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Resource misallocation in the Chinese wind power industry: The role of feed-in tariff policy

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ABSTRACT

This article analyzes resource misallocation in the Chinese wind power industry by examining wind power development in relation to implementation of feed-in tariff (FIT), an electricity price subsidy policy. We construct a plant-level dataset to explore the extent of distortions exacerbating resource misallocation in the wind power industry from 2000 through 2013. Our results show that distortions have been exacerbated since 2009, when the Chinese government implemented FIT, and that the potential production improvement of the wind power industry was relatively high after 2009. FIT provides added incentives for low-productivity plants to enter the industry, especially in regions better endowed with resources. This suggests that the increased distortion in resource allocation of most wind power plants is largely due to government subsidies. In addition, higher FIT rates significantly lower average capital productivity of wind power plants while having no significant effect on average labor productivity. Plants with better production technologies face worse growth rates in the region most richly endowed with relevant resources and there is no significant difference in these productivity impacts between new and already existing power plants. We postulate that similar relationships between subsidies and efficiency are likely to occur in other renewable energy sectors receiving government subsidies.

1. Introduction

To ameliorate the extent and effects of climate change, renewable energy has rapidly grown in recent decades. The renewable energy industry initially often realizes explosive growth, boosted by government policies designed to protect this infant industry, including controls imposed on market entry and, prominently, subsidies. Stimulated by such public 'industrial policies,' renewable energy has progressed technologically and achieved increasing cost-competitiveness, attracting vast investments and substantially increasing installed capacity globally. As governments have played an increasingly active role in expanding this industry, a strand of literature has emerged discussing how to design and manage public policies in relation to renewable energy to best promote economic growth and enhance social welfare (Aghion et al., 2015; Acemoglu et al., 2016).

Increasing evidence has meanwhile documented the undesirable effects of government intervention on newly-distorted markets more generally (Baldwin, 1969; Stigler, 1971; Stiglitz et al., 2013). For example, Baldwin (1969) casts doubt on the view that infant industry protection is necessary as well as on the value of entry controls typically sought by a limited number of firms with political influence. The issue that has received more attention recently is whether 'supportive' intervention by governments actually harms industrial productivity. Some studies have argued that supportive governmental policies distort resource allocation among production units, resulting in misallocation in the 'supported' industry (Restuccia and Rogerson, 2008), and that reductions of such misallocation could significantly increase total factor productivity (TFP) of countries and industries, since reallocation of production inputs from less to more capable firms enhances equalization of marginal products of production inputs and therefore overall efficiency and productivity (Banerjee and Duflo, 2005; Hsieh and Klenow, 2009).

The renewable energy industry, which receives vast subsidies for industrial development across the world, does not appear to represent an exception to the more general problem of resource misallocation and in turn, declining TFP. Many studies have discussed the effect of subsidies on the renewable energy industry from different perspectives (Carrasco et al., 2006; Bockman et al., 2008; Abadie, 2009; Fan and Zhu, 2010; Frondel et al., 2010; Edenhofer et al., 2013; Gass et al., 2013; Gómez et al., 2015; Abrell et al., 2019; Johnston, 2019; Song et al., 2019; Yang et al., 2019; Zhu et al., 2019). As noted by the IMF (2017), poorly designed policies often hinder the growth of efficient firms in the industry but provide an opportunity for inefficient firms to survive, resulting in

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more severe resource misallocation that lowers TFP (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Syverson, 2011). Reducing this resource misallocation to increase TFP is an essential task of government when developing renewable energy policies. Although some studies have investigated the impacts of subsidies on renewable energy industry productivity (lo Storto and Capano, 2014; Johansson and Kristrom, 2019; Li et al., 2019), studies that explore resource misallocation are relatively rare. This paper is an attempt to provide a framework for evaluating productivity gains or losses resulting from supportive industrial policy in terms of industry-wide resource misallocation, using recent Chinese wind power industry data.

The Chinese government's enormous investment in developing a renewable energy industry is an illustrative case of industry-specific support policy that has clearly helped bring about rapid growth of renewable energy in China (Bourcet, 2020; Wang et al., 2012; Zhang et al., 2016a). Relevant supportive policies for renewable energy enterprises include the 50% immediate refund upon payment of the value-added tax (VAT), the preferential tax policy of three-year exemption and three-year half-payment, establishment of a renewable energy development fund for subsidizing projects and guaranteed buyout of electricity generated by renewable energy sources. Feed-in tariff (FIT), which ensure a government-guaranteed cost-based price to energy producers were meanwhile also introduced into the renewable energy industry to stimulate investment.

In fact, FIT are arguably one of the most important policy tools worldwide for promoting renewable energy development (Butler and Neuhoff, 2008; Couture and Gagnon, 2010; Schmidt et al., 2013; Jenner et al., 2013; Kwon, 2015; Ye et al., 2017). At the end of 2018, there were 111 jurisdictions at the national, states or provincial levels having FIT policies (REN21, 2019). Implementing FIT usually require substantial subsidies, creating a major financial burden for such governments (Ciarreta et al., 2017; Zhang et al., 2017). While government subsidies stimulated investment in renewable energy in China, these also seem to result in the problem of wind curtailments (Zhang et al., 2016b; Dong et al., 2018; Xia et al., 2020), in which electricity generation outputs of wind plants are reduced to levels below the maximum potential generation at full utilization of installed capacity, representing significant losses in economic and energy efficiency. As reported by the Chinese National Energy Administration, during 2011–2017, a total of 187 billion kWh (15.6% of total wind generation) was ‘curtailed,’ and most curtailments occurred in the best-endowed resource region (The Three-North Area). Although some studies have discussed the impacts of FIT policy (Ritzenhofen and Spinler, 2016; Haan and Simmler, 2018; Hitaj and Löschel, 2019), only a few studies have addressed FIT policy effects on productivity gain or loss caused by resource misallocation.

We found that plant-level distortions in the wind power industry have been exacerbated since 2009, when the Chinese government implemented FIT. Potential production improvement (the incremental estimate of what production would be if distortions were totally removed) of the Chinese wind power industry was relatively high after 2009; potential production improvement of plants built under FIT policy is significantly higher than that of plants built before. The entry of new and relatively inefficient plants exacerbates resource misallocation, enlarging potential production improvement. After implementing FIT policy, average capital productivity (APK) of wind power plants was significantly lowered while average labor productivity (APL) showed no significant difference. The results indicate that differential FIT rates have slightly reduced the impact of capital distortion variations on changes in aggregate output. Plants having better production technology experienced lower APK and APL growth rates under lower FIT rates, and there was no significant difference in growth rates between those of new power plants and longstanding power plants. These results raise questions about whether what governments may regard as supportive policies for pursuing renewable energy development actually enable optimal renewable energy industry development in the long run.

This study contributes to the existing literature in several ways. First, we emphasize the application of the misallocation model proposed by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), who assume that firms have constant returns to scale (CRTS) technology in analyzing productivity in the differentiated goods industry. In this study, however, we revise the assumption inherited from Lucas (1978) that firms produce homogeneous final goods by decreasing returns to scale (DRTS) technology since electricity is a homogeneous good and the CRTS assumption would result in plants' indeterminate sizes. The DRTS assumption is more realistic in analyzing the wind power industry and can be applied to other homogeneous goods. To better calculate the source of misallocation, we counterfactually decompose the changes in aggregate output of the industry to examine disparities from the perspective of different types of distortion under the DRTS assumption.

Secondly, this study is the first to examine resource misallocation related to FIT policy in the renewable energy industry, using firm-level data of the Chinese wind power industry from 2000 through 2013. Previous studies about improving productivity of the renewable energy industry mainly focus on technology efficiency (Del Río, 2012; Gawel et al., 2017; Callaway et al., 2018; Kwon, 2020; Lin and Zhu, 2019). However, Restuccia and Rogerson (2017) suggested that the key to increasing productivity is not only improving technology but also allocating limited production resources across firms. This study fills in that research gap.

Third, we apply an empirical model to examine underlying causes of misallocation differences, which in turn suggests policy implications for future development of the wind power industry and other renewable energy modalities in China and elsewhere. The analytic framework proposed in this study is general and thus applicable to other countries using supportive government policies to help develop renewable energy. Besides FIT, renewable portfolio standards (RPS) and auction-based policies are also being implemented in many countries to advance renewable power, and the productivity issue and resource misallocation should be addressed when planning implementation of these policies.

Fourth, this paper provides rich ‘micro’ evidence to support the TFP measure, replicable for other renewable energy industries in other countries. The TFP measure is constructed through characteristics of hypothetical industrial production structures, not requiring initial knowledge of the causes of resource misallocation. Supportive policy effects on productivity and resource misallocation can therefore be examined using counterfactual analysis for policy references.

The rest of the paper proceeds as follows: We review the research literature on resource misallocation, productivity and industry policy along with specific development of the renewable energy industry in Section 2. We discuss the institutional background of renewable energy development in China in Section 3. Section 4 introduces a theoretical framework on resource misallocation. Section 5 presents data on the extent of resource misallocation in the Chinese wind power industry and the effects of FIT and explores underlying determinants of distortions. In Section 6, we offer conclusions and policy implications.

2. Literature review

This paper links to several strands of the literature. First, it is related to studies on the consequences of misallocation across heterogeneous firms. Pioneering work in this field, such as Restuccia and Rogerson (2008), considered firm heterogeneity and argued that aggregate TFP is potentially affected by misallocation of resources across firms. Hsieh and Klenow (2009) explored resource misallocation in both China and India using a quantitative approach and micro-level enterprise data, finding that resource misallocation plays a crucial role in both China's and India's low manufacturing TFP relative to that of the United States. Brandt et al. (2012) stated that resource reallocation from inefficient firms to more efficient ones can remarkably improve firm-level productivity efficiency and in turn enhance aggregate TFP in Chinese manufacturing.

Since then, more studies have conducted in-depth systematic analysis on distortion of resource allocation from the perspectives of varying causes of distortions (Banerjee and Moll, 2010), changes in TFP caused by distortions (Midrigan and Xu, 2014; Bond et al., 2013; Lee and Wang, 2017) and TFP differences across countries (Bento and Restuccia, 2017; Jones, 2011). Banerjee and Moll (2010), for example, argued that long-term distortion of resource allocation may be affected by financing constraints, market failures and taxes as well as other factors, but that the extent of misallocation and changes in TFP need more empirical analysis. Bento and Restuccia (2017) emphasized that a relatively small proportion of efficient producers potentially caused aggregate TFP losses, findings realized through analyzing manufacturing industries in 134 countries.

This paper also contributes to a second strand of the literature, the growing body of research on the effects of governmental industry policy. An extensive body of research on the renewable energy industry has focused mainly on industry policy, development status and strategies (Lund, 2009; Grau et al., 2012; Bazilian et al., 2013). Most studies argue that an overall pro-renewable policy environment plays a crucial role in the rapid development of renewable energy. Subsidies and preferential tax policies provided by governments have stimulated enterprises to invest (Borenstein, 2012; Driouchi and Bennett, 2012; Frondel et al., 2010; Ritzenhofen and Spinler, 2016; Hitaj and Löschel, 2019; Yang et al., 2019; Zhu et al., 2019; Li and Taeihagh, 2020) while also promoting technological innovation (Xu et al., 2014; Wang and Zou, 2018; Hotte, 2020; Sung, 2019). Zhu et al. (2019) conducted semi-structured interviews with Chinese state-owned enterprise managers and found that motivated policies for developing renewable energy contribute to long-term benefit expectations of state-owned enterprises, which are still willing to invest in the wind power industry despite the problem of wind curtailments. Yang et al. (2019) studied renewable energy companies, finding that government subsidies have a notable effect on prompting renewable energy companies to invest and are in fact the main force supporting small and medium-sized company investment.

Even with development of renewable energy stimulated by motivated government policies, major issues remain. Construction of the power grid is far behind installation of wind power capacity (Zhang et al., 2016b; Zhao et al., 2014); the economic growth slowdown in China resulted in a lack of strong demand for renewable energy sources, leading to frequent wind curtailments (Dong et al., 2018). Dang and Motohashi (2015) argued that though R&D subsidy policies have increased the number of relevant patents, the fundamental problem of insufficient core technology innovation in the wind power industry remains (Kang et al., 2012). Chen et al. (2017) analyzed that correction of distorting industry policies would be beneficial to industry-level TFP in the long term.

A third strand of the literature focuses on FIT policy itself and comparisons between FIT and alternative supportive policies (Butler and Neuhoff, 2008; Jenner et al., 2013; Sun and Nie, 2015; Zhang et al., 2017; Guild, 2019). For example, Jenner et al. (2013) argued that FIT policy drives the rapid growth of wind power and photovoltaics in the European Union (EU), but this effect is likely to be exaggerated if the heterogeneity of political systems across countries is neglected. Butler and Neuhoff (2008) studied government support policies for renewable energy development in the UK and Germany, finding that FIT offers lower risk and better supports profitability than RPS and also more strongly stimulates renewable energy development. Zhang et al. (2017) argued that the renewable energy certificate (REC) strategy, RPS and FIT should be implemented together as complementary policies rather than independently.

The drawbacks of FIT policy have also been widely discussed in the literature (Hoppmann et al., 2014; Ciarreta et al., 2017; Xia et al., 2020; Du and Takeuchi, 2020). Hoppmann et al. (2014) suggested that although FIT policy has promoted rapid development of the German photovoltaic industry, it has also contributed to a series of unresolved problems such as slowing construction of the power grid supporting it. Ciarreta et al. (2017) conducted a simulation analysis of the renewable energy industry in Spain, concluding that FIT will mean a huge financial burden to the government when the installed capacity of renewable energy reaches a certain level. Xia et al. (2020) found that FIT policy increases the probability of excessive investment in the Chinese wind power industry and in turn aggravates the problems of wind curtailments.

To sum up, there is still a research gap in terms of examining whether productivity is declining due to resource misallocation resulting from governmental policies supporting the renewable energy industry. Using a rigorous analytic framework, our study should contribute to these streams of literature by providing TFP and resource misallocation measures to investigate the unintended effects of productivity loss on the renewable energy industry when implementing FIT.

3. Institutional background

China has experienced rapid development of its renewable energy industry generally and the installed capacity of wind power accounts for over 55% of non-hydroelectric power generation in China.[1] By the end of 2018, the total installed capacity of onshore wind power in China had reached 206 Gigawatts (GW), nearly a hundred times more than the 2.07 GW level of 2006, and which accounted for 36% of global installations (568 GW, onshore capacity), far ahead of the United States (96 GW), Germany (2.4 GW) and India (2.2 GW).[2] Also by the end of 2018, solar photovoltaic power in China reached 185 GW of cumulative installations, 36% of global total installed capacity (505 GW), followed by the United States (11.9%), Japan (10.3%) and Germany (8.5%).[3]

Before 2003, China's wind power industry was in an early stage and mainly government-led; pricing was through government administrative examination and approval. In 2003, China's National Development and Reform Commission (NDRC) first launched the concession bidding policy, bringing market competition into the wind power industry. In 2005, the Chinese government promulgated the Renewable Energy Law of the People's Republic of China, proposing to support renewable energy projects through a special fund for renewable energy development and asking power grid enterprises to purchase the full amounts of electricity generated on a renewable basis. Then, in 2006, the NDRC promulgated The Provisional Regulations on Price and Cost Sharing Administration of Renewable Energy Power Generation, which proposed that the on-grid price of wind power projects be decided through government-'guided' pricing, implying that the tariffs would be based on bidding prices.

After 2009, in order to further promote the development of the wind power industry, the NDRC proposed the Notice on Improving the Pricing Policy for On-Grid Wind Power Prices, which divided the country into four regions in accordance with their wind energy resource endowments and established different corresponding FIT rates, e.g. 0.51, 0.54, 0.58 and 0.61 CNY/kWh, for resource regions I, II, III and IV, respectively, as shown in Table 1. The national government would subsidize on-grid tariffs that exceeded local benchmark tariffs for on-grid power generated by coal-fired generators and took responsibility for the costs of constructing power grids nationwide to connect locations where wind energy was generated. The poorer the wind resource endowments of a region, the higher the tariff subsidy. Therefore, despite the rapid development of the wind power industry motivated by government subsidies, wind curtailments frequently occurred because of not only the lack of timely planning and coordination between the power grids and wind power generators, but also the existence of electricity trade barriers between provincial markets (Xia and Song, 2017; Lu et al., 2016;

[1] See the China Electric Power Yearbook (2018).
[2] See the Global Wind Report (2018) by the Global Wind Energy Council (GWEC).
[3] See the Renewables Global Status Report (2019) by REN21.

Table 1
Classifications of wind resource regions.

Regions	FIT rates[a] (CNY/kWh)	Administrative divisions
Region I	0.51	All regions in Inner Mongolia Autonomous Region except Chifeng City, Tongliao City, Xing'anmeng and Hulunbeir; Urumqi City, YiliKazak Autonomous Prefecture, ChangjiHui Autonomous Prefecture, Karamay City, Shihezi City in Xinjiang Uygur Autonomous Region
Region II	0.54	Zhangjiakou City and Chengde City in Hebei Province; Chifeng City, Tongliao City, Xing'anmeng and Hulunbeir in Inner Mongolia;Zhangye City, Jiayuguan City and Jiuquan City in Gansu Province
Region III	0.58	Baicheng City and Songyuan City in Jilin Province; Jixi City, Shuangyashan City, Qitaihe City, Suihua City, Yichun City, DaxinganlingArea in Heilongjiang Province; all regions in Gansu Province except Zhangye City, Jiayuguan City and Jiuquan City; all regions in Xinjiang Uygur Autonomous Region except Urumqi, Yili Kazak Autonomous Prefecture, ChangjiHui Autonomous Prefecture, Karamay City and Shihezi City; Ningxia Hui Autonomous Region
Region IV	0.61	Other regions not identified in Regions I, II and III

[a] There have been three rate adjustments to FIT rates in 2015, 2016 and 2018.

Davidson et al., 2016; Luo et al., 2016). Such ineffective utilization of early investment provides us a good case to examine resource misallocation in the Chinese wind power industry.

4. Theoretical framework

Building on the work of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), a competitive wind power industry features heterogeneous establishments in terms of different plant-level productivity levels with a decreasing return-to-scale technology. The wind power industry consists of M wind power plants, and each power plant generates and sells an amount of homogeneous electricity, Y_i, which can be aggregated into industrial output as

$$Y=\sum_{i=1}^{M} Y_i \tag{1}$$

Plant i's homogeneous output Y_i is represented by:

$$Y_i=A_i\left(L_i^{\alpha}K_i^{1-\alpha}\right)^{\gamma},\gamma\in(0,1),\alpha\in(0,1) \tag{2}$$

where A_i is the technology level of plant i, L_i is the labor input of plant i, K_i is the capital input of plant i, α is the labor share, and γ governs a plant's 'operative returns to scale,' also named after the 'span-of-control' parameter in Lucas (1978), and which is between zero and one to capture the decreasing returns-to-scale technology in the production function.

Since plants in the wind power industry are assumed to be heterogeneous in A_i, L_i and K_i, we introduce output distortion, τ_{Yi}, and capital distortion, τ_{Ki}, into the profit function of plant i following Hsieh and Klenow (2009). τ_{Yi} simultaneously affects capital and labor productivity levels, and τ_{Ki} drives up the productivity of capital relative to that of labor. Hence plant i's profit function is given by

$$\pi_i=(1-\tau_{Y_i})PY_i-wL_i-(1+\tau_{K_i})RK_i \tag{3}$$

where P, w and R are homogeneous electricity price, labor wage and capital cost, respectively. We assume that the electricity price of each plant is the same based on the standard first-order condition of demand, that is, for every plant i in the wind power industry,

$$P_i=P \tag{4}$$

Greater output distortions (τ_{Yi}) or greater capital distortions (τ_{Ki}) will each drive power plant i to a higher marginal revenue product of labor and capital:

$$MRPL_i\triangleq\alpha\gamma\frac{PY_i}{L_i}=w\frac{1}{1-\tau_{Y_i}} \tag{5}$$

$$MRPK_i\triangleq(1-\alpha)\gamma\frac{PY_i}{L_i}=R\frac{1+\tau_{K_i}}{1-\tau_{Y_i}} \tag{6}$$

Eq. (5) and (6) imply that plants with highly distorted productivity will have an equilibrium scale of production smaller than the optimal scale, with diminishing returns to labor and capital inputs and firms' lower productivities. Hence, we obtain the following labor demand function, capital demand function and output function of plant i:

$$L_i=L_i(A_i,\tau_{Y_i},\tau_{K_i})\propto\left(\frac{A_i(1-\tau_{Y_i})}{(1+\tau_{K_i})^{\gamma(1-\alpha)}}\right)^{\frac{1}{1-\gamma}} \tag{7}$$

$$K_i=K_i(A_i,\tau_{Y_i},\tau_{K_i})\propto\left(\frac{A_i(1-\tau_{Y_i})}{(1+\tau_{K_i})^{(\alpha\gamma-1)}}\right)^{\frac{1}{1-\gamma}} \tag{8}$$

$$Y_i=Y_i(A_i,\tau_{Y_i},\tau_{K_i})\propto\left(\frac{A_i(1-\tau_{Y_i})}{(1+\tau_{K_i})^{\gamma(\alpha-1)}}\right)^{\frac{1}{1-\gamma}} \tag{9}$$

By aggregating the plants' labor, capital and output into the whole industry, we can redefine the industry-level output as

$$Y=TFP\times L^{\alpha}\times K^{1-\alpha} \tag{10}$$

where TFP measures the aggregate production efficiency of the wind power industry, and $L=\sum_{i=1}^{M}L_i$ and $K=\sum_{i=1}^{M}K_i$ represent the aggregate value of labor and capital devoted to generation activities, respectively. Following Hsieh and Klenow (2009), TFP is further differentiated between physical productivity (TFPQ) and revenue productivity (TFPR), expressed as follows:

$$TFPQ_i\triangleq\frac{Y_i}{\left(L_i^{\alpha}K_i^{1-\alpha}\right)^{\gamma}} \tag{11}$$

$$TFPR_i\triangleq\frac{PY_i}{L_i^{\alpha}K_i^{1-\alpha}} \tag{12}$$

Ideally, assuming factor markets are perfectly competitive, TFPQ should be plant-specific and TFPR should be industry-specific without any distortions, implying that plants with higher TFPQs are able to utilize more inputs for outputs until all plants' TFPRs are equalized, when those plants experience the same input prices within the wind power industry. In other words, all $TFPR_i$ would equal the industry-specific revenue productivity without any distortions, i.e.

$$TFPR_i=\overline{TFPR} \tag{13}$$

As plant i's revenue productivity ($TFPR_i$) can be presented in terms of the average of the marginal revenue products of labor and capital; by using Eq. (5) and (6), we can rewrite $TFPR_i$ as:

$$TFPR_i\propto\left[\left(\frac{MRPL_i}{w}\right)^{\alpha}\left(\frac{MRPK_i}{R}\right)^{1-\alpha}\right]^{\tau}\propto\left[(1-\tau_{Y_i})^{\alpha}\left[\frac{(1-\tau_{Y_i})}{(1+\tau_{K_i})}\right]^{1-\alpha}\right]^{-\gamma} \tag{14}$$

Eq. (14) further illustrates Eq. (13) that $TFPR_i$ will not vary across wind power industry plants when there is no input distortion. When either plant-specific output and/or capital distortions exist

($\tau_{Y_i}>0$ or $\tau_{K_i}>0$), $TFPR_i$ would deviate from the industry-specific level. From Eq. (14), we can see that plant i will exhibit a smaller scale of output than the efficient scale when experiencing many distortions. The marginal products of capital and labor are also raised by higher outputs and greater capital distortions. Therefore, $TFPR_i$ could be an indicator of distortions and the dispersions of $TFPR_i$ could illustrate the severity of resource misallocation in the wind power industry.

In addition, by using Eq. (14) and simplifying the linear aggregate of the industry production function, the aggregate TFP of the wind power industry can be represented as:

$$TFP=\frac{Y}{L^{\alpha}K^{1-\alpha}}=\frac{\left[\sum_{i=1}^{M}\left(TFPQ_i\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma}}{\left(L^{\alpha}K^{1-\alpha}\right)^{1-\gamma}} \tag{15}$$

where TFP is the industry-level productivity efficiency depicted by a CES function aggregated across all plant-specific TFPQs, $TFPQ_i$, which is weighted by the ratio of industry-specific revenue productivity ($\overline{TFPR}$) to a plant-specific revenue productivity ($TFPR_i$). $\overline{TFPR}$ is a harmonic average of the average marginal revenue products of capital and labor in the wind power industry and the ratio equals one when $TFPR_i=\overline{TFPR}$. Hence the ratio $\overline{TFPR}/TFPR_i$ can present the extent of distortions; in other words, the dispersion of $TFPR_i$ illustrates the severity of resource misallocation. Furthermore, TFP without any input distortion can be represented as follows:

$$\overline{A}=\frac{\left(\sum_{i=1}^{M}A_i^{\frac{1}{1-\gamma}}\right)^{1-\gamma}}{\left(L^{\alpha}K^{1-\alpha}\right)^{1-\gamma}} \tag{16}$$

We can evaluate the loss of efficiency in the wind power industry resulting from resource misallocation through Eq. (15) and (16), and the ratio of output under current input utilization to output under efficient input utilization can be represented as

$$Y_R=\frac{Y}{Y_{efficient}}=\left[\sum_{i=1}^{M}\left(\frac{A_i}{\overline{A}}\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma} \tag{17}$$

The inverse of Y_R, i.e. $Y_{efficient}/Y$, is the potential production improvement, which is an increment of production with distortions totally removed.

Although Hsieh and Klenow (2009) divided distortions into output distortion (τ_{Yi}) and capital distortion (τ_{Ki}), they did not analyze the effects of these two types of distortion on the aggregate output of an industry. Restuccia and Rogerson (2017) mentioned that firms' inputs and outputs are usually affected by government policies. Intervention policies, such as tariffs and export subsidies, affect output, causing output distortion; fiscal policies that subsidize capital lead to capital distortion. They also emphasized that research should focus on the effects of these distortions on the industry instead of the type of distortion. The differentiated prices caused by such governmental policies would result in inability to optimally allocate productive resources within an industry based on firms' productivities. Therefore, the use of labor and capital in high-productivity firms would be significantly below the optimal scale, affecting the aggregate output of the industry. Hence, besides identifying the extent of input distortion, it is essential to identify the effects of the variations of these two types of distortion on aggregate industry output. This study thus further decomposes resulting changes in aggregate output.

Since the optimal scale of each firm in the industry can be determined by its optimal use of labor and capital, we can obtain the following equation from Eq. (7) to (9):

$$\left(\frac{Y_i}{A_i}\right)^{\frac{1}{\gamma}}=\left[\frac{(1-\tau_{Y_i})PA_i\alpha\gamma}{w^{\alpha}}\right]\left(\frac{1-\alpha}{\alpha}\right)^{\frac{1-\alpha}{1-\gamma}}\left[\frac{1}{(1+\tau_{K_i})R}\right]^{\frac{1-\alpha}{1-\gamma}} \tag{18}$$

Taking the logarithm and deriving the total differentiation, the change in the output of an individual firm is expressed as follows:

$$\frac{dY_i}{Y_i}=\frac{-\gamma d\tau_{Y_i}}{1-\tau_{Y_i}}-\frac{\gamma(1-\alpha)}{1-\gamma}\frac{d\tau_{K_i}}{1+\tau_{K_i}} \tag{19}$$

Eq. (19) shows that the variations of output distortion and capital distortion ($d\tau_{Yi}$ and $d\tau_{Ki}$) simultaneously determine the change in the output of an individual firm. Thus, we sum up the changes in output of firms and obtain the change in the aggregate output of the industry:

$$\begin{aligned}\frac{dY}{Y}&=\sum_{i=1}^{M}\left\{\frac{Y_i}{Y}\times\left[\frac{-\gamma d\tau_{Y_i}}{1-\tau_{Y_i}}-\frac{\gamma(1-\alpha)}{1-\gamma}\frac{d\tau_{K_i}}{1+\tau_{K_i}}\right]\right\}\\&=\underbrace{\sum_{i=1}^{M}\left(\frac{Y_i}{Y}\times\frac{-\gamma}{1-\tau_{Y_i}}\right)\times d\tau_{Y_i}}_{\text{from the changes of output distortion}}+\underbrace{\sum_{i=1}^{M}\left(\frac{Y_i}{Y}\times\frac{-\gamma(1-\alpha)}{1-\gamma}\frac{1}{1+\tau_{K_i}}\right)\times d\tau_{K_i}}_{\text{from the changes of capital distortion}}\end{aligned} \tag{20}$$

From Eq. (20), the change in the aggregate output of the industry is decomposed into two parts: one due to the variation in output distortion and the other due to the variation in capital distortion. The change in the aggregate output of the entire industry can be measured by the slight variation of input distortion of each firm in the industry. By dividing $\frac{dY}{Y}$, we finally obtain Eq. (21):

$$1=\underbrace{\frac{\sum_{i=1}^{M}\left(\frac{Y_i}{Y}\times\frac{-\gamma}{1-\tau_{Y_i}}\right)\times d\tau_{Y_i}}{\frac{dY}{Y}}}_{\text{from the changes of output distortion}}+\underbrace{\frac{\sum_{i=1}^{M}\left(\frac{Y_i}{Y}\times\frac{-\gamma(1-\alpha)}{1-\gamma}\frac{1}{1+\tau_{K_i}}\right)\times d\tau_{K_i}}{\frac{dY}{Y}}}_{\text{from the changes of capital distortion}} \tag{21}$$

The first and second terms in the right side of Eq. (21) represent the proportion of changes in aggregate output due to variations of output and capital distortion, respectively. Using Eq. (21) we can calculate the proportion of the changes in the aggregate output due to distortion variations.

5. Resource misallocation in the wind power industry

5.1. Data set for the Chinese wind power industry

The data used in this study are drawn from the Chinese Industrial Survey, a census conducted by China's National Bureau of Statistics. The raw data includes all state-owned industrial firms plus all nonstate firms for which annual revenues exceeded five million Chinese yuan in years through 2011 and 20 million yuan for years after 2011. As wind power in China started developing in the late 1990s, we used firm-level data from 2000 through 2013, in which specifically 2010 data was excluded because of abnormality and lack of credibility. We separated out the wind power plants (hereafter, we often refer to wind power firms as 'wind power plants') from the raw data in several steps. Until 2011, wind power plants had no specific four-digit code in the Chinese Standard Industrial Classification (CSIC) and were classified in the category of 'other electricity generation' (code 4419), which also includes geothermal, tidal power, bioenergy and others. We therefore identify wind power plants by industry name and main product. In 2011, CSIC was modified and assigned wind power plants an independent CSIC code (4414).

The variables that we use are value added, total fixed assets and employee benefits payable. However, not every sample had complete information and we deleted abnormal samples whose key variables were null or incompatible with accounting standards, referring to

Table 2
Summary statistics of main variables.

Variables	Obs.	Mean	S.D.	Min.	Max.
Value added (Y)	902	99,350	142,454	166	2,093,905
Total fixed assets (K)	902	603,272	756,689	263	8,193,936
Employee benefits payable (L)	902	2,929	3,720	84	36,054
Average capital productivity (APK)	902	0.207	0.254	0.016	2.467
Average labor productivity (APL)	902	47.594	51.713	0.685	393.306

Note: Units are thousands of yuan.

Brandt et al. (2012). Value added was meanwhile not reported after 2008 and we thus calculated it for those years by using gross industrial output value and subtracting estimated intermediate inputs and VAT.[4]

We also used total fixed assets instead of net value of fixed assets since information on net values was also not reported after 2008. Though net value of fixed assets can normally be obtained by calculating fixed assets' original cost less accumulated depreciation, the fixed assets' original costs were missing in the dataset after 2008. The total fixed assets is between net value of fixed assets and fixed assets' original cost, and we use pre-2007 data that fully reported these three values to examine the robustness of the variable, total fixed assets, for the later period. This showed a consistent robust result between the three values, and hence we confidently use total fixed assets in the following analysis. Moreover, we calculate APL and APK, which are used as references to truncate both the top and bottom 5% of our samples. We obtained 902 observations, and Table 2 reports summary statistics of variables.

5.2. Computation of misallocation in the wind power industry

The key parameters (labor share, rental rate of capital and diminishing returns in production) for calculating the effects of resource misallocation are set as follows: The labor share is set to $\alpha = 0.1$ as the wind power industry is capital-intensive, which is a different assumption from Hsieh and Klenow (2009). We adopt the method of full depreciation amortization within five years on fixed capital, referring to Chinese Accounting Standards to set a 20% depreciation rate (δ) and a 3% real interest rate (ρ), giving the rental rate of capital (excluding distortions) $R = \delta + \rho = 0.23$. The parameter of diminishing returns in production is set to $\gamma = 0.8$, referring to Basu and Fernald (1995), Basu (1996) and Basu and Kimball (1997).

5.2.1. Dispersion of industry-specific revenue productivities (TFPRs)

Eq. (15) implies the dispersion of TFPRs, which can be used to infer the extent of resource misallocation, and the calculated $TFPR_i$ is annually standardized.[5] Fig. 1 illustrates the deviation of TFPRs from the mean of TFPR, that is $TFPR_i - \overline{TFPR}$, in the wind power industry from 2000 through 2013. Each point represents the extent of dispersion of a specific plant in a specific year, and the higher the dispersion, the larger the resource misallocation. The horizonal red dotted lines in Fig. 1 signify one standard deviation above, zero standard deviation and one standard deviation below, respectively, and bound the area into four zones, i.e. zone 1 to zone 4 from bottom to top. Zero standard deviation, for example, indicates that plant *i*'s TFPR equals the $\overline{TFPR}$, implying no resource misallocation. But resource misallocation exists when the plant *i*'s mean centered $TFPR_i$ $(TFPR_i - \overline{TFPR})$ deviates from zero standard deviation, and the more the deviation, the more severe the resource misallocation.

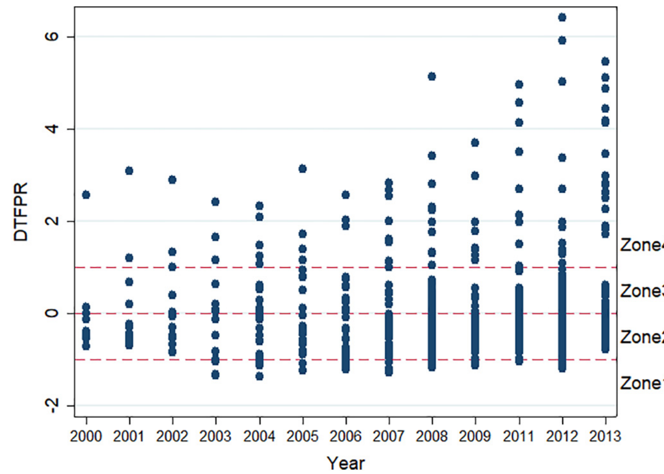

Fig. 1. Distribution of plant-level mean centered TFPRs in the wind power industry.

Table 3
Potential production improvement and source variation of changes in aggregate output.

Year	Entire industry	Plants built before FIT policy (pre-2009)			Plants built under FIT policy (2009 or later)		
	Ye/Y	Ye/Y	Aggregate output change from		Ye/Y	Aggregate output change from	
			$d\tau_{K_i}$	$d\tau_{Y_i}$		$d\tau_{K_i}$	$d\tau_{Y_i}$
2000	2.22	2.22	91.5%	8.5%	–	–	–
2001	2.56	2.56	93.6%	6.4%	–	–	–
2002	2.38	2.38	93.4%	6.6%	–	–	–
2003	1.48	1.48	90.5%	9.5%	–	–	–
2004	1.46	1.46	92.0%	8.0%	–	–	–
2005	2.39	2.39	89.6%	10.4%	–	–	–
2006	1.77	1.77	92.4%	7.6%	–	–	–
2007	1.97	1.97	93.4%	6.6%	–	–	–
2008	2.06	2.06	88.6%	11.4%	–	–	–
2009	1.66	1.66	84.1%	15.9%	–	–	–
2011	3.02	3.28	87.6%	12.4%	3.75	87.2%	12.8%
2012	2.38	2.62	90.5%	9.5%	2.89	88.5%	11.5%
2013	3.03	3.37	89.4%	10.6%	3.62	86.9%	13.1%

Note: Ye/Y (annual potential production improvement) denotes the increment of production when distortions have been totally removed. The higher the value, the more severe the input distortion.

As shown in Fig. 1, the deviation from the mean of TFPR of plants did not exceed three positive standard deviations before 2007, but it has increased since 2008, implying that resource misallocation in the wind power industry has worsened. If plant *i*'s mean centered $TFPR_i$ $(TFPR_i - \overline{TFPR})$ lies in zones 1 and 2, that implies that plant *i*'s revenue productivity is below the industrial average, i.e. $TFPR_i < \overline{TFPR}$. Plants with lower revenue productivities remain in the market without being eliminated, likely largely because of government subsidies. The strong support of subsidy policies provides an incentive to firms to invest in wind power plants regardless of whether their productivities are relatively efficient, and both labor and capital inputs remain at the inefficient wind power plants rather than migrating to high-efficiency power plants, contributing to the resource misallocation. The results in Fig. 1 show that the distortion of resource allocation of most wind power plants is largely due to subsidies.

5.2.2. Annual potential production improvement (Ye/Y)

We further calculate the annual potential production improvement, the gap between actual and efficient production levels of the wind power industry and defined as $Y_{efficient}/Y$. Generally, a higher potential production improvement implies a more severe resource misallocation.

[4] Because of the problem of incomplete information, value added is also calculated using either gross industrial output value, and then subtracting inventory and VAT, or sales, subtracting opening inventory and adding ending inventory, intermediate inputs and VAT.

[5] $(TFPR_i - \overline{TFPR})/\sigma$.

As mentioned in the studies of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), the improvement in resource misallocation is delineated as the process of eliminating idiosyncratic shocks from firm-level distortions that potentially either raise or lower real input costs in the production process. They conclude that the worst resource allocation situation occurs when the least capable firms (i.e. firms with the lowest TFPQs) utilize a large share of the economy's available production inputs, resulting in lowered production outputs by the economy. Alternatively, the greatest improvement occurs whenever all firm-level distortions have been eliminated.

The results of annual potential production improvements are reported in Table 3. As shown in column (1), the potential production improvement of the Chinese wind power industry was relatively high in 2011–2013, and we believe the Chinese government's 11th Five-Year Plan for the previous, 2006–2010, period induced the investment boom in wind power plant construction. The plan clearly proposed to accelerate development of renewable energy such as wind, solar photovoltaic and biomass. Wind power generation has particularly received substantial support from the government as a priority development project and attracted the highest subsidies. But these subsidy policies had the strong potential to become excessive, attracting more new and relatively inefficient firms to enter the wind power industry, resulting in rapidly increasing potential production improvement since 2011 and illustrating significant policy distortions embedded in governmentally supported wind power development.

As FIT policy was implemented August 1, 2009, we divided wind power plants into two groups – plants built before FIT policy (pre-2009) and plants built under FIT policy (2009 or later), to calculate potential production improvements. Columns (2) and (5) of Table 3 report the results. From 2011 to 2013, the annual potential production improvement of plants built under FIT policy is significantly greater than that of plants built before FIT policy, implying that plants built under FIT policy face more severe distortions. It is likely that plants built before FIT policy were contracted through concession bidding, which might have favored the relatively efficient firms entering the market. The introduction of FIT policy may have allowed more low-productivity wind power plants to enter the industry, thus exacerbating resource misallocation. These findings are consistent with the conclusions of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).

We then calculate the proportion of the changes in aggregate output due to changes in output distortion and capital distortion with Eq. (21). The newer plants are relatively inefficient since they enter and remain in the industry mainly because of government subsidies rather than cost or technological advantages; thus, as presented in Table 3, most of the changes in aggregate industry output are due to variation in capital distortion. We focus on the results for 2011 through 2013 to compare the source variation of changes in aggregate output of plants built under FIT policy with that of plants built before FIT policy. Our results show that plants built under FIT policy have a higher proportion of changes in aggregate output due to variation of output distortion than do plants built before FIT policy, suggesting that implementing different FIT rates has at least slightly reduced the impact of capital distortion variations on changes in aggregate output.

In summary, although implementing FIT reduces the effect of capital distortion variations, it exacerbates the resource misallocation in the wind power industry. High productivity firms are unable to obtain better allocations of productive resources. Since FIT are likely to stimulate significant investment in resource regions III and IV, where wind resources are relatively scarce and FIT rates are high.

Table 5
Potential production improvement and source variation of changes in aggregate output in four wind resource regions.

Resource regions		Entire regions	Plants built before FIT policy (pre-2009)			Plants built under FIT policy (2009 or later)		
	Year	Ye/Y	Ye/Y	Aggregate output change from		Ye/Y	Aggregate output change from	
				$d\tau_{K_i}$	$d\tau_{Y_i}$		$d\tau_{K_i}$	$d\tau_{Y_i}$
Region I	2011	5.02	5.15	90.0%	10.0%	7.56	89.3%	10.7%
	2012	3.54	3.60	90.2%	9.8%	5.81	95.4%	4.6%
	2013	4.33	4.48	90.1%	9.9%	6.26	92.0%	8.0%
Region II	2011	4.02	4.15	82.4%	17.6%	5.93	90.9%	9.1%
	2012	3.22	3.58	88.5%	11.5%	3.85	90.9%	9.1%
	2013	3.85	4.22	88.4%	11.6%	4.71	86.6%	13.4%
Region III	2011	5.43	5.75	90.5%	9.5%	7.19	91.4%	8.6%
	2012	3.87	4.28	90.9%	9.1%	4.67	81.0%	19.0%
	2013	4.97	6.10	90.1%	9.9%	5.43	78.1%	21.9%
Region IV	2011	3.32	3.73	89.9%	10.1%	3.89	86.0%	14.0%
	2012	2.69	3.01	91.6%	8.4%	3.17	87.2%	12.8%
	2013	3.57	4.08	90.0%	10.0%	4.11	88.2%	11.8%

Note: Ye/Y (annual potential production improvement) denotes the increment of production when distortions have been totally removed. The higher the value, the more severe the input distortion.

5.2.3. Regional differences

To compare the extent of resource misallocation in four wind resource regions, we divided the sample into four region-specific groups by identifying the location of each wind power plant and calculated annual potential production improvements from 2000 through 2013 (excluding 2010). As shown in Table 4, resource regions I and III have a relatively larger gap between their actual and efficient production levels than the other two regions; thus, on the average, the more severe resource misallocation is in regions I and III.

Moreover, potential production improvements of all regions from 2011 through 2013 (after implementing FIT) are significantly higher than potential production improvements before implementing FIT. The entry of new and relatively inefficient firms exacerbates resource misallocation, enlarging potential production improvements. Potential production improvement in region IV is the lowest among the four regions. This is likely to be due to the enormous curtailments in regions I, II, and III, much territory of which is in The Three-North Area, where power grid infrastructure has fallen behind the level of wind farm construction, in turn exacerbating resource misallocation.

We calculated annual potential production improvements and source variations of changes in aggregate output for plants built under FIT policy and those built before FIT policy in each resource region from 2011 through 2013. Table 5 shows that in all the resource regions, the extent of resource misallocation of plants built under FIT policy is significantly more severe than that of plants built before FIT policy, implying that a larger gap exists between TFPQ of new plants and that of plants built before 2009. The new plants located in resource region I,

Table 4
Potential production improvement in four wind resource regions from 2000 through 2013.

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2011	2012	2013
I	2.47	3.28	2.96	1.98	1.89	3.21	2.28	2.68	2.71	2.65	5.02	3.54	4.33
II				2.10	1.99	3.02	2.46	2.47	2.61	1.88	4.02	3.22	3.85
III						5.91	3.07	3.22	3.33	2.84	5.43	3.87	4.97
IV	2.79	2.79	2.69	1.64	1.68	2.81	2.07	2.39	2.54	2.12	3.32	2.69	3.57

Note: Blanks imply that plant amounts are too small to be calculated.

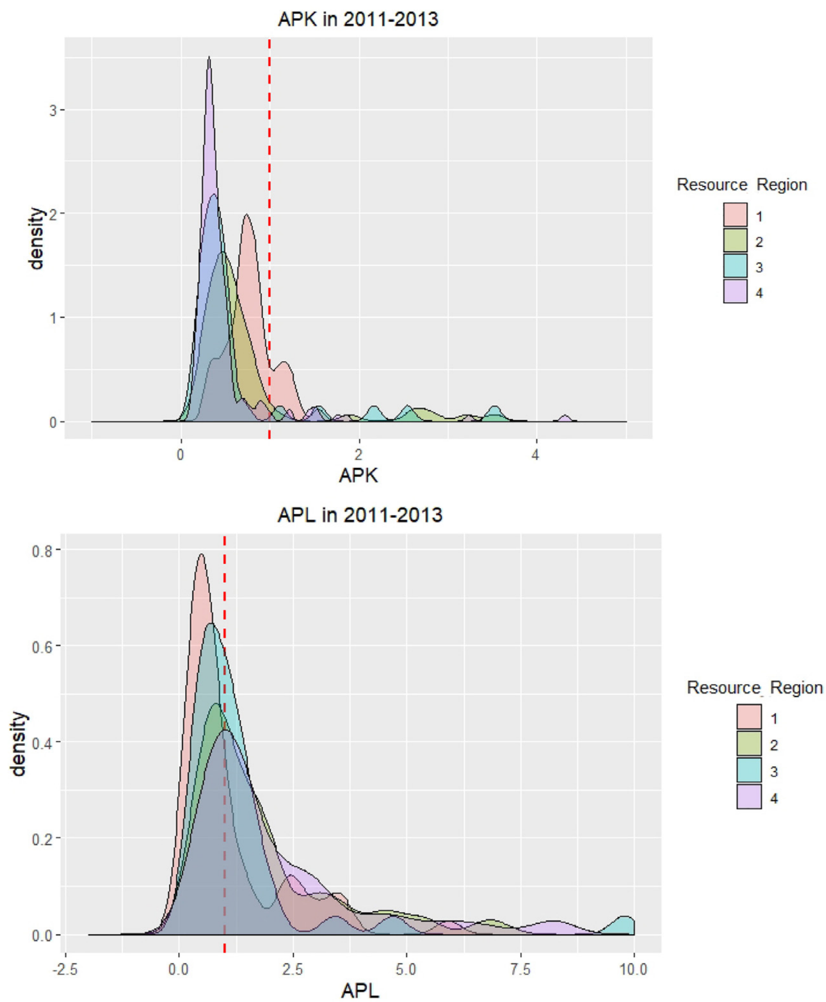

Fig. 2. Density of average labor productivity (APL) and capital productivity (APK). Note: Labor productivity is normalized by the employee benefits payable weighted mean of labor productivity of plants in 2006-2008, while capital productivity is normalized by the net value of the fixed assets weighted mean of capital productivity of plants in 2006-2008. Observations for each firm are weighted by firm employee benefits payable and net value of fixed assets.

which is the best-endowed wind resource region, have the most severe resource misallocation. The results indicate that FIT provides more opportunities for low-productivity plants to enter the industry.

In addition, Table 5 shows that plants built under FIT policy in regions III and IV have a relatively higher proportion of changes in aggregate output due to the variation of output distortion than plants built under FIT policy in regions I and II, implying that different FIT rates have slightly increased the impact of output distortion variations on changes in aggregate output. In resource regions I and III, where the resource misallocation is relatively severe, the proportion of changes in aggregate output due to variation of capital distortion in region I has significantly increased, whereas that in region III has significantly decreased. Therefore, applying FIT policy does not alleviate the resource misallocation in the wind power industry in more endowed resource regions effectively; misallocation is more likely due to insufficient power grid infrastructure or lack of market exit mechanisms.

5.3. Productivity in the wind power industry

5.3.1. Regional differences of productivity

To further verify that firms in different resource regions have consistently different productivities, we calculate both the average capital productivity (APK) and average labor productivity (APL) of each plant to illustrate marginal revenue products of capital (MRPK) and marginal revenue products of labor (MRPL).[6] We have the comparison period (2011−2013) and benchmark period (2006–2008), and take the arithmetical average of the three-year APK and APL of each period for brevity. We normalize the APK and APL of the latter, benchmark period to one, which is represented by the vertical red dotted line in Fig. 2, and the density distribution of APK and APL of the four resource regions are each then presented.

The top sketch of Fig. 2 shows that the APK of wind power plants in the comparison period was significantly lower than in the benchmark period as the density is skewed left of the red dotted line, regardless of the region in which wind power plants were located. The implementation of FIT has obviously reduced average capital productivity. An original hypothesis implicit in FIT policy was that differences in profitability between plants could encourage competition between them to increase operating efficiency (Melitz, 2003). But the results seem to reflect the contrary. Lower average capital productivity after 2009 suggests that FIT implementation contributed to lower operating efficiency in the wind power industry. The recent APKs of resource regions III and IV have the largest differences from those of the benchmark period. We believe that wind resources in regions III and IV are relatively scarce

[6] As from Eq. (5), $MRPL_i \triangleq w\frac{1}{1-\tau_{Y_i}}$, and $APL_i \propto \frac{1}{1-\tau_{Y_i}}$; $MRPK_i \triangleq R\frac{1+\tau_{K_i}}{1-\tau_{Y_i}}$, and $APK_i \propto \frac{1}{1-\tau_{K_i}}$.

Table 6
Definitions, data sources and descriptive statistics.

Variable description	Definition	Data source	Mean	Std. Dev.
Growth rate of APK: APK_g	$APK_g = \frac{APK_{t+1} - APK_t}{0.5 * (APK_{t+1} + APK_t)}$	Calculated using Y, K and L	0.179	0.547
Growth rate of APL: APL_g	$APL_g = \frac{APL_{t+1} - APL_t}{0.5 * (APL_{t+1} + APL_t)}$	Calculated using Y, K and L	0.043	0.654
Physical productivity: $\ln\left(\frac{TFPQ_{it}}{\overline{TFPQ_t}}\right)$	Relative physical productivity of plant i in year t	Calculated using Eq. (11)	1.558	0.588
Resource region	Four resource regions, dummy variable	China's National Development and Reform Commission (NDRC)	14.52% located in region I; 16.74% located in region II; 8.65% located in region III; 60.09% located in region IV	
Ownership	***Foreign-invested:*** registered in Hong Kong, Macau, Taiwan and foreign firms ***State-owned:*** registered as State-owned, State joint ownership, State and collective joint ownership and wholly State-owned firms ***Privately-owned***: all besides foreign-invested and State-owned firms	the Chinese Industrial Survey	27.05% is foreign-invested; 42.46% is state-owned; 30.49% is private-owned	
Large-sized firm (1 = Yes)	Total assets are greater or equal to 400 million yuan	the Chinese Industrial Survey	60.98% are large-sized firms	
Built under FIT policy (1 = Yes)	Wind plants built under FIT policy	the Chinese Industrial Survey	28.71% were built under FIT policy	
CDM	Firms with CDM projects.	Clean Development Mechanism in China	48.12% are CDM	
GDP per capita	GDP/population in natural logarithm	China city statistical yearbook	10.355	0.687
Ratio of industrial output to GDP	Value of industrial output/GDP	China city statistical yearbook	48.427	7.831
Ratio of FDI to GDP	FDI/GDP	China city statistical yearbook	2.427	2.377

Note: The classification standard of firm size follows the 'Interim Measures for Statistical Definitions of Large, Medium and Small Enterprises,' published by the Chinese National Bureau of Statistics in 2003.

compared to those of the other regions, leading to costly construction but insufficient generation.

There is no significant difference in the distribution of APL between regions, as shown in the bottom sketch of Fig. 2. This might be because the wind power industry is quite capital-intensive. Indeed, our data also shows that labor input accounts for less than 5% of the value of capital input. Compared with APK distributions, overstaffing may not be as severe as the sketch of APL is quite evenly distributed across different resource regions. The embedded mechanism is that labor distortions would cause uneven distributions of MRPL in different resource regions, which can

Table 7
Physical productivity and the growth rates of APK and APL in four resource regions.

Variables	(1)	(2)	(3)	(4)
	APK growth rate	APL growth rate	APK growth rate	APL growth rate
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$	−0.520***	−0.430***		
	(0.041)	(0.048)		
Resource Region II (1 = Yes)	0.424***	0.374**	−0.220	0.113
	(0.141)	(0.186)	(0.308)	(0.566)
Resource Region III (1 = Yes)	0.502***	1.002***	0.320	0.575
	(0.168)	(0.360)	(0.361)	(0.698)
Resource Region IV (1 = Yes)	0.339**	0.948***	−0.164	0.552
	(0.150)	(0.337)	(0.253)	(0.591)
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$ * Resource Region I			−0.773***	−0.660**
			(0.123)	(0.278)
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$ * Resource Region II			−0.419***	−0.490***
			(0.079)	(0.095)
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$ * Resource Region III			−0.714***	−0.378*
			(0.170)	(0.206)
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$ * Resource Region IV			−0.521***	−0.395***
			(0.048)	(0.053)
Constant	−0.735	0.086	−0.288	0.508
	(0.702)	(0.921)	(0.715)	(0.982)
Year Fixed Effect	YES	YES	YES	YES
Province Fixed Effect	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES
Observations	452	452	452	452
R-squared	0.457	0.365	0.465	0.368

Note: Cluster standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Physical productivity and the growth rates of APK and APL under FIT implementation.

Variables	(1) APK growth rate	(2) APL growth rate	(3) APK growth rate	(4) APL growth rate
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$	−0.519***	−0.425***	−0.527***	−0.417***
	(0.041)	(0.048)	(0.048)	(0.057)
Built under FIT policy (1 = Yes)	0.027	0.103	−0.032	0.165
	(0.077)	(0.076)	(0.144)	(0.168)
$\ln\left(\frac{TFPQ}{\overline{TFPQ}}\right)$* Built under FIT policy			0.038	−0.040
			(0.087)	(0.087)
Constant	−0.711	0.177	−0.688	0.153
	(0.702)	(0.921)	(0.713)	(0.921)
Year fixed effect	YES	YES	YES	YES
Province fixed effect	YES	YES	YES	YES
Other controls	YES	YES	YES	YES
Observations	452	452	452	452
R-squared	0.457	0.367	0.458	0.367

Note: Cluster standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cause different distributed patterns of APL. We can observe in the sketch that densities of APL exhibit similar patterns across resource regions.

5.3.2. The role of physical productivities (TFPQs) and FIT

In Section 5.2, we concluded that FIT might allow more low-productivity plants to enter the industry, thus exacerbating resource misallocation. According to Hsieh and Klenow (2009), $TFPQ_i$ represents plant-specific productivity from all factors except labor and capital, and it is a heterogeneous plant's production technology, represented by A_i in Eq. (2), when other factors, such as resource endowment, ownership and firm size are controlled. Generally, the higher the production technology, the lower the increase in productivity can be due to technological progress. Thus, an empirical analysis is conducted to explore the role of TFPQs on the growth rates of APL and APK, using the following reduced form of an econometric model:

$$G_{it} = \alpha + \beta \ln\left(TFPQ_{it}/\overline{TFPQ_t}\right) + \boldsymbol{X_{it}\delta} + \boldsymbol{W_{jt}\gamma} + \mu_p + \theta_t + \varepsilon_{it} \tag{22}$$

G_{it} denotes the growth rate of APK or APL of plant i in year t; $\ln\left(TFPQ_{it}/\overline{TFPQ_t}\right)$ measures the relative physical productivity of plant i in year t; $\boldsymbol{X_{it}}$ are dummies to indicate resource region, ownership, whether plant i is large-sized, whether plant i is new (built under FIT policy) and whether plant i belongs to the CDM project in year t[7]; j denotes the prefectural-level city in which plant i is located, and $\boldsymbol{W_{jt}}$ is a vector of city characteristics, including gross domestic product (GDP) per capita, ratio of industrial output to GDP and that of foreign direct investment (FDI) to GDP in year t; μ_p is province fixed effect where p denotes the province in which plant i is located; θ_t is year fixed effect. Table 6 reports the definition, source and summary statistics of variables.

As shown in columns (1) and (2) in Table 7, the growth rates of APK and APL are significantly lower for plants with higher physical productivity. The growth rates of APK and APL in three resource regions are significantly higher than that of resource region I. Columns (3) and (4) report the heterogeneous effects of physical productivity on the growth rate of APK and APL in four resource regions. The results imply that regarding plants with better production technology, those in resource region I have worse growth rates than those in the other three regions. Therefore, plants with higher physical productivities are more likely to invest in the other three regions than resource region I.

Table 8 further examines whether there are differences in the impact of the physical productivity of new and existing power plants on the growth rate of APK or APL, and the results show that there are not significant differences. Table 5 has shown that in all the resource regions, new power plants built under FIT policy have higher potential production improvements. Although under the FIT policy, the government provides subsidies to encourage investments in wind power, the new power plants do not have production technology advantages, and they are even typically lower-productivity plants using productive resources. The lack of investment from high-quality firms appears to be a crucial factor hindering the development of wind power.

6. Concluding remarks and policy implications

The debate in the economic literature over the functions of industrial policy is longstanding, and the Chinese government-led development of the renewable energy industry is widely viewed as an exemplar of the implementation of such policy. This study tries to contribute to this debate by evaluating the impacts of industrial policy on industry-wide resource misallocation in Chinese wind power development. It starts from the perspective of resource misallocation and takes the lead in revising Hsieh and Klenow's (2009) model as applied to the study of wind power industry development.

This study finds that the FIT policy exacerbates industry-wide resource misallocation, thus lowering productivity in the wind power industry. Although FIT policy reduces the impact of capital distortions on the aggregate output of the industry, high-productivity firms are unable to obtain better resource allocation. Such effects result mainly from the excessive investment stimulated by subsidies. A possible explanation is that the so-called 'administrative subcontract' in China exacerbates excessive investment (Zhou, 2014). This is a form of vertically decentralized authoritarianism in the Chinese political system in which the national bureaucratic system devolves governance responsibilities such as taxation, employment, law and order, and education, to regional and local bureaucracies. In developing the wind power industry, this pattern of governance is likely to drive local governments to over-invest to accomplish their assignments. The results of this study also show that new wind power plants built under FIT policy tend not to be high-productivity firms, nor ones that have production technology advantages. It shows that constructing or investing in wind power plants still requires government approval but the approved projects are chosen mainly through bidding or are government-led, hindering the entrance of firms with high physical productivity or high-technology capabilities.

Different FIT rates in the four wind resource regions clearly drives disparities on output distortions. The empirical results show that higher physical productivity plants located in regions with larger endowments

[7] The clean development mechanism (CDM) is considered an exceptional way for wind power enterprises to acquire subsidies, i.e. applying to be a CDM project can help enterprises obtain low-interest loans from banks and revenues from additional CERs for certified emission reductions.

of wind resources suffer from lower average productivity growth. This may be due to insufficient grid infrastructure (transmission facilities) or poorly designed market entry and exit mechanisms. However, we are unable to investigate this due to limited data. Also we should further consider different types of industry policy, including RPS and auctions, when analyzing such distortion effects in future research. Such future researchers can also examine whether similar problems emerge in regard to renewable energy technologies in other national economies pursuing ambitious industry development goals.

CRediT authorship contribution statement

Chin-Hsien Yu: Formal analysis, Writing - original draft, Project administration, Funding acquisition. **Xiuqin Wu**: Data curation, Software. **Wen-Chieh Lee**: Methodology, Validation, Funding acquisition. **Jinsong Zhao**: Conceptualization, Investigation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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