One Belt and One Road strategy has brought about a rebound in international market demand. However, the overall level is still not satisfactory. Capacity utilization of 95% enterprises is centralized below 70%.

Basic Regression Analysis

In this section, this study uses a balanced panel data of PV enterprises to establish four panel models and then carries out basic regression analysis on the overcapacity situation about the three segments and the whole PV industry (see **Table 3**). Through Hausman test, this study uses fixed effect to regress models (1) and (4) and uses random effect to regress models (2) and (3). In order to provide a robust result, this study uses robust standard error in each model.

Considering the endogeneity of subsidy, this study chooses enterprise state and size as the instrumental variables of subsidy. This study uses the generalized method of moments (GMM) to re-regress models (1)–(4). Since GMM is a robust estimation method whose assumptions are weak; the autocorrelation and heteroscedasticity can be allowed (see **Table 4**). The number of instrumental variables is more than the number of endogenous variables, which means that there is an overidentification problem. According to the results of the Sargan test, there is no over identification problem in models (1)–(3). In model (4), due to the collinearities, the instrumental variable (state) is dropped, and there is no overidentification problem in model (4). The *p* value of LM statistics is <0.01, indicating that there is no underidentification problem. The value of Cragg-Donald Wald F shows that the instrumental variables are valid.

Results in column (1) of **Table 3** show that the coefficients of four explanatory variables are all positive and significant. It means that no matter which policy is, the enhancement of policy intensity has exacerbated overcapacity of PV industry. The generalized method of moments (IV-GMM) regression results in **Table 4** are largely consistent with it. Specifically, the most "powerful" policy is *subsidy*, coefficient of which is 0.638 and is

TABLE 3 | Basic regression results.

Ovcp	Whole industry (1)	Upstream (2)	Midstream (3)	Downstream (4)
Subsidy	0.122***	0.227***	0.094***	0.158***
	(0.018)	(0.047)	(0.022)	(0.035)
Tax	0.059***	0.050***	0.037***	0.090***
	(0.009)	(0.018)	(0.012)	(0.019)
Finance	0.022**	0.004	0.045***	0.014
	(0.010)	(0.023)	(0.017)	(0.014)
Land	0.213***	0.395***	0.179***	0.221***
	(0.030)	(0.070)	(0.033)	(0.069)
Age	0.000	−0.025	0.044**	0.000
	(0.000)	(0.023)	(0.020)	(0.000)
Growth	0.001	0.000	0.001*	0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Lev	0.007***	0.010***	0.007***	0.004
	(0.001)	(0.003)	(0.002)	(0.003)
Ret	−0.001**	−0.001	−0.000	−0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Year	−0.170***	−0.291***	−0.154**	−0.100
	(0.046)	(0.103)	(0.066)	(0.084)
Constant	10.030***	8.001***	9.969***	9.618***
	(0.267)	(0.557)	(0.386)	(0.592)
Observation	495	108	198	189
Method	FE	RE	RE	FE
R^2	0.658	0.798	0.614	0.650

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; **p < 0.01.*

TABLE 4 | Instrumental variable–generalized method of moments (IV-GMM) regression results.

	Whole Industry	Upstream	Midstream	Downstream
Subsidy	0.638***	1.169***	0.521***	0.476***
	(0.081)	(0.197)	(0.117)	(0.112)
Tax	0.030**	−0.061	0.044**	0.055**
	(0.015)	(0.044)	(0.018)	(0.024)
Finance	−0.029	−0.084	−0.042	−0.010
	(0.019)	(0.047)	(0.035)	(0.024)
Land	0.020	−0.132	0.097	0.079
	(0.058)	(0.137)	(0.080)	(0.092)
Age	0.010	−0.056***	0.035***	0.010
	(0.006)	(0.019)	(0.009)	(0.009)
Growth	0.000	0.002	0.005***	−0.003*
	(0.001)	(0.002)	(0.002)	(0.001)
Lev	0.003*	0.016***	0.001	0.005
	(0.002)	(0.005)	(0.003)	(0.003)
Ret	−0.001	−0.004***	−0.002**	0.001*
	(0.247)	(0.001)	(0.001)	(0.001)
Year	−0.035	−0.407*	0.074	0.024
	(0.104)	(0.243)	(0.149)	(0.154)
Constant	8.766***	7.731***	8.833***	8.861***
	(0.244)	(0.660)	(0.394)	(0.361)
Observation	495	108	198	189
Method	GMM	GMM	GMM	GMM
R^2	0.487	0.596	0.519	0.563
F	75.85***	23.70***	28.93***	32.97***
LM	74.274***	23.767***	25.458***	32.565***
Cragg–Donald Wald F	42.735	13.684	13.802	37.262
Sargan	0.267	3.014*	5.363**	Exactly identified

t/z statistics in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

significant at the level of 1%. The possible reason is that it is difficult to supervise the use of funds because of the improper subsidize ways, such as "subsidize in advance" and "one size fits all." When one enterprise obtains government's industrial support fund, scientific research subsidy, or project subsidy, it has incentive to use funds for short-term expansion, which makes the effect of *subsidy* is not ideal. Furthermore, under another principal–agent relationship between local governments and enterprises, subsidies flow to capacity expansion rather than technical innovation (Zeng et al., 2014; Chen, 2015; Lei, 2017). The second one is *tax*, whose coefficient is 0.030 and is significant at the level of 5%. Possibly because the government provides PV industry large tax preferences. In comparison with other industries, the tax burden on the PV industry is relatively low. Therefore, low-tax burden would attract many enterprises to enter the photovoltaic field and increase the overcapacity (Haley and Haley, 2013; Shi et al., 2018). The third one is *land*; its coefficient is 0.020 with a low significance level. This indicates that when the land-use right of PV enterprises increases by 1%, spare capacity will increase by 0.020% on average. It is found in some annual reports that enterprises take some land as collateral to get loans from banks (Shepherd, 2016). The last one is *finance*, whose policy effect in IV-GMM is contrary to our expectation, but it is not significant.

The study turns to regression of four policies on three segments of PV industry; see models (2)–(4). The following can be concluded:

In columns (2)–(4), the coefficients of fiscal subsidy are all positive with the significance level of 1%, which indicates that fiscal subsidy leads to overcapacity in the three segments of PV industry. Specifically, the coefficient of *subsidy* is 1.169, 0.521, and 0.476 in upstream, midstream, and downstream, respectively (see **Table 4**). The positive effect of fiscal subsidy on overcapacity of upstream enterprises is greatest and that of downstream enterprises is lightest (Zhang et al., 2017). The potential reason is that the entry threshold of PV enterprises in upstream and midstream is low, and they can obtain return in a short time. Most of fiscal subsidies flood to the PV enterprises of upstream and midstream with the aim of massive production. Therefore, fiscal subsidy leads to the capacity expansion of PV enterprises rather than technological innovation, and the overcapacity in upstream and midstream is greater than in downstream.

The coefficient of *tax* in midstream and downstream is positive and significant at the level of 5% (see **Table 4**). The effect of *tax* on spare capacity of upstream is contrary to the result of basic regression, but it is not significant. The coefficient of *tax* in model (3) is 0.044, indicating that when tax policy intensity increases by 1%, spare capacity of enterprises in midstream would increase 0.044% on average. The coefficient of *tax* in model (4) is 0.055, which means that for every 1% increase in tax policy intensity, idle capacity of enterprises in downstream would increase 0.055% on average. The one possible reason is that tax preference makes enterprises have more capital to support massive production. Another significant reason could be that tax preference attracts more enterprises entering photovoltaic field (Zhang et al., 2018).

Financial support has positive effect on spare capacity of PV enterprises in upstream and downstream with a low significance level and in midstream at the level of 1% (see **Table 3**), which means that financial support results in the overcapacity of PV enterprises. The financial support reduces the capital cost of PV enterprises and further helps them expand (Jiang et al., 2012). The result of IV-GMM is contrary to it, but not significant.

The coefficient of land support in models (2)–(4) is positive with the significance level of 1% (see **Table 3**). It indicates that land support is also a negative policy in reducing overcapacity. The land support would attract more enterprises to establish factories, which would give rise to redundant construction and overcapacity. In addition, the PV enterprises can use land to obtain mortgages from banks, reduce their own capital, and expand capacity. The results of IV-GMM are not significant.

With respect to other control variables, *age* is significant in models (2) and (3) but with opposite sign. It means that the effect of *age* is vague. Similarly, the effect of *growth* is also ambiguous. *Lev* is significant in model (2) with a positive sign. It indicates that *lev* has a positive effect on PV enterprises' spare capacity. The higher the *lev*, the less their own capital, so the PV enterprises are more inclined to expand capacity. *Ret* is significant in models (2) and (3), with a negative sign, which shows that *ret* could reduce PV enterprises' overcapacity. A high *ret* represents a good business status and strong competitiveness of PV enterprises, so enterprises with higher *ret* are not prone to excess capacity. It is worth noting that *year* is significant with a negative sign in model (2). It proves that comparing the spare capacity in 2011, the spare capacity is gradually reduced in recent years.

EXTENDED REGRESSION

Facing the "chronic and stubborn" overcapacity in strategic emerging PV industry of China, the State Council issued *Suggestions* in July 2013. The main contents of *Suggestions* can be summarized as expanding domestic PV market, controlling total PV capacity, and improving industrial technology level. The policy varies much in terms of diverse segments of PV industrial chain. Specifically, for the upstream and midstream, polysilicon, solar cell, and component projects, which are newly declared by enterprises, are strictly controlled with the aim of expanding capacity, accelerating enterprises merger and reorganization, and raising the industry access threshold. For the downstream, major efforts are devoted to exploit PV applications on the user side, encourage local governments to use financial funds to support PV power generation, increase financial support, and provide more land to those PV power plants located in desert. As an important adjustment for PV industry, it has been more than 6 years since *Suggestions* was implemented, but few researches on PV have mentioned it. Thus, this study attempts to examine the implementation effect of the policy in this part.

Since all the observations in this study were affected by the policy at the same time, they cannot be divided into the control group and experimental group. Therefore, difference-in-difference (DID) method fails to evaluate policy effectiveness in this study. The study turns to the method of piecewise regression to compare the changes of estimation coefficients before and after the implementation of *Suggestions*. This study regards the implementation of *Suggestions* as a policy shock that took place in 2013. Considering the sample size matching and the time lag for the policy to take effect, this study regards year 2011–2013 as the investigation period before the occurrence of policy shock, the following 3 years, 2014–2016, as the investigation period after the shock occurred, and the following 3 years, 2017–2019, as the investigation period after the shock occurred to research the time effect of policy comparing with years 2014–2016.

Table 5 shows the piecewise regression results of the whole PV industrial chain. Through the Hausman test, this study uses fixed effect to regress models (1) and (3) and uses random effect to regress model (2). In the first 3 years after implementing *Suggestions*, the coefficient of *subsidy* increased with the significance level of 1%. It indicated that the increase in fiscal subsidy would promote overcapacity. In the second 3 years after *Suggestions* was implemented, the coefficient of *subsidy* decreased with a low significance level. In 2014–2016, the coefficient of *tax* decreased with the significance level of 5% and then continued to decline in 2017–2019 but with a low significance level. The coefficient of *finance* decreased with a low significance level. In the first 3 years after *Suggestions* was implemented, the coefficient of *land* increased with the significance level of 1%. Then, the coefficient decreased in the second 3 years. Generally, on the one hand, the short-term effectiveness of *Suggestions* is not satisfactory. On the other hand, *Suggestions* will promote healthy development of PV industry in the long term. It takes a lot of time to reduce positive effect of policies on overcapacity.

TABLE 5 | Whole industry piecewise regression.

	2011–2013 (1)	2014–2016 (2)	2017–2019 (3)
Subsidy	0.054**	0.114***	0.041
	(0.027)	(0.031)	(0.027)
Tax	0.064***	0.035**	0.013
	(0.013)	(0.014)	(0.017)
Finance	0.013	0.002	0.009
	(0.015)	(0.012)	(0.015)
Land	0.019	0.392***	0.300***
	(0.064)	(0.055)	(0.076)
Age	0.000	0.014	0.000
	(0.000)	(0.013)	(0.000)
Growth	0.001	0.001	−0.001
	(0.001)	(0.001)	(0.001)
Lev	0.007***	0.004*	−0.008**
	(0.003)	(0.002)	(0.004)
Ret	−0.001**	−0.000	0.000
	(0.001)	(0.001)	(0.001)
Year	−0.125***	0.000	0.000
	(0.043)	(0.000)	(0.000)
Constant	12.269***	8.829***	11.062***
	(0.602)	(0.438)	(0.694)
Observation	165	165	165
Method	FE	RE	FE
R^2	0.451	0.656	0.571

t/z statistics in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6 shows the piecewise regression results of upstream. Through the Hausman test, this study uses random effect to regress models (1) and (2) and uses fixed effect to regress model (3). The coefficient of *tax* and *land* decreased in 2017–2019 with a low significance level compared to 2011–2013. It indicates that it would take some time for *Suggestions* to play positive effect on promoting healthy development of PV enterprises in upstream.

Table 7 shows the piecewise regression results of midstream. Through the Hausman test, this study uses random effect to regress models (1) and (3) and uses fixed effect to regress model (2). After the *Suggestions* was implemented, the coefficient of *subsidy* decreased with a low significance level. In the first 3 years after the *Suggestions* was implemented, the coefficient of *tax* was negative, which means that *tax* had a positive impact on reducing overcapacity. However, the coefficient of *tax* increased between 2017 and 2019, which means that the positive effect of *tax* on reducing overcapacity was limited. The coefficient of *finance* first increased and then decreased, which means that the implementation of *Suggestions* helped reduce the positive impact of *finance* on

TABLE 6 | Upstream piecewise regression.

	2011–2013 (1)	2014–2016 (2)	2017–2019 (3)
Subsidy	0.093	0.197**	0.135
	(0.067)	(0.084)	(0.100)
Tax	0.013	0.075**	−0.087
	(0.023)	(0.032)	(0.076)
Finance	−0.024	0.003	0.052
	(0.042)	(0.022)	(0.042)
Land	0.383***	0.192	0.355
	(0.135)	(0.136)	(0.269)
Age	0.027	0.006	0.000
	(0.043)	(0.039)	(0.000)
Growth	0.000	0.002	0.002
	(0.001)	(0.001)	(0.002)
Lev	0.012**	−0.001	−0.030*
	(0.005)	(0.006)	(0.015)
Ret	−0.001	−0.000	−0.004*
	(0.001)	(0.001)	(0.002)
Year	−0.108	0.000	0.000
	(0.090)	(0.000)	(0.000)
Constant	8.823***	10.101***	11.120***
	(1.203)	(1.091)	(2.025)
Observation	36	36	36
Method	RE	RE	FE
R^2	0.687	0.803	0.180

t/z statistics in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 7 | Midstream piecewise regression.

	2011–2013 (1)	2014–2016 (2)	2017–2019 (3)
Subsidy	0.058*	0.000	0.010
	(0.033)	(0.028)	(0.036)
Tax	0.028	−0.031**	0.028
	(0.018)	(0.013)	(0.021)
Finance	0.016	0.051**	0.015
	(0.025)	(0.022)	(0.024)
Land	0.122**	0.778***	0.434***
	(0.051)	(0.102)	(0.087)
Age	0.080***	0.000	0.035
	(0.023)	(0.000)	(0.024)
Growth	0.002**	−0.000	0.000
	(0.001)	(0.001)	(0.001)
Lev	−0.000	0.002	−0.003
	(0.003)	(0.002)	(0.004)
Ret	−0.002***	−0.002**	0.002
	(0.001)	(0.001)	(0.001)
Year	−0.110*	0.000	0.000
	(0.058)	(0.000)	(0.000)
Constant	11.020***	6.205***	9.116***
	(0.563)	(0.901)	(0.830)
Observation	66	66	66
Method	RE	FE	RE
R^2	0.620	0.537	0.586

t/z statistics in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 8 | Downstream piecewise regression.

	2011–2013 (1)	2014–2016 (2)	2017–2019 (3)
Subsidy	0.063	0.135**	0.171***
	(0.046)	(0.061)	(0.038)
Tax	0.104***	0.034	0.062***
	(0.023)	(0.048)	(0.022)
Finance	0.012	0.001	−0.021
	(0.022)	(0.020)	(0.019)
Land	0.232*	0.320**	0.337***
	(0.125)	(0.120)	(0.081)
Age	0.039	0.000	−0.012
	(0.025)	(0.000)	(0.020)
Growth	−0.002	0.001	−0.001
	(0.002)	(0.001)	(0.001)
Lev	−0.011**	−0.002	−0.003
	(0.005)	(0.006)	(0.004)
Ret	−0.001	−0.003	0.002***
	(0.001)	(0.002)	(0.001)
Year	0.030	0.000	0.000
	(0.083)	(0.000)	(0.000)
Constant	9.385***	9.842***	9.526***
	(0.948)	(1.130)	(0.632)
Observation	63	63	63
Method	RE	FE	RE
R^2	0.648	0.455	0.762

t/z statistics in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

overcapacity in a long time. Furthermore, the coefficient of *land* first increased and then decreased but still remained high. On the whole, the effectiveness of *Suggestions* is not satisfactory in midstream.

Table 8 shows the piecewise regression results of downstream. Through the Hausman test, this study uses fixed effect to regress model (2) and uses random effect to regress models (1) and (3). The coefficient of *finance* decreased after *Suggestions* was implemented. Specially, the coefficient of *finance* showed a negative sign in 2017–2019. It denoted that the implementation of *Suggestions* would enable *finance* to play a positive role in reducing overcapacity. The coefficient of *tax* decreased and then increased a little, which means that the positive effect of *tax* was limited. It is a pity that the coefficient of *subsidy* and *land* increased after the *Suggestions* was implemented. It means the role of fiscal subsidy and land support in promoting overcapacity has been significant enhanced in downstream of PV industry.

CONCLUSION

Based on the construction of overcapacity mechanism of PV industry in China, this study uses the data of 55 listed PV companies in Shanghai and Shenzhen A-share markets between 2011 and 2019. It aims to investigate the impact of policy intensity on overcapacity via production function and empirical model (9) and conduct the heterogeneity analysis by dividing the PV industrial chain into upstream, midstream, and downstream. Our main research work includes (1) using production function to estimate capacity utilization of PV enterprises, (2) analyzing the impact of major policies on overcapacity of PV industry, (3) conducting the heterogeneity analysis to estimate the impact of major policy instruments on different segments of PV industrial chain through piecewise regression, and (4) investigating the policy effectiveness of *Suggestions*.

The findings suggest that the following: first, China's PV industry belongs to the industry of diminishing returns to scale, and the improvement of economic efficiency depends on technological progress. Second, the capacity utilization rate of PV industry in China is generally low during the study period; overcapacity exists in every segment and presents structural overcapacity. The utilization rate has been rising slowly since 2015, probably mainly due to the increase in domestic demand and foreign demand. However, the overall level is still not satisfactory. Third, from 2011 to 2019, the increase in policy intensity exacerbates the overcapacity of PV industry. Fiscal subsidy has the largest positive effect in promoting overcapacity, followed by tax preference and land support. For the three segments of PV industrial chain, fiscal subsidy, land support, and tax preference play a significant role in promoting overcapacity in each segment; the increase in financial support exacerbates overcapacity in midstream. Finally, the short-term effectiveness of *Suggestions* is not satisfactory. However, *Suggestions* will promote healthy development of PV industry in the long term. It takes a lot of time to reduce positive effect of policies on overcapacity.

Based on the conclusions, we can draw the following recommendations.

First, the government needs to set up innovation-promoting incentives to encourage PV enterprises to conduct R&D activities and promote technological progress of enterprises. Technological progress can improve economic efficiency, save materials and costs, and improve competitiveness. China's PV industry is an industry of diminishing returns to scale, and the only way to improve productivity is innovation. The PV industry is urgent for independent research and development to convert "Made in China" into "Created in China."

Second, the government should pay attention to the increase in capacity utilization rate. The capacity utilization rate of PV industry in China is generally low during the study period. On the one hand, government should attach importance on the cultivation of talents in related majors. The talents can provide technical support for the increase in capacity utilization rate. On the one hand, for different enterprises and different production processes, the government should adopt different and well-directed policies.

Third, it is essential for the government to encourage small-scale and distribute solar photovoltaic power generation to expand the domestic demand. On the one hand, it can reduce overcapacity. on the other hand, it can reduce the dependence on the international market. In addition, enterprises should make scientific and reasonable production decisions to meet market demand. In 2020, the National Energy Administration issued a notice on the formulation of the 14th Five-Year Plan for the development of renewable energy. The 14th Five-Year is a critical period for wind and photovoltaic power generation to achieve full unsubsidized parity.

Fourth, the government should synthetically utilize various policies to achieve the purpose of promoting healthy development of the industry. For ineffective policy instruments, it should continue to perfect the implementation of policies and improve policy efficiency. Furthermore, it is necessary to reinforce demand-type policies and improve green certification transactions which are forms of incentive policies instead of subsidies (Yan et al., 2019; Zhou et al., 2020).

Finally, the government should deal with the inconsistency between central policy formulation and local policy implementation. Corwin and Johnson (2019) found that the future development of China's solar PV market will dependent upon enforcement of central policy and aligning the policy objectives and incentives between the central and local levels. Changing evaluation mechanisms is necessary for local government.

DATA AVAILABILITY STATEMENT

All datasets presented in this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

HH and YW finished the research and wrote the manuscript. PT and YW are responsible for data collection and analysis. YZ and DH worked with the other authors for the *Empirical Results*. All authors contributed to the article and approved the submitted version.

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