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The role of feed-in tariff in the curtailment of wind power in China

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ABSTRACT

While China's wind power initiative has experienced rapid growth, serious curtailment issues persist. Though some studies have investigated this matter, we explain this phenomenon from the novel perspective of excess capacity. We first set up a theoretical model to explore the mechanism behind excess investment and find that the 'sticky' feed-in tariff (FIT) and declining costs of wind power generate high mark-up for wind power investors, leading to a higher probability of excessive investment. The theoretical prediction is empirically tested with a probit and tobit model using provincial-level data between 2009 and 2016. The estimation results show that a 0.1 yuan increase in the mark-up leads to a 2%–3% increase in the rate of curtailed wind power. Based on the estimation results, we simulate several scenarios to assess quantitatively how an improved policy design could have alleviated the curtailment issue. Simply increasing the frequency of the FIT rate adjustment while maintaining the same subsidy reduction level between 2009 and 2016 could have reduced the curtailed wind power by 23 to 27 billion kwh, accounting for 15%–17% of actual curtailed wind power. If the policy were better designed to reflect the declining trend of wind power costs more accurately, the curtailment rates could have been further reduced by 2.81%, corresponding to a reduction in wasted wind energy of >43 billion kwh (or 28% of actual curtailment). Although accepting curtailment for a certain period could help to accelerate renewable energy deployment, our analysis shows that the FIT policy design could have been improved to reduce welfare loss. These findings can not only assist the Chinese government in framing effective policies, but also may be applied to other emerging technologies or industries that require subsidy support.

1. Introduction

To reduce the reliance on fossil fuel-based energy and increase energy independence, China has been actively promoting renewable energy (including wind power), thereby transitioning to a low carbon energy mix. The cumulative installed capacity of wind power in China has grown from <1 GW at the end of the last century to >150 GW in 2017, with an average annual growth rate of nearly 50%. In 2011, China became the world's largest installed base of wind power capacity.

However, wind curtailment rates in China are unusually high.[1] As shown in Fig. 1, the lowest curtailment rate between 2011 and 2017 is 8%, and in most of the years, the rate is higher than 10%. Curtailment issues happen worldwide but not to a similar extent as in China. For instance, Wiser et al. (2015) report that the US wind curtailment rate is approximately 2%. The highest curtailment rate ever recorded in the US was 11% in 2009, although curtailment quickly decreased to levels far below this historical peak. At the regional level, the Electric Reliability Council of Texas, one of the nine independent US system operators, reported a peak curtailment rate of around 17% in 2009. By 2014, only 0.5% of the potential wind energy generation within the Electric Reliability Council of Texas was curtailed (Lam et al., 2016).

Given that the Chinese government sets an ambitious development target for renewable energy, one could argue that accepting curtailment for a certain period is simply an efficient way to promote renewable energy deployment. There could be a trade-off between rapid deployment growth and curtailment.[2] Nevertheless, the curtailment issue is usually severe and lasts for a decade long. Such a situation negatively affects the sustainable development of wind power. First, the resources are wasted as millions of watts of installed wind power capacity sits idle and clean energy is curtailed. From 2009 to 2017, 190 billion kwh, or as much as 15% of overall wind generation, was curtailed. This is equivalent to 61 million tons of coal consumption or 170 million tons of CO_2 emissions that could have been otherwise avoided.[3] Second, the curtailment issue reduces the profitability of wind power projects and hurts the

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[1] The curtailment rate is the share of the curtailed wind power out of the maximum potential generation at full utilization of installed capacity.

[2] We appreciate one anonymous reviewer for this point.

[3] The carbon emission number is similar to the total emissions of Vietnam in 2017.

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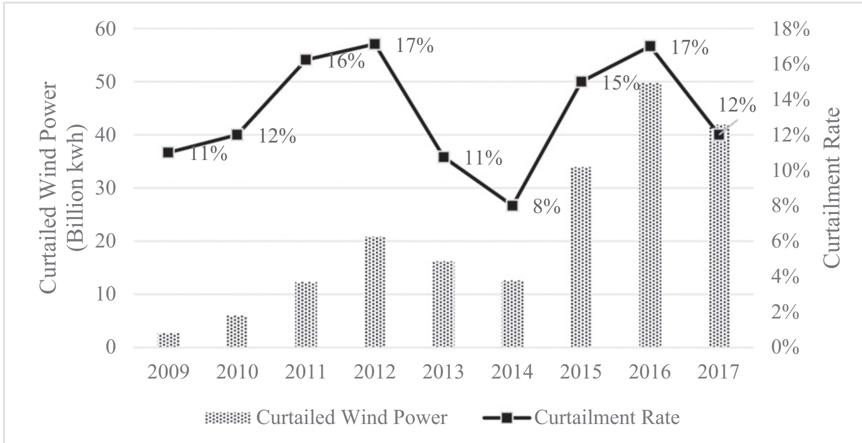

Fig. 1. Wind curtailment in China.

industry's long-term sustainability (National Energy Administration, 2018). Lastly, the unexpected high curtailment rates have increased the cost of carbon mitigation substantially. Lam et al. (2016) estimate that the actual levelized cost of wind electricity of the Clean Development Mechanism (CDM) projects is 0.5 to 2 times higher than expected and consequently, the cost of carbon mitigation is 4 to 6 times higher than the *ex-ante* estimates.[4]

Our study investigates the factors that cause China's serious and persistent wind power curtailment issue, particularly focusing on the role of feed-in tariff. The literature mentions lagging grid access, limited transmission capacity, system inflexibility, and electricity trade barriers (discussed in the following section) as factors. While such studies help us understand the factors that drive the unusually high wind power curtailment in China, the role of the underlying policy has received little attention. Our study complements the literature by offering a new perspective and examining how the renewable energy subsidy policy contributes to the wind power industry's excess capacity. A theoretical model is first set up to explore the mechanism of how the government subsidy affects excess investment. Subsequently, a theoretical prediction is tested using unique provincial-level data between 2009 and 2016.

Our study contributes to the literature in three aspects. First, it deepens the understanding of wind power curtailment by providing a rigorous and quantitative analysis of the governmental subsidy policy's role in this issue, which has not been examined in the literature. Second, it enriches a growing body of research that evaluates the effects of renewable energy policies. Recently, the efficiency of incentive schemes and other economic consequences of the policy design have become the focus of many studies (Hitaj and Löschel, 2019; May and Neuhoff, 2017; Ritzenhofen et al., 2016). Third, the analysis also supplements the literature on excess capacity by providing a case study of the unintended consequence of governmental intervention in a newly emerging industry.

2. Literature review

Our work builds on three streams of research, specifically, those that analyse the driving factors of wind curtailment, assess the relevant renewable energy policies, and study the mechanism of excess capacity or investment.

Bird et al. (2016) review the levels, causes, and methods of mitigating wind and solar curtailment in 11 countries and find that most countries only have mild wind curtailment, with rates below 3%, except for Italy and Texas (United States). These two places experienced in 2009 curtailment rates of 10.7% and 17.1%, respectively, primarily caused by transmission and distribution capacity constraints (Bird et al., 2014). Adding new transmission lines greatly alleviated the problem. Other methods such as adding storage, improving forecasting, and integrating the market were also used to deal with system-balancing challenges related to oversupply situations and ramp events. Lacerda and van den Bergh (2016) provide another comprehensive review of the possible explanations of curtailment, including system flexibility and market integration barriers.

Meanwhile, unlike other countries, China's curtailment rates have remained high for many years, much longer and more serious than other countries, which may indicate more complicated causes. The literature explains the issue in several ways. First, grid construction lagged far behind the rapid growth of wind power capacity due to coordination problems between grid companies and wind farms (Luo et al., 2016). Second, the current coal-dominant electricity system lacks flexibility to incorporate variable and intermittent wind power (Long et al., 2011; Lu et al., 2016; Pei et al., 2015). Finally, there exists a spatial mismatch between wind electricity supply and demand since majority of the wind capacity is concentrated in the 'Three North Area' and the load centre is located in the coastal provinces (Xia and Song, 2017; Zhao et al., 2012). The transmission across provinces or regions faces two major obstacles: lack of physical transmission lines and province-based regulatory structure (Dong et al., 2018; Zhao et al., 2012). These studies have helped deepen our understanding of what causes high curtailment in China but have not adequately addressed the mechanism behand the low capacity utilization.

Excess capacity has been a concern in China's economy for many years (Yang et al., 2015; Dong et al., 2015). Zhang and Jiang (2017) find that the overall utilization rate of China's economy between 2001 and 2011 was only 60%, but the level varies by region, industry, and enterprise type. Han (2012) first points out that excess capacity has occurred in renewable energy but does not provide any in-depth analysis. The literature offers several theoretical explanations for the occurrence of excess capacity. Studies that focus on developed countries explain the phenomenon from the perspective of enterprises' strategic behaviour. For example, overinvestment is considered a firm's coping strategy when faced with the threat of potential entry (Kamien and Schwartz, 1972), a collusive equilibrium in an oligopolistic market (Davidson and Deneckere, 1990), or as an operating option in an uncertain environment (Pindyck, 1988). Meanwhile, researchers from developing countries or emerging markets are concerned more with the role of governmental intervention (e.g. Brahm, 1995; Eckhard, 2000). In the

[4] The CDM allows a country with an emission-reduction or emission-limitation commitment under the Kyoto Protocol (Annex B Party) to implement an emission-reduction project in developing countries. Such projects can earn saleable certified emission reduction (CER) credits, each equivalent to one tonne of CO_2, which can be counted toward meeting Kyoto targets.

case of China, Xu et al. (2017) point out that the competition for subsidy among local governments in China leads to land price distortion and significantly stimulates the overinvestment of manufacturing enterprises. The empirical evidence behind these theoretical explanations is mixed. In a review by Cheng (2017), the author concludes that the causes of excess capacity or overinvestment are complex and may vary across countries, industries, and market structure.

The third stream of literature concerns the evaluation of different policies that support renewable energy, such as the feed-in tariff (FIT) and the renewable portfolio standard (RPS). Many studies find that FITs are significantly more effective than a quantity instrument (such as RPS) in promoting the deployment of renewable energy (e.g. Butler and Neuhoff, 2008; Ragwitz et al., 2006; and REN21, 2013). An emerging body of research began to shift the attention from the first-order effects toward second-order effects, such as the cost of these support schemes, market integration of the particular renewable sources supported, and price effects. Schmidt et al. (2013) and Pechan (2017) argue that the subsidy scheme may influence the location choice of wind turbines while May (2017) studies the subsidy scheme's impact on the technology choice. Ritzenhofen et al. (2016) quantitatively compare the effect of RPS, FIT, and market premium schemes on electricity price, reliability, and sustainability of electricity supply. Ciarreta et al. (2017) compare the cost-effectiveness of FIT and RPS using a calibrated Spanish electricity market model and conclude that FIT is less cost-effective. Our study contributes to this stream of literature by pointing out that the FIT may have some unintended effect of encouraging wastage of resources.

3. Theoretical analysis of the excess investment in the wind power industry

3.1. The determining factors of wind power investment profit

To understand the wind farm investors' incentive for excessive investment, we need to know how their profits are determined. Since wind power in China has not been cost-competitive with conventional power (e.g. coal-fire power or hydropower), the investment profit in wind power is largely determined by the relevant governmental policies, which affect all the determining factors of profit, including price, quantity, and investment costs.[5]

3.1.1. Feed-in tariff policy

Wind farm investors receive a fixed sell price determined by the central government according to the FIT policy introduced in 2009.[6] It divides the whole country into four categories based on the geographical distribution of wind resources and project engineering-related factors. Fig. 2 presents the distribution of the four categories. Regions with good resources have the lowest rate, reflecting low expected production costs. A single province could have more than one rate if it belongs to different resource regions. After the FIT's introduction in 2009, the rates were not changed until 2015. After that, the FIT rates were reduced again in 2016 and 2018, as summarized in Table 1.

3.1.2. Mandatory access and 'equal share' dispatch

To understand how the quantity of wind power generation is determined, it is important to know how China's electricity system (especially the dispatch system) works. More details on China's generation dispatch system can be found in Kahrl et al. (2013), Zhong et al. (2015), Ho et al. (2017), and Wei et al. (2018). In summary, generation dispatch in China can be characterized as equity-based rather than efficiency-based as opposed to the practices in many western countries. The Renewable Energy Law explicitly requires grid companies to purchase the full amount of renewable energy produced by registered producers. However, given that the wind power is random and intermittent, the grids can reject it for safety reasons. In a planned electricity system like China's, in which the grid company is the only buyer as well as the one in charge of the dispatch, the production decision is not essentially made by wind farms, but by grid allocation. The allocation follows an 'equal share' principle, where generators in a given class (e.g. wind power plants) are allocated the same annual utilization hours. In other words, the market shares are allocated to the wind farms equally.[7]

3.1.3. Cost structure of wind power investment

Wind power investment has high fixed investment costs and low variable costs. The equipment, construction, and grid connection costs during the construction stage can account for 70% to 80% of total costs. Once constructed, a wind farm typically remains in service for 20 years, during which the operation and maintenance costs only account for a relatively small part of the total costs.

Since 2009, wind farms have enjoyed various tax exemptions, including for income tax and value-added tax. The equipment costs can be deducted from value-added tax. All the tax exemption policies are homogeneous across the whole nation and remain constant over the years.

3.2. Theoretical model

Lin et al. (2010) use the term 'wave phenomenon' to describe China's excess investment. The basic idea is that firms, due to information asymmetry, are prone to have consensus on the next promising industry and invest in this industry. Built on the investment model of Lin et al. (2010), we construct a two-phase wind energy investment model that incorporates the above-discussed features and show how the FIT can increase the probability of excess capacity.

Suppose there are n homogeneous investors in the market that simultaneously have plans to build wind farms. In the first phase, the investors make an investment decision and choose the quantity of the installed capacity, denoted by k_i. In the second stage, they generate electricity, sell to the grid, and make a profit. The cost of installation in the first stage is assumed to be a function of k_i, $C(k_i) = ck_i$, where c is a positive constant. The operation and maintenance costs of production are assumed to be zero. At the first stage, the number of investors n is not known, there is only a prior estimate of the number (n), with the probability distribution of $F(n) = \Pr(n < N)$.

In the second stage, the wind power producers generate power, sell to the grid company, and receive an on-grid price according to the FIT rates, which is denoted by p and $p > 0$. Suppose that the total demand

[5] Coal power production has the externalities of air pollution and carbon emission. Since the costs of these externalities are not reflected in the coal power's costs, it could be one of the reasons why wind power is still not cost-competitive in China.

[6] The evolution of China's wind power pricing policies can be roughly classified into three stages. The first stage was before 2003, when there was very little wind power production and prices were mostly approved by the government on a case-by-case basis. The second stage was between 2003 and 2008, when a concession-bidding pricing policy and approval-pricing policy co-existed. During this period, the Chinese central government conducted wind concession programs for large-scale wind farms. The bidding price later became the basis for building new wind power projects for provinces that already had experience (Qiu and Anadon, 2012).

[7] Its current dispatch system is dominated by the administrative allocation of annual generation quotas by provincial governments. Provincial governments administer the production of power units inside their jurisdictions through the Annual Power Generation Plan, which determines the annual generation hours of power units. Toward the end of each calendar year, the provincial governments make a forecast of total electricity demand for the next year, and then allocate this demand to generators within the province and imports from outside the province. Provincial grid companies are responsible for carrying out the plan by disaggregating it into monthly and daily dispatch plans. This equal share dispatch rule was established in the 1980s, when the state monopoly was ended and private investment in generation was permitted. The intention was to guarantee an equitable chance of cost recovery for all investors (Qi et al., 2018).

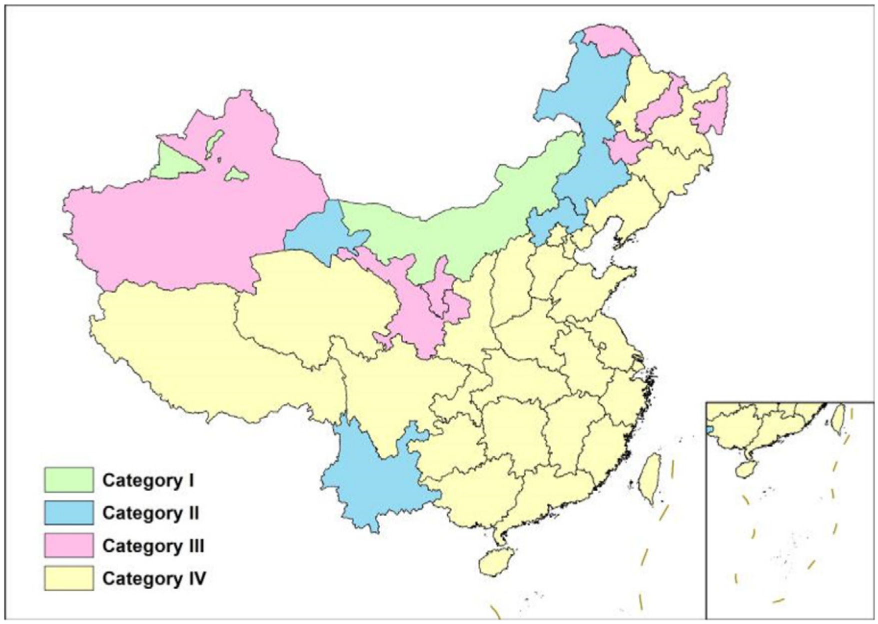

Fig. 2. Categories of feed-in tariff rates for onshore wind power.

for wind power in the market is Y, and the total demand is divided equally among the wind power producers according to the 'Equal Share Dispatch Rule'. As such, at this stage, the wind power producers generate the quantity that is dispatched by the grid company according to $q_i = Y/n$. Note that at this stage, the number of investors is known to all.

The production quantity q_i depends on the investor's own installed capacity k_i, which cannot exceed the upper bound at which the capacity is fully utilized. For simplicity, the production function is linear in k_i. In addition, since the total demand is divided equally among the wind power producers, each investor's production quantity q_i also depends on other investors' installed capacity (k_{-i}) and the number of investors n. Then, a representative investor, i's profit can be expressed as $pq_i(k_i, k_{-i;}; n)$, and his/her objective is to maximize the following profit function by choosing the installed capacity k_i:

$$\text{Max } E_n\pi_i(k_i, k_{-i}; \mathrm{n}) = E_n\{pq_i(k_i, k_{-i;}; n)\} - ck_i \tag{1}$$

in which E_n indicates the expected value given a distribution of n. Because the enterprises are homogeneous, the equilibrium solution is expected to be symmetric; that is, in equilibrium, the investors would install the same amount of capacity. Assuming n^* is the number of investors such that each investor' installed capacity, denoted by k^*, happens to be utilized fully, that is, $k^* = Y/n^*$. When $\mathrm{n} < n^*$, investor i's capacity can be fully utilized; then, increasing additional units of capacity can generate an additional profit. If $\mathrm{n} \geq n^*$, the production is constrained by the total market demand so that the installed capacity cannot be utilized. Thus, at equilibrium, the following equation would be satisfied:

$$\mathrm{p} * \mathrm{F}(n^*) = \mathrm{p} * \mathrm{F}\left({}^{Y}\!/_{k}*\right) = c \tag{2}$$

Table 1
Adjustment of FIT rates (Unit: Yuan).

	2009	2015	2016	2018
Category I	0.51	0.49	0.47	0.40
Category II	0.54	0.52	0.50	0.45
Category III	0.58	0.56	0.54	0.57
Category IV	0.61	0.61	0.60	0.59

in which the left-hand side is the ***expected*** marginal benefit of increasing an additional capacity, and the right-hand side is the associated cost. The equation implies that the investors will increase the installed capacity until the expected incremental benefit is equal to the marginal cost.

According to the definition of game equilibrium, investors can estimate this boundary value of the number of investors in equilibrium (n^*) according to Eq. (2), but they do not know the exact number of investors in the first stage. When the realized number of investors n exceeds the boundary value n^*, excess capacity happens in the industry. Furthermore, according to condition (2), the probability of excess capacity in the industry would satisfy Eq. (3):

$$1 - \mathrm{F}(n^*) = 1 - \frac{c}{p} \tag{3}$$

In Fig. 3, the shaded area indicates the probability of the realized number of investors n being smaller than the critical value n^*, or in other words, the probability of that capacity being fully utilized. A simple comparative statics analysis can help us see that a higher price or a lower cost will decrease the boundary value n^*. The lower the critical value of n^* is, the higher the probability of the realized number of

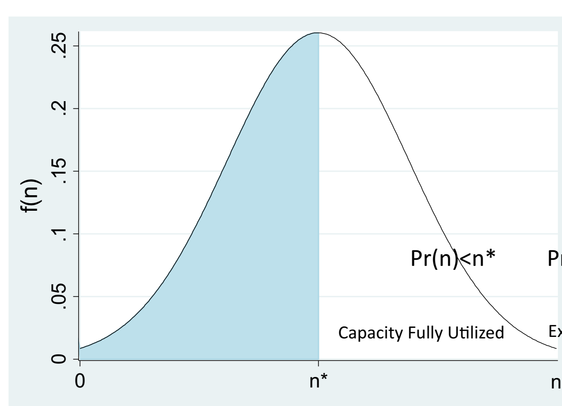

Fig. 3. An illustration of the relationship between n* and excess capacity.

Table 2
Parameters of LCOE calculation.

Cost parameters		Data source
Capital expenditure		
Turbine cost	Homogeneous across counties, decreases over time	Yu et al. (2017)
Land cost	Varies across counties and time	
Construction cost	Homogenous across counties, constant over time	Liu et al. (2015)
Grid connection cost	Homogeneous across counties, constant over time	Liu et al. (2015)
Tax and other miscellaneous expenses	Homogenous across counties, constant over time	Liu et al. (2015)
Operation and Maintenance Costs	Homogenous across counties, constant over time	Liu et al. (2015)
r	0.08	Liu et al. (2015)
FIT rates	Vary across counties and time	
Capacity factor	Varies across counties	McElroy et al. (2009)

investors exceeding n^*will be, leading to excess capacity. Intuitively, a higher price or a lower cost would cause the mark-up and profitability to increase, attract more investors, and become more likely to have excess capacity.[8]

In the next section, employing a panel of provincial-level data, we empirically test whether a high mark-up level increases excess capacity.

4. Empirical analysis

4.1. Estimation model and data

The theoretical model can be converted to:

$$Y_{it} = \beta S_{it} + \gamma X_{it} + T_t + \lambda_i + \varepsilon_{it} \tag{4}$$

where Y_{it} is the measurement of excess capacity in wind power for province i in year t. S_{it} is the mark-up computed by subtracting the cost of wind power generation from the on-grid price. Based on the theoretical analysis, it is expected that the coefficient of the mark-up variable is positive and significantly associated with the measurement of excess capacity. X_{it} is a vector of other control variables that could affect the utilization of wind power; T_t is a vector of year dummies that capture the common trends affecting every province; λ_i are the province-fixed effects controlling for time-variant province characteristics; and ε_{it} is the error term, which is allowed to be correlated within the province.

4.1.1. Measurement of excess capacity

There are two indicators of excess capacity: whether the wind curtailment happens and the curtailment rate. The National Energy Administration has released annual reports of wind power development in China since 2011, which include annual wind curtailment rates at the provincial level. The 2009 and 2010 statistics are obtained from Song and Berrah (2013).

4.1.2. Measurement of mark-up

The mark-up of wind energy is computed by subtracting the levelized costs of electricity (LCOE) from the on-grid price per kwh. The LCOE is the expected net present value of the unit-cost of electricity over the lifetime of a generating asset. The LCOE can be derived using the following equation:

$$\mathrm{LCOE}_{wind} = \frac{C_{capex} * r + C_{OM}}{Capacity\ Factor * 8760} \tag{5}$$

[8] If the cost function is convex, the increase installed capacity will lead to increasing marginal cost and thus a quicker decline in markup compared with the constant cost case. Consequently the probability of the excess capacity will become lower.

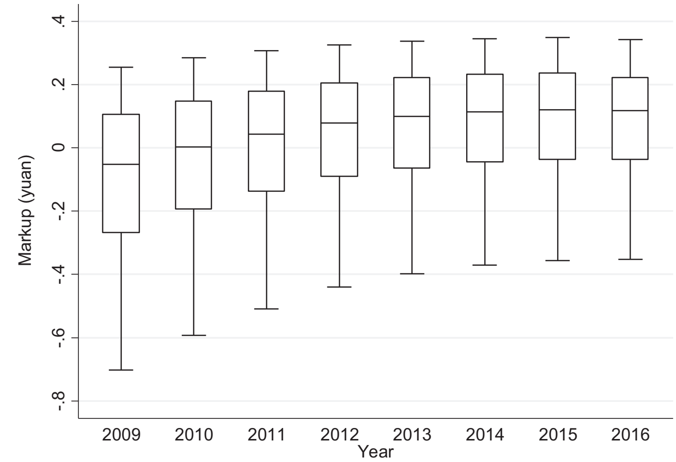

Fig. 4. Box plot for mark-up (yuan) by year.

where C_{capex} is the capital cost of a wind farm; r is the capital recovery factor (%) that converts a present value into a stream of equal annual payments over the power plant's lifetime at a specified discount rate r; and C_{OM} is the operation and maintenance cost.

The capacity factor is the fraction of the rated power potential of a turbine that is actually realized over the course of a year, given expected variations in wind speed. The figure 8760 is the number of hours in a year. The product of these two parameters gives the operation hours of a wind farm.

Eq. (5) implies that the LCOE can be affected by several factors, including the cost and capacity. Within a province, even though the cost factors may not vary much, the variations in wind resources may result in wide variations in the capacity factor of wind farms. To take into account the heterogeneity within a province, the provincial-level mark-up is constructed by aggregating the county-level mark-up, weighted by county area.

Capital expenditure includes wind turbine, land, grid connection, and design and construction costs, as well as other miscellaneous expenses. Generally, the cost of wind turbines dominates the total investment costs (Lantz et al., 2012; Williams et al., 2017). The national average price of wind turbines is obtained from Yu et al. (2017) and the China Wind Energy Association (CWEA, 2016). As these studies point out, the wind turbine price shows little spatial variation but exhibits a declining trend over time, driven by the scale and learning

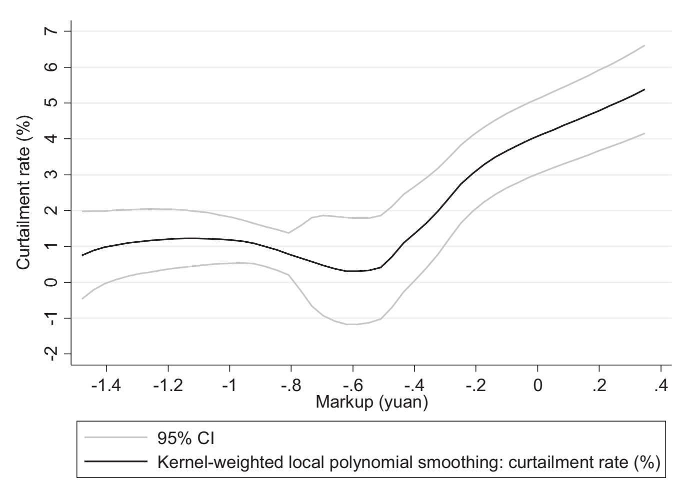

Fig. 5. Non-parametric regression of mark-up on rate of curtailed wind power.

Table 3
Descriptive statistics by year.

	2009	2010	2011	2012	2013	2014	2015	2016
Rate of curtailed wind power (%)	1.983	2.183	3.678	3.321	3.631	2.933	6.000	6.867
	(4.768)	(5.465)	(7.409)	(7.185)	(6.768)	(5.051)	(11.197)	(11.956)
Mark-up (yuan)	−0.171	−0.106	−0.057	−0.016	0.008	0.024	0.029	0.026
	(0.428)	(0.391)	(0.364)	(0.341)	(0.327)	(0.318)	(0.312)	(0.307)
GDP (billion yuan)	1216	1455	1736	1920	2112	2278	2408	2568
	(9,66)	(1131)	(1309)	(1417)	(1554)	(1681)	(1804)	(1958)
Share of primary sector (%)	11.375	10.888	10.542	10.453	10.450	9.936	9.930	9.763
	(5.776)	(5.534)	(5.382)	(5.295)	(5.232)	(5.062)	(5.146)	(5.178)
Share of secondary sector (%)	47.134	48.632	49.092	48.297	47.897	46.124	43.243	41.543
	(7.515)	(7.466)	(7.950)	(7.781)	(7.901)	(7.932)	(7.791)	(7.772)
Share the tertiary sector (%)	41.491	40.480	40.367	41.250	41.653	43.940	46.827	48.693
	(8.302)	(8.612)	(9.028)	(8.983)	(9.104)	(8.913)	(8.711)	(8.655)
Population (10 thousand)	4405	4436	4458	4483	4507	4531	4559	4588
	(2693)	(2709)	(2713)	(2721)	(2728)	(2740)	(2759)	(2785)
Thermal power (10 thousand kw)	2170	2365	2560	2731	2899	3077	3295	3512
	(1628)	(1744)	(1863)	(1937)	(2079)	(2159)	(2339)	(2529)
Hydro power (10 thousand kw)	653	719	775	830	933	1013	1058	1102
	(788)	(878)	(966)	(1071)	(1314)	(1526)	(1620)	(1716)
Length of transmission (km)	40,353	43,857	43,857	48,585	50,943	53,318	53,318	53,318
	(20,018)	(21,518)	(21,518)	(23,119)	(24,415)	(25,246)	(25,246)	(25,246)
Number of observations	30	30	30	30	30	30	30	30

effects.[9] The real price of wind turbines has decreased by over 60% between 2008 and 2015. Land acquired for wind farms is usually from marginal land. Land rental costs are based on the provincial standards for land acquisition and collected through provincial governmental documents. Grid connection costs, design and construction costs, other miscellaneous expenses, and operation/maintenance costs that account for a small part of the initial investment costs are obtained from Liu et al. (2015). These parameters are assumed to be spatially homogeneous.[10]

Operation hours depend primarily on the distribution of wind resources and therefore, have substantial spatial variations. We evaluate the spatial capacity factor following a method reported by McElroy et al. (2009) and then infer the capacity factor for each county through a weighted-average approach for all valid data in that county.

Wind resources are evaluated using historical meteorological data from version 5 of the U.S. National Aeronautics and Space Administration's Goddard Earth Observing System Data Assimilation System. In the analysis, we restrict our attention to regions where the wind power capacity factor is 20% or greater. Forested areas, areas covered by water, areas occupied by permanent snow or ice, urban or developed areas, and areas with slopes of >20% are also excluded. The detailed parameters and the data sources employed to calculate the LCOE of wind power are presented in Table 2.

Fig. 4 summarizes the panel data of the calculated provincial markup of wind investment by box plot. It clearly shows that there exist large spatial variations, as well as an increasing trend over the period from 2009 to 2015.

The non-parametric regression in Fig. 5 also illustrates a positive relationship between the mark-up and the rate of curtailed wind power, particularly for mark-ups larger than −0.6 yuan, which covers 70% of the observations in our sample.[11] These provide preliminary evidence for our econometric investigation of curtailed wind power caused by the mark-up. However, a more rigorous analysis needs to include other control variables, as conducted in the next section.

4.1.3. Other control variables

Other variables that could affect the utilization of wind power, denoted by X_{it}, include local demand, the accessibility of the electricity transmission grid, and other types of electricity sources. Proxy variables of local demand include the logarithm of the gross domestic product (GDP) and the shares of secondary and tertiary sectors. Transmission capacity is measured by provincial grid density. Both local demand and transmission capacity are expected to affect the utilization of wind power capacity positively, which means their signs are expected to be negative. Other types of electricity sources include thermal power and hydropower in logarithm, the sign of which is expected to be positive due to the substitution effect. Table 3 presents the descriptive statistics on variables used in our analysis.

4.2. Identification strategy and estimation results

A probit model can be used to investigate how the price mark-up affects the likelihood of curtailing any wind power in a province for a particular year. As 70% of the observations in our sample did not curtail any wind power (which should be considered the optimal choice as opposed to representing missing values), a tobit estimator of eq. (1) is also estimated. One concern is that the price mark-up may be affected by the curtailment rate, thus leading to reverse causality. Since the price mark-up is constructed by using the FIT, which is set by the central government, netted out of the ***expected*** generation costs rather than the ***actual*** generation costs, the reverse causality problem can be ruled out.

Another concern is how to deal with the unobserved heterogeneity λ_i in nonlinear panel models. The assumption of independence between the covariates and λ_i is too strong. To relax the assumption, we model λ_i using a framework called the Mundlak–Chamberlain device or correlated random-effects model, following the works of Mundlak (1978) and Chamberlain (1984). To employ the Mundlak–Chamberlain device in eq. (2), we include a vector of variables containing the means for province i of all time-varying covariates, denoted by $\overline{X_i}$. These variables have the same value for each province in every year but vary across provinces. One benefit of the Mundlak–Chamberlain device estimator is that by including the vector of time-averaged variables, we still control for time-constant unobserved heterogeneity as with fixed-effects while avoiding the problem of incidental parameters in nonlinear

[9] Studies using learning curve models show that the learning rate of wind turbine in the early period (covering 2003 to 2007) ranged around 4.1% to 4.3%, while in the more recent period (2008 to 2013) it could be above 12% (Di et al., 2012).

[10] For a mature technology, the investment cost usually increases with the installed capacity. For renewable energy, such as wind power, technological progress/the economy pushes the cost down. In the early stage, the decreasing trend dominates the increasing trends. When the technology becomes mature, the convex cost may become dominant; then, the mark-up disappears.

[11] The remaining 30% of the observations include Fujian and Yunan (all eight years) and Chongqing (2009).

Table 4
Average partial effect of subsidy on curtailed wind power.

	Likelihood of curtailing any wind power			Rate of curtailed wind power		
	(1)	(2)	(3)	(4)	(5)	(6)
Mark-up	2.484***	2.062*	2.331**	24.555**	30.689*	29.358*
	(0.824)	(1.176)	(1.083)	(12.041)	(17.217)	(17.390)
Ln (GDP)		−0.486	−0.504		−13.437**	−12.871***
		(0.303)	(0.309)		(5.304)	(4.905)
Share of GDP from the secondary sector		−0.043	−0.052*		−0.681	−0.634
		(0.029)	(0.028)		(0.445)	(0.445)
Share of GDP from the tertiary sector		−0.029	−0.037		−0.757*	−0.742*
		(0.038)	(0.033)		(0.404)	(0.408)
Ln (population)		4.448**	1.914**		42.102	25.165
		(2.001)	(0.847)		(28.161)	(16.132)
Ln (thermal power)		0.375**	0.283*		9.160**	8.557**
		(0.173)	(0.153)		(3.738)	(3.519)
Ln (hydro power)		0.097	0.032		1.896	1.031
		(0.114)	(0.096)		(1.639)	(1.372)
Ln (length of transmission)			0.551			1.023
			(0.340)			(4.858)
Year 2010	−0.113***	−0.024	−0.063	−1.058**	0.524	0.460
	(0.034)	(0.051)	(0.051)	(0.490)	(0.915)	(0.915)
Year 2011	−0.043	0.135	0.112	0.572	3.972**	3.994**
	(0.085)	(0.120)	(0.115)	(1.203)	(1.917)	(1.775)
Year 2012	−0.163*	−0.024	−0.091	−1.085	2.322	2.396
	(0.099)	(0.128)	(0.113)	(1.655)	(2.092)	(2.040)
Year 2013	−0.148	0.000	−0.089	−0.652	3.341	3.350
	(0.107)	(0.142)	(0.130)	(1.818)	(2.641)	(2.630)
Year 2014	−0.177*	−0.060	−0.144	−1.345	3.033	3.158
	(0.101)	(0.160)	(0.148)	(2.041)	(2.874)	(2.919)
Year 2015	−0.204**	−0.161	−0.210	−0.292	3.850	4.365
	(0.104)	(0.157)	(0.130)	(2.360)	(3.401)	(3.458)
Year 2016	−0.177*	−0.166	−0.203	0.426	4.659	5.279
	(0.107)	(0.164)	(0.135)	(2.351)	(3.671)	(3.692)
Observations	240	240	240	240	240	240
Pseudo R-squared	0.079	0.293	0.412	0.034	0.135	0.162

Note: Mundlak-Chamberlain approach is applied to regressions to control for province-fixed effects. Robust standard errors reported in parentheses are clustered by province. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

models. As Wooldridge (2010) points out, the identification strategy from a correlated random-effects model is simple and provides the advantages of a fixed-effects model when the regression function is nonlinear and fixed-effects estimation is not appropriate.

Table 4 reports the average partial effects from the probit and tobit models using the Mundlak—Chamberlain device. The coefficients for the price mark-up are significant and stable, regardless of the control for the demand and the supply of electricity. An increase in the mark-up by 0.1 yuan led to a 0.2% (columns 1 to 3) increase in the likelihood of curtailing any wind power and a 2% to 3% (columns 4 to 6) increase in the rate of curtailed wind power. In addition, the signs of the other control variables are consistent with our expectation. The GDP reduced the rate, suggesting that the demand for electricity decreased the rate of curtailed wind power. In line with demand-reduced curtailment, the GDP from the secondary and tertiary sectors, which are more electricity-intensive than the primary sector, significantly reduced the likelihood of curtailing any wind power (columns 1 to 3) and the rate of curtailed wind power (columns 4 to 6), respectively. The competing electricity sources, particularly thermal power, indeed increased curtailed wind power in terms of both the likelihood (columns 1 to 3) and the rate (columns 4 to 6). The coefficient of transmission line is statistically insignificant in both models.

4.3. Counterfactual policy scenario simulation

The previous analysis shows that wind power curtailment issues in China results from (at least partly) the high mark-up due to the slow adjustment of feed-in tariff rates. Until 2015, the feed-in tariff had not changed from when it started in 2009, while during the same period, the LCOE had been substantially driven down by the rapid decline in turbine price. Based on our estimation results, simulations are performed to quantitatively assess to what extent more frequent adjustments of FIT can alleviate the curtailment issue. A dynamic adjustment of FIT to reflect the cost reduction in renewable technology has been adopted by Germany (Grau, 2014; Hitaj and Löschel, 2019). Three counterfactual policy scenarios are considered. Scenarios 1 and 2 assume that the FIT rates are adjusted by the same amount as the existing policy during the study period but more frequently, specifically, every other year for scenario 1 and every year for scenario 2. Scenario 3 assumes that the FIT rates are adjusted according to the decline in the LCOE. During the period from 2009 to 2012, the wind turbine price declined from $900/kw to $600/kw, which translates to a 15% decline in the LCOE. Consequently, we assume that FIT rates are reduced by 15% in total

Table 5
Counterfactual policy scenarios.

	2009	2010	2011	2012	2013	2014	2015	2016
Scenario 1: FIT rates adjusted biennially (RMB/kwh)								
Category I	0.51	0.51	0.49	0.49	0.47	0.47	0.40	0.40
Category II	0.54	0.54	0.52	0.52	0.50	0.50	0.45	0.45
Category III	0.58	0.58	0.56	0.56	0.54	0.54	0.57	0.57
Category IV	0.61	0.61	0.61	0.61	0.60	0.60	0.59	0.59
Scenario 2: FIT rates adjusted annually (RMB/kwh)								
Category I	0.51	0.50	0.49	0.48	0.47	0.43	0.40	0.40
Category II	0.54	0.53	0.52	0.51	0.5	0.47	0.45	0.45
Category III	0.58	0.57	0.56	0.55	0.54	0.51	0.49	0.49
Category IV	0.61	0.61	0.61	0.60	0.60	0.59	0.59	0.59
Scenario 3: FIT rates adjusted according to LCOE (RMB/kwh)								
Category I	0.51	0.49	0.47	0.45	0.43	0.42	0.41	0.40
Category II	0.54	0.52	0.50	0.48	0.47	0.46	0.45	0.45
Category III	0.58	0.56	0.54	0.52	0.51	0.49	0.48	0.47
Category IV	0.61	0.59	0.57	0.55	0.54	0.53	0.52	0.51

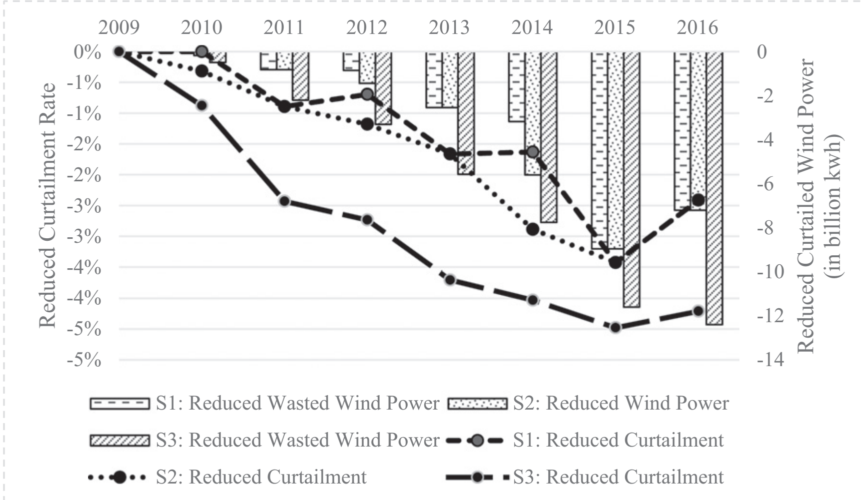

Fig. 6. Simulated reduction curtailment rates and wasted wind power.

during the said period and are evenly allocated every year (e.g. 0.02 RMB/year). These FIT rates for each scenario are summarized in Table 5 and used in the tobit model to obtain the predicted curtailment rates of each province in each year. The difference between the actual curtailment rates and the predicted rates indicate the simulated policy effects.

Fig. 6 shows the simulated reductions in the curtailed wind power in the three scenarios. In scenario 1 where FIT is adjusted every other year, the curtailed wind power is reduced by 23,584 million kwh between 2009 and 2016. In scenario 2, by simply increasing the adjustment frequency of FIT rates every year, the wasted wind power is reduced by 26,781 million kwh. If the policy were designed better to reflect more accurately the declining trend of wind power costs as shown in scenario 3, the curtailed wind power could have been reduced by 43,363 million kwh. The actual total output of wind power from 2009 to 2016 was 978.7 billion kwh while the curtailed wind power during this period was 154 billion kwh. The simulated reduced curtailment in scenarios 1, 2, and 3 accounts for 15%, 17%, and 28% of actual curtailed wind power, respectively; or 2.4%, 2.7%, and 4.4% of the total wind power output.

The reduction in FIT rates may reduce curtailment through reductions in installed capacity, as the investors may receive lower investment incentives Clearly, higher levels of FIT can lead to rapid deployment of renewable energy. The government may be motivated by their ambitious renewable energy development target to set a high level of FIT. Thus, curtailment may be considered an efficiency loss that the society has to bear for the government to achieve its target.[12] Theoretically, there is an optimal level of subsidy that maximizes social welfare. However, in reality, it is difficult for the government to ascertain this optimal level of subsidy. Determining to what extent the curtailment can be tolerated needs further exploration.

5. Discussion and conclusion

Our study provides a novel explanation for China's persistent and serious wind power curtailment from the perspective of excess capacity. A theoretical model is first set up to depict the investment decision of wind farm investors. This model illustrates that when the number of investors is uncertain, a higher mark-up results in a lower boundary value of the number of investors at which point the capacity is fully utilized and thus, leads to a higher extent of excess investment. The theoretical prediction is consistent with the observation that since the introduction of FIT, the mark-up of wind power investment did show an upward trend, as the FIT rates were adjusted slowly while the investment costs declined quickly. A more rigorous analysis is conducted by estimating a probit and tobit model using a panel of provincial-level data between 2009 and 2016. The model results show that a 0.1 yuan increase in the mark-up leads to a 2% to 3% increase in the rate of curtailed wind power.

Based on the estimation results, several scenarios are simulated to assess quantitatively how a better policy design could have alleviated the curtailment problem. Simply increasing the FIT rate adjustment frequency, while maintaining the same reduction level of subsidy between 2009 and 2016, could have reduced the curtailed wind power by 23 to 27 billion kwh. If the policy were better designed to reflect the declining trend of wind power costs more accurately, the curtailment could have been further reduced by >43 billion kwh.

Our findings have several important policy implications. First, one directly relevant policy implication has to do with solving China's wind power curtailment issue. To avoid further excessive investment, the subsidy scheme should be adjusted in a more timely manner to reflect the decline in investment costs as well as more regularly to stabilize expectations of investors. Second, the findings shed light on how to design policies that support renewable energy more effectively. Renewable energy has received substantial amounts of governmental support worldwide. FITs represent the most widespread support scheme in 2015, implemented in 110 countries (REN21, 2016). Our analysis shows that the economic efficiency of FIT could be improved with a design that better reflects the temporal and geographical variations of the generation costs. The subsidy level should be capable of timely responding to the changes in market conditions, such as declines in investment costs or improvements in utilization efficiency. Third, the findings may be applied to other emerging technologies or industries that require subsidy support and in which the costs are expected to decline over time.

As discussed, the wind power curtailment issue in China is caused by several factors, including lack of transmission lines and system flexibility as well as flaws in policy design. The Chinese government aims to reduce the curtailment rate to a reasonable level. The 'Clean Energy Consumption Action Plan 2018-2020' was released in 2018. Reducing the curtailment rate below 5% has become a political mandate. Some mitigating methods have been adopted, such as constructing grid lines to transport renewable energy from the west to the east and retrofitting for flexible thermal power generation, thereby alleviating the problem, with the curtailment rate declining to 8% in 2018.

However, completely solving the curtailment issue presents tremendous challenges. Due to China's vast geography, constructing transmission lines between the eastern and western regions could be very costly.

[12] We appreciate one anonymous reviewer for this point.

There is a trade-off between transporting wind power from a distance and building wind farms locally. In addition, if the policy and institutional barriers remain unchanged, the results may be temporary, as what happened in 2013 to 2014. As the penetration of renewable energy continues to intensify, solutions may become costlier. Solving this complicated problem requires both technological efforts, such as adding new transmission lines or increasing system flexibility, and institutional changes.

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Appendix A. Supplementary data

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