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Epidemic, rank, stock and order effects in renewable energy diffusion: a model and empirical evidence from the China's wind power sector

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Abstract

In this article we construct a theoretical model that disentangles the epidemic effect and profitability effect in the renewable energy diffusion. A reduced form of this model, that incorporates the main factors discussed in different theories of technology diffusion, is applied to data on wind energy diffusion in China. We find strong evidence in support of the dominant role of the epidemic effect. We also provide new evidence on stock and order effects that generate a reducing marginal effect of profitability in inducing technology adoption. Our numerical simulation demonstrates that such epidemic effect can play a quantitatively important role in the spread of renewable energy technology and markedly enhance the optimal social welfare. Our findings convey important policy implications for regulators when choosing two most commonly used instruments to induce technology diffusion - information provision and subsidies.

Key words: Technology diffusion, Incentive policies, Renewable energy, Technological change

1. Introduction

Addressing increasing environmental and energy concerns needs to accelerate technological change around the world. A technology can have a significant impact on the economy only if it is widely adopted by producers and accepted by consumers. The question remains open – How will a renewable energy technology, once introduced, diffuse at a reasonably rapid pace?

The wind power sector in China provides a stylized fact. Even though China had virtually no wind power capacity in 2001, the country has led the global wind market with the highest installed capacity since 2010. As one of relatively mature renewable technologies, wind energy technology showed two deployment paths in the past decade. While most countries have failed to accelerate wind technology diffusion, China's wind energy has been surging. Some questions arise. How could an economy catch up a technology so rapidly? Are there any specifics on the pattern of technological change? What are the quantitative effects of various factors?

To answer these questions, a vast literature provides two key concepts. One is based on the economic rationale. By correcting market failure, policy intervention brings the system to its optimal state, where social costs equal social benefits. The other is derived from the spread of information. The technological change is a result of an interactive process that involves many actors at the micro level. With a more systemic approach, this literature highlights the role of the national innovation system that governs in fact these interactions. It still lacks a concrete theory and empirical framework of investigating these market and nonmarket-based forces in a comprehensive manner. This article aims to fill in this gap and support improved policy decision making in the choice of policy instruments.

In this article, we develop a model that incorporates the main theoretical streams in the technology diffusion literature – epidemic, rank, stock and order effects. Then, we validate the model with the historical data of the China's wind energy sector. Finally, depending on these market and nonmarket factors, we numerically simulate the pathways of optimal subsidy in the form of electricity production subsidy for maximizing the social welfare in the china's context.

2. Epidemic, rank, stock and order effects in the literature of technology diffusion

As defined by the well-known Schumpeterian trilogy of technological change, technology diffusion is the process of gradual adoption of a new technology by an economy (Schumpeter, 1934). This process is generally analyzed within two theoretical frameworks: nonmarket intermediated (or information based) and market intermediated (or pecuniary) approaches.

Nonmarket approach relies on an analog to the spread of an *epidemic*. The more firms/people are "infected" (those that have adopted the technology), the more likely the others will also be "infected". Adoption occurs once potential adopters become aware of the new technology. Increasing spread of information between previous and potential adopters reduces the uncertainty surrounding the technology and leads further rapid adoption. Earlier works used probability density functions and Bass models to develop the concept of information acquisition (Mansfield 1963; Bass 1969, 2004). All these epidemic-type models specify an S-shaped curve of technology diffusion: the number of adopters will increase over time while the adoption process is accelerated initially and then decelerated until the satiation point is reached.

This epidemic effect is likely to be systemic and related to the national systems of innovation (NSI). The concept of the NSI was developed successively by Freeman (1987), Lundvall (1992), Nelson (1993), and Metcalfe (1995). Their definitions of the NSI share some common points.

They all emphasize on the network of institutions whose interactions determine the performance of technology development and diffusion, and the coordinating role of the government in influencing these interactions.

Unlike the epidemic models assuming that potential adopters will use the technology once they learn about it, a few models focus on the market-intermediated effects. The technology adoption is modeled as an individual choice based on profitability consideration. Therefore, it is the expected net gain rather than information acquisition that determines the adoption decision. Three effects are identified in the literature: rank effect, stock effect and order effect (Karshenas and Stoneman 1993).

The *rank effect* models, also known as Probit models, rank firms in terms of the benefit from technology adoption, mostly determined by a firm's characteristics such as firm size, age, capital structure, learning and search costs, switching costs and opportunities costs. Those firms with the highest ranks adopt the technology earlier than others.

The game-theoritical models suggest that the stock effect and order effect may negatively affect technology diffusion. The *stock effect* assumes that the benefit to the marginal adopter of a new technology decreases as the number of previous adopters increases. Adoption of a cost-reducing process technology could lead to more production by all firms in the industry, thereby lowering prices in the output market and stimulating demand for the products. Consequently, for any given cost of technology acquisition, a number of adopters may suffer losses if adoption is too wide to keep a reasonable supply of their products (Reinganum 1981). The *order effect* results from the assumption that the return to a firm from adopting new technology depends upon its position in the order of adoption, with high-order adopters achieving a greater return than low-order adopters. The order effect is usually related to first-mover advantage which can obtain prime geographic sites or preempt the pool of skilled labor. Thus, decisions of high-order adopters can affect the adoption dates of low-order adopters (Fudenberg and Tirole 1985).

This article contributes to the literature from the perspective of analysis method and scope. There is a limited body of literature focused on renewable energy diffusion. The majority of literature on technology diffusion mostly involves new process technologies and durable goods. Explict modelling renewable energy diffusion is less common. Karshenas and Stoneman (1993) and Stoneman and Kwon (1996) have used a hazard function to study these effects in the diffusion of new process technologies. In the real-world market, a utility-scale renewable energy project involves new investment opportunity, mostly decided by a parent company (e.g. utility group). Additionally, given fairly homogeneous renewable technology (e.g. wind turbine and PV panel), the project company's characteristics may have little impact on the project-specific scale. Therefore, the hazard function may fail to distinguish possible differences in the hazard rates between the independent establishments and those with corporate affiliation (Karshenas and Stoneman 1993). In this study, we specify a logistic demand function on newly installed capacity of renewable energy at continuous time, which explicitly captures two components. One component represents the profitability effect and the other the epidemic effect. Furthermore, we generate a reduced form equation, relating the technology adoption level to time dependence (epidemic effect), Net Present Value (NPV) and quadratic form of NPV of renewable energy investments (aggregating rank and order effects) and the level of previous adoption (stock effect). Our model fits well to the historical data of wind power diffusion in China. While the empirical literature in technology diffusion found little support for the stock and order effects, this study may provide an empirical support of epidemic, rank, stock and order effects in a real-world renewable energy diffusion process. We find that China's wind energy diffusion shows a fairly stronger epidemic effect and also the stock and order effects have different implications on the profitability of investments. We also numerically demonstrate that to which extent an optimal renewable subsidy will be affected by these market and nonmarket effects.

3. Theoretical model

Following Benthem, Gillingham et al.(2008), we first specify a logistic demand function with two components. One component captures the profitability effect and the other captures the epidemic effect. Our theoretical underpinnings rely on disentangling non-market and market intermediated factors, discussed above in the technology diffusion literature.

$$\mathrm{Q_t} = \frac{a_t \cdot Q^{max}}{a_t + (Q^{max} - a_t) \cdot e^{-b \cdot NPV_t}} + Dif_t \qquad (1)$$

Where $\mathrm{Q_t}$ is new adoption of a renewable energy technology at any time $t \geq 0$ in the form of newly installed capacity at time t; NPV_t is the net present value of the renewables investment at time t to capture the profitability effect; Dif_t is technology diffusion level attributed to the epidemic effect at time t; Q^{max} is the maximal market potential for energy installation; a_t is a parameter determined by cumulative installed capacity at time t; and b is a fixed parameter.

The parameter a_t is adjusted over time. Based on the epidemic theory, it serves to incorporate the previous time's diffusion Dif_t into the current time's base demand, accounting for higher information penetration and decreasing technology uncertainty when adoption is accumulated. The parameter a_t can be expressed by

$$a_t = a_{t-\mathrm{h}} \cdot \left(\frac{Q_{t-\mathrm{h}} + Dif_{t-\mathrm{h}}}{Q_{t-\mathrm{h}}} \right) \qquad (2)$$

Where h is a small time interval.

The second term Dif_t on the right hand side of Eq. (1) represents the technology deployment attributed to the epidemic effect. It is also modeled as a logistic growth function of previous time's demand level.

$$\mathrm{Dif_t} = \gamma \cdot \mathrm{Q_{t-h}} \cdot \left(1 - \frac{\mathrm{Q_{t-h}}}{\mathrm{Q^{max}}}\right) \qquad (3)$$

Where γ is a fixed parameter indicating the magnitude of the epidemic effect. The epidemic effect will asymptotically converge to zero as the new installed capacity in previous time approaches its maximal capacity. Since $\lim_{h \to 0} \mathrm{Q_{t-h}} \to \mathrm{Q_t}$, Eq. (3) can be expressed by

$$Dif_t = \gamma \cdot Q_t \left(1 - \frac{Q_t}{\mathrm{Q^{max}}}\right) \qquad (4)$$

as $h \to 0$.

Furthermore, we will decompose the profitability effect into rank, stock and order effects and derive an empirical model to test the magnitude of these effects.

Notice that Eq. (2) can be rewritten as

$$a_t - a_{t-\mathrm{h}} = a_{t-\mathrm{h}} \frac{Dif_{t-\mathrm{h}}}{Q_{t-\mathrm{h}}}$$

Which is equivalent to

$$\frac{da_t}{dt}\frac{1}{a_t} = \frac{dlna_t}{dt} = \frac{Dif_t}{Q_t}$$

When $h \to 0$. By inserting Eq. (4), the above equation becomes

$\frac{d\ln a_t}{dt} = \frac{Dif_t}{Q_t} = \gamma \cdot \left(1 - \frac{Q_t}{\mathrm{Q^{max}}}\right) = \frac{d[\gamma \cdot t]}{dt} - \frac{\gamma}{\mathrm{Q^{max}}} \frac{d\left(\int_0^t Q_v dv\right)}{dt} = \frac{d[\gamma \cdot t]}{dt} - \frac{\gamma}{\mathrm{Q^{max}}} \frac{d(QS_t)}{dt}$, where $QS_t = \int_0^t Q_v dv$ is the cumulative capacity at time t. Hence,

$$a_t = e^{\gamma \cdot \left(t - \frac{QS_t}{\mathrm{Q^{max}}}\right)} \; by\ assuming\ a_0 = 1 \text{ and } t \geq 0. \qquad (5)$$

By inserting Eq. (4) into Eq. (1) and rearranging terms, we have

$$\frac{\gamma}{\mathrm{Q^{max}}} {Q_t}^2 + (1-\gamma) Q_t - \frac{1}{\frac{1}{Q^{max}} + \left(\frac{1}{a_t} - \frac{1}{Q^{max}}\right) \cdot e^{-b \cdot NPV_t}} = 0$$

Hence, we obtain the only reasonable solution for $\mathrm{Q_t}$,

$$\mathrm{Q_t} = \sqrt{\frac{1}{4}\left(\frac{1-\gamma}{\gamma}\mathrm{Q^{max}}\right)^2 + \frac{1}{\frac{1}{Q^{max}} + \left(1/a_t - \frac{1}{Q^{max}}\right) \cdot e^{-b \cdot NPV_t}}} - \frac{1-\gamma}{2\gamma}\mathrm{Q^{max}} \qquad (6)$$

If Q^{max} is large, then $\frac{1}{Q^{max}} \cong 0$. It is noted that with the regression results below, we can test the validity of this assumption.

By inserting Eq. (5) to Eq. (6), we have

$$\mathrm{Q_t} = \left(\sqrt{1 + \frac{e^{\gamma \cdot \left(t - \frac{QS_t}{\mathrm{Q^{max}}}\right) + b \cdot NPV_t}}{\left(\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}\right)^2}} - 1\right) \cdot \frac{1-\gamma}{2\gamma}\mathrm{Q^{max}} \qquad (7)$$

In case that the ultimate market potential is large compared to the technology adoption level at the early stage, $\frac{e^{\frac{1}{2}\left[\gamma \cdot \left(t - \frac{QS_t}{\mathrm{Q^{max}}}\right) + b \cdot NPV_t\right]}}{\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}}$ is very close to zero, then

$$1+\frac{e^{\gamma\cdot\left(t-\frac{QS_t}{\mathrm{Q^{max}}}\right)+b\cdot NPV_t}}{\left(\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}\right)^2}\cong\left(1+\frac{e^{\frac{1}{2}\left[\gamma\cdot\left(t-\frac{QS_t}{\mathrm{Q^{max}}}\right)+b\cdot NPV_t\right]}}{\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}}\right)^2$$

Which results Eq. (7) to

$$\mathrm{Q_t}\cong\frac{e^{\frac{1}{2}\left[\gamma\cdot\left(t-\frac{QS_t}{\mathrm{Q^{max}}}\right)+b\cdot NPV_t\right]}}{\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}}\cdot\frac{1-\gamma}{2\gamma}\mathrm{Q^{max}}=e^{\frac{1}{2}\left[\gamma\cdot\left(t-\frac{QS_t}{\mathrm{Q^{max}}}\right)+b\cdot NPV_t\right]} \tag{8}$$

The double log form of Eq. (6) is

Model A: $\ln(\mathrm{Q_t})\cong\frac{1}{2}\gamma\cdot\mathrm{t}-\frac{\gamma}{2\mathrm{Q^{max}}}QS_t+\frac{1}{2}b\cdot NPV_t$, where$t\geq 0$. (9)

Eq. (9) is the basic model that we will estimate for testing the epidemic, rank, stock and order effects. In the presence of the epidemic effect, the newly installed capacity should show positive time dependence. The estimated coefficient of t should be around $\frac{1}{2}\gamma$. The coefficient of QS_t captures the stock effect. According to the literature, the profit gain to an adopter will fall as the number of users increases and also that later adopters will make lesser gains than earlier adopters. Therefore, we expect this coefficient to be negative. The coefficient of NPV_t captures the aggregate impact of rank and order effects on the expected profitability of technology adoption.

To clarify, the expected profitability of a renewable project is measured with the net present value ($\mathrm{NPV_t}$) by discounting future cash flows in comparison to an alternative investment with equivalent risk-return conditions, assuming full information and rational behavior among investors. Consequently, $\mathrm{NPV_t}$ needs to be non-negative to incentivize renewable installations. Policy makers can alter the speed or total level of diffusion of a new technology by internalizing positive or negative externalities associated with the technology adoption. With reference to the China's context, we assume that policy makers can implement feed-in-tariff and carbon pricing policies in order to create favorable conditions for investors in renewable energy technology. $\mathrm{NPV_t}$ can be calculated by

$$NPV_t = -C_t^{Invest} + \sum_{n=1}^{T} \frac{(FIT_t + P_t^{CO2} \cdot \pi^{emission}) \cdot yield - C_t^{Operation}}{(1+i)^n} \quad (10)$$

Where C_t^{Invest} and $C_t^{Operation}$ are, respectively, capital costs and operation & management (O&M) costs of renewable project at time t; FIT_t and P_t^{CO2} denotes, respectively, the feed-in-tariff for renewable electricity and CO2 price; $\pi^{emission}$ is the emission factor of the conventional electricity output replaced by renewable electricity; $yield$ represents the full load operating hours corresponding to theoretical output efficiency by considering wind quality and technology performance; i denotes the investor's discount rate and t is life time of a renewable project.

$\mathrm{NPV_t}$ is a proxy that captures the rank and order effects on the expected profitability of renewable investments. In the case of renewable energy projects, the order effect, relative to the first-mover advantage, mainly comes from the site-specific characteristics and electricity purchase price, because the earlier adopters may benefit from the most favorable sites with higher emission intensity of the local electricity system ($\pi^{emission}$), and higher renewable resources endowment ($yield$). Also, the earlier adopters may receive a higher electricity production subsidy (FIT_t), because a periodic tariff degresssion can be implemented by the regulator. The rank effect, associated with firms' specific characteristics such as size, age, and capital structure, is mostly represented by the capital costs of a renewable project (C_t^{Invest}). The data of capital costs in our empirical part includes wind turbine cost and also expenses related to grid connection, civil works and other miscellaneous items. The difference in the capital costs for a given time may be determined by firms' characteristics.

Additional to Model A expressed by Eq. (9), we will estimate two other regression models:

Model B: $\ln(\mathrm{Q_t}) \cong \frac{1}{2}\gamma \cdot \mathrm{t} - \frac{\gamma}{2\mathrm{Q^{max}}} QS_t + \frac{1}{2} b \cdot NPV_t + \mathrm{c} \cdot NPV_t^2$ (11)

Model C: $\ln(\mathrm{Q_t}) \cong \frac{1}{2}\gamma \cdot \mathrm{t} + \frac{1}{2} b \cdot NPV_t + \mathrm{c} \cdot NPV_t^2$ (12)

In both alternative models, we introduce a quadratic term of NPV_t, which can capture the diminishing marginal effect of NPV_t on the technology adoption level. Hence, we expect the coefficients of the quadratic term of NPV_t to be negative. In fact, the stock effect may affect the technology adoption through the investment profitability. Therefore, we remove QS_t in Model C to better understand to which extent the impact of QS_t on $\mathrm{Q_t}$ is partially captured by NPV_t. We check the robustness of the empirical results derived from models A, B and C.

4. Data

Models A, B and C are estimated using a panel of province-wide data over the period of 2004-2011. The dataset is constructed by surveying the primary data relative to all 1207 Chinese wind projects, either registered or undergoing validation in the Clean Development Mechanism (CDM), as of the end of 2011. The CDM is the biggest global carbon offset mechanism to date, which allows industrialized countries to partly meet their binding commitments by earning Certified Emission Reduction (CER) credits derived from the mitigation projects carried out at lower costs in developing countries. In fact, the CDM project participants are required to submit a Project Design Document (PDD) that aims to demonstrate the project additionality[1] and emission reductions. Since nearly all the wind projects in China have participated into the CDM, the sampling bias, resulted from the dataset constructed via the CDM, does not raise a concern for representing the whole wind energy market. For a minor of wind projects that are

[1] The CDM rests fundamentally on the concept of additionality - the proposed project would not have occurred in the absence of CDM support.

implemented without the CDM support, the projects are mostly identified as recipient of special government funding or foreign aid.[2]

The detailed project-specific data derived directly from the PDD includes installed capacity, FIT price, capital cost, the plant load factor and emission factor of the connected electricity grid. The dataset of the CDM projects is classified in terms of the project starting date and located province as stated in the PDD. This study takes into account the sum of CDM-supported wind capacity in each province for a given year. Accordingly, capital cost, the plant load factor, FIT price and emission factor used here represent the average of all CDM projects within the same province for a given year. All prices and costs have been deflated to 2010 prices using the China-specific GDP deflator published by the IMF.

The capital costs include all items of the project's initial investment. Apart from turbine cost, the expenses related to grid connection, civil works and other miscellaneous items are also included. This provides a comprehensive estimate of investment costs because this aspect of expenses may represent about 24%-29% of onshore wind capital costs (Wiser et al. 2011). The operational and maintenance costs are assumed to represent 2% of the initial investment.

The lifetime of wind projects is considered to be 20 years. The discount rate for calculating the NPV of wind investment is assumed to be 8% according to the common practice in the Chinese market.

As stated in a vast majority of PDDs, the expected CER price is assumed to be 100 Yuan RMB/ton CO2, because the Chinese government has been implementing a CER price floor policy in the wind projects. Even though this price signal may not fully reflect 'over-the-counter'

[2] According to the CDM rules, each CDM project needs to compare its proposed project activity to the common practice in the applicable geographical area.

trading of the CDM activities, the financial feasibility study of China's CDM wind projects has largely adopted this price floor to make final investment decision.

The starting date of a CDM project activity is the earliest date at which either the implementation or construction or real action of a project activity begins. A vast majority of the CDM wind projects in China have chosen the starting date as the date on which contracts have been signed for the ordering of wind turbines or committing to civil works. This is quite consistent with the technology adoption concept – the decision concerning when and whether to adopt certain technology that the firm knows to be available. The CDM activities are determined well in advance of real wind farm installations.[3] The CDM approval is a lengthy process - project developers had to wait at least one year before final approval by the CDM Executive Board over our study period. Consequently, it is appropriate to consider contemporaneous price signals in the regression models.

Table 1. Summary statistics

Variable	Unit	Mean	Std. Dev.
NPV	Yuan /KW	0.696	1.203
Cumulative capacity	MW	1113.699	2287.368
Time duration	Year	3.5	2.296
Capital costs of wind projects (2010 Yuan RMB)	1000 Yuan/kW	8.13	1.04
FIT price (2010 Yuan RMB)	Yuan/Kwh	0.49	0.08
Plant load factor	%	0.2372	0.2589
Emission factor of the electricity system	Ton CO2/Kwh	0.9492	0.092

5. Empirical analysis and discussion

We use the fixed effect models to estimate Models A, B and C. Each province has its own unobserved characteristics, notably associated with wind resource endowment, energy

[3] A clear determination of the project start date is vital for the additionality test, because the consideration of the benefits of the CDM prior to this date should be demonstrated by means of credible evidence.

production and consumption patterns, infrastructure conditions and institutional arrangements, which may be constant over time and correlated with the regressors. The fixed-effect model enables the removal of these time-invariant and site specific characteristics and the avoidance of the estimation bias. The estimate results are showed in Table 1.

Table 2. Estimation results: newly installed capacity ($\ln(Q_t)$)

Variables	Model A	Model B	Model C
Time duration (t)	0.45 (0.05) ***	0.42 (0.05) ***	0.38 (0.03) ***
Net present value (NPV_t)	0.02 (0.02)	0.16 (0.10) *	0.18 (0.07) **
Cumulative capacity (QS_t)	-0.00009* (0.00005)	-0.00008 (0.53)	
NPV_t^2		-0.04 (0.02) **	-0.05 (0.02) ***
Constant	6.15 (0.36) ***	6.07 (0.35) ***	5.51 (0.28) ***
Provincial fixed effects	Yes	Yes	Yes
Adj. R-Squared	0.733	0.744	0.745
Number of observations	117	117	144
F-test value (Model)	11.61***	11.86***	14.04***
F-test value (provincial effects)	7.05***	6.02***	10.03***

Note: Standard errors in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

These results across models are complementary. In all the models, the adjusted R-squared is acceptable at a level of around 0.74.

The estimated coefficients for time duration are statistically significant, indicating that one additional year may lead to an increase of newly installed capacity by around 40%. In the presence of epidemic effect, the annually installed capacity of renewable energy shows positive time duration dependence, as the estimates of time duration are statistically significant in all three models. In the case of china’s wind energy diffusion, the epidemic effect is found to be quite strong compared to the profitability effect. Based on the regression results, the coefficient of the epidemic effect (γ) in Eq. (3) is estimated to be in the range of 0.76-0.9. This finding is consistent with our intuition. Because China's leapfrog in wind energy occurred when relatively mature wind technology had already been widely used in developed countries, the marginal cost reduction of technology deployment is significantly decreasing, leading to a reducing profitability effect. Our finding supports the dominant role of the epidemic effect in inducing wind energy diffusion in such a context.

The estimated coefficient for $\mathrm{NPV_t}$ is insignificant in Model A, but becomes significant and relatively stable in the other two models, where the quadratic term of $\mathrm{NPV_t}$ is added as one of the independent variables. This shows that in order to better represent newly installed capacity of China's wind energy, a quadratic term of $\mathrm{NPV_t}$ needs to be included in Eq. (1). With the order effect, the most wind favorable sites will be first used. The emissions intensive regions will also be better incentivized to install wind projects via a carbon pricing policy. This first-mover advantage may exercise a negative impact on the profitability of future adoption, which is embedded in NPV through output efficiency ($yield$) and the emission factor of the electricity grid ($\pi^{emission}$). According to Fudenberg and Tirole (1985), for a given acquisition cost, adoption is only profitable to some point in the order after which diffusion will only extend as the acquisition cost falls. In the China's wind energy sector, a FIT policy is put in place to guarantee a stable profitability of wind investment over the project lifetime. The FIT prices for new wind projects are gradually degressed given the technology penetration level[4]. Meanwhile the acquisition cost of wind technology falls as well. Under these combined effects, the expected profitability of wind investment (NPV) shows an upward trend. Hence, we do not find that the expected benefit to the marginal adopter of wind technology decreases as the number of previous

[4] Over our study period, the Chinese wind power sector experienced different stages of development, from initial demonstration to accelerated diffusion. At the early stage, the Chinese government granted higher price signals, notably through five rounds of country-wide concession-bidding programs before applying four levels of tariff differentiated with geographical wind resources quality.

adopters increases[5]. However, the NPV has a decreasing marginal effect on wind technology diffusion. This turning point is estimated to be NPV= 0.18/ (2*0.05) =1.8 in Model C.

As expected, the negative sign of cumulative capacity ($\mathrm{QS_t}$) confirms the impact of stock effect on technology diffusion as discussed in the theoretical literature. Most of epidemic models use existing stock of adopters to represent the endogenous information effects on technology diffusion. However, our model explicitly specifies a time-varying baseline demand of technology adoption to capture the epidemic effect. This makes the negative stock effect more visible. Thus, we can empirically test the negative stock effect and the positive epidemic effect in a coherent framework. Our evidence suggests that the negative stock effect is largely outweighed by the positive epidemic effect in the case of China's wind power deployment. It is worth noting that this quite small magnitude of the coefficient of $\mathrm{QS_t}$ confirms the validity of our assumption on Q^{max} (If Q^{max} is large, then $\frac{1}{Q^{max}} \cong 0$) in Eq. (6). This also suggests that due to a large potential of renewable energy resources, the stock effect resulted from early-stage technology adoption may not be very important.

Furthermore, we notice that the estimated coefficient of cumulative capacity $\mathrm{QS_t}$ is significant in Model A, where the quadratic term of $\mathrm{NPV_t}$ is absent, but becomes insignificant in Model B, where the quadratic term is present. This indicates that a large part of the effect of $\mathrm{QS_t}$ has been captured by the quadratic term of $\mathrm{NPV_t}$. As stated in Reinganum (1981), prices of output product and market demand might change along with technology diffusion, leading to a negative impact on profitability of marginal adoption. Our empirical results show that the stock

[5] Due to the intermittency and non-dispatchable nature of wind energy, grid integration may raise a serious technical problem. In fact, the Chinese grid operators had to abandon a significant part of wind electricity. It is noted that the output efficiency (yield) in NPV is the theoretical best-guess of wind power output considering wind resources quality and technology performance at the stage of investment decision. This expected profitability may be reduced if a significant loss of revenue occurs due to the grid constraints.

effect of QS_t on newly installed capacity is actually channeled through the project profitability. This is further confirmed by the results in Model C, because the coefficient of NPV_t^2 proves economically more important and statistically more significant compared to Model B.

6. Numerical simulation of optimal social welfare

To further put our empirical results in the perspective of policy implications, we numerically simulate the optimal social welfare, depending on the market and nonmarket factors.

The goal of the policy maker is to set up a time path of subsidies which maximizes the discounted present value of net social benefits. In this analysis, we assume that there are two streams of the benefits from wind technology adoption. The first involves the avoided external environmental costs from fossil-fuel electricity replaced by wind electricity. The second takes the form of customer benefits from policy-induced learning effects.

This dynamic optimization problem is summarized as:

$$\max_{S_t} W\,(S_t) = \sum_{t=1}^{T} \frac{Q_t\,(S_t)\cdot\{C^{ext}\cdot yield + CB_t(S_t, QS_t) - S_t\cdot yield\}}{(1+r)^t} \qquad (13)$$

Where

- Q_t is the new installed capacity in year t (MW);
- QS_t is the cumulative installed capacity at the beginning of year t (MW)
- C^{ext} is fixed environmental benefit (RMB Yuan/kWh);
- CB_t is customer benefit per kWh;
- yield is the average operational hours at the full load for the wind power sector;
- S_t is the level of subsidy
- $\pi^{emission}$ is the emission factor of the fossil fuel electricity (ton $CO2/MWh$);
- r is the social discount rate;

The net level of subsidy represents the difference between the FIT price and the electricity price from a benchmark fossil fuel source.

$S_t = FIT_t - P_t^{elec}$ (14)

Where

- FIT_t is the average feed-in tariff in the wind power sector for the year t (RMB/kWh);
- P_t^{elec} is the average electricity price generated from fossil sources for the year t(RMB/kWh).

The customer benefits are calculated from actual costs for investment and operations and maintenance (O&M) for a wind farm under the optimal FIT policy in comparison to a no-policy case. O&M costs accrue over the project lifetime and need to be discounted.

$$CB_t = \left[C_t^{Invest\ (no\ policy)} - C_t^{Invest}\right] + \sum_{n=1}^{20} \frac{C_t^{Operation\ (no\ policy)} - C_t^{Operation}}{(1+r)^l} \quad (15)$$

Where

- l is the average lifetime period of the wind farm;

With the common learning curve, we specify the investment and O&M costs as following:

$$C_t^{Invest} = C_0^{Invest} \cdot \left(\frac{QS_t}{QS_0}\right)^{-\beta} \quad (16)$$

$$C_t^{Operation} = C_t^{Invest} \cdot \alpha \quad (17)$$

Where

- C_0^{Invest} and QS_0 are, respectively, capital costs and cumulated installed capacity at the starting point;
- C_t^{Invest} and $C_t^{Operation}$ are, respectively, capital costs and O&M costs of wind technology at year t;
- β is the learning-by-doing coefficient;
- α is a parameter determining average annual O&M costs as a percentage of capital costs of a wind farm.

We first calibrate the models with the base year data in 2010. Then, we simulate two policy scenarios from 2011 through 2030 by setting up the epidemic effect coefficient as $\gamma = 0.75$ and $\gamma = 0.05$, respectively. The FIT subsidy and lifetime of the wind projects are assumed to be 20 years in China's context.

It is worth noting that based on our empirical results, we add the quadratic term of NPV in Eq. (1) to better simulate stock and order effects in the demand function. Thus, $Q_t = \frac{a_t \cdot Q^{max}}{a_t + (Q^{max} - a_t) \cdot e^{-b \cdot NPV_t + c \cdot NPV_t^2}} + Dif_t$.

The wind project yields environmental benefits over its lifetime. Since electricity generation heavily depends on coal, we assume that the environmental benefits of wind-generated electricity come from the replacement of coal-generated electricity. This externality involves the total costs occurred in the life cycle of the coal power plant, from coal mining, washing, transport, to air pollution gases like SO2, NOx, Particulates, and also includes the climate damage caused by CO2 emissions. The environment benefits associated with CO2 emissions are estimated based on Euros 20/ton CO2e. The costs of other pollutants are based on the specific Chinese values. According to Zhu et al. (2008), the total environmental benefits are estimated to be Euro 0.0254 /kWh (RMB Yuan 0.27/kWh with an exchange rate of 10.75 Yuan/Euro in 2010).

The EU Directive in 2009 stipulated that the credits from the CDM projects registered from 1 January 2013 onward would be prohibited in the third phase of the EU Emissions Trading Scheme (ETS), with the exception of those from the least developed countries. Therefore, we assume that the CO2 price for the wind projects installed after 2013 will become null. This supposes that the feed-in-tariff will be the sole subsidy to support the wind power investments in China.

Relying on the same panel dataset, we empirically estimate the learning rate of wind energy in China. The learning coefficient (α) is estimated to be 0.066, which leads to a learning rate of 4.4%. Our estimate is in the low range of “rule-of-thumb” learning estimates for renewable energy technologies. This may reflect the fact that due to the maturity of onshore wind technology, the marginal cost reduction effect from the technology deployment is decreasing.

The key parameters used in our simulation are displayed below in Tab. 3.

Table 3. Parameter values in the simulation

Parameter	Value	Unit
Cumulated installed capacity by the end of 2010	44,733	MW
Installed capacity in 2010	18,928	MW
Capital cost in 2010	9,500	RMB/kW
Lifetime of the wind farm	20	Year
Average Feed-in tariff (net VAT)	0.537	RMB/kWh
Fossil fuel electricity price in 2010	0.40	RMB/kWh
Annual growth rate of fossil fuel electricity price	2%	
Carbon price	100 (=0 after 2013)	RMB/ton CO2
Emission factor of the coal power plants	0.82	ton CO2/MWh
Yield (full load operating hours)	2,015	Hours/year
Environmental externality cost	0.27	Yuan/kWh
Maximum annual installed capacity	50,000	MW
Learning coefficient	0.066	
Ratio O&M costs/capital costs	2%	
Social discount rate	3%	
Investment discount rate	8%	
Demand function parameter a_0	7840	
Coefficient of NPV (b)	0.35	
Coefficient of NPV^2 (b)	-0.05	
Parameter of the epidemic effect γ	0.75 or 0.05	

Depending on the different values of the epidemic effect, we simulate the optimal social welfare, annually installed wind capacity, environmental benefits, customer benefits and subsidy cost, respectively. The results are detailed below.

Table 4. Optimal social welfare (Unit= billion RMB)

γ =0.75	γ =0.05
8642	3487

Figure 1. Annually installed wind capacity (Unit=MW)

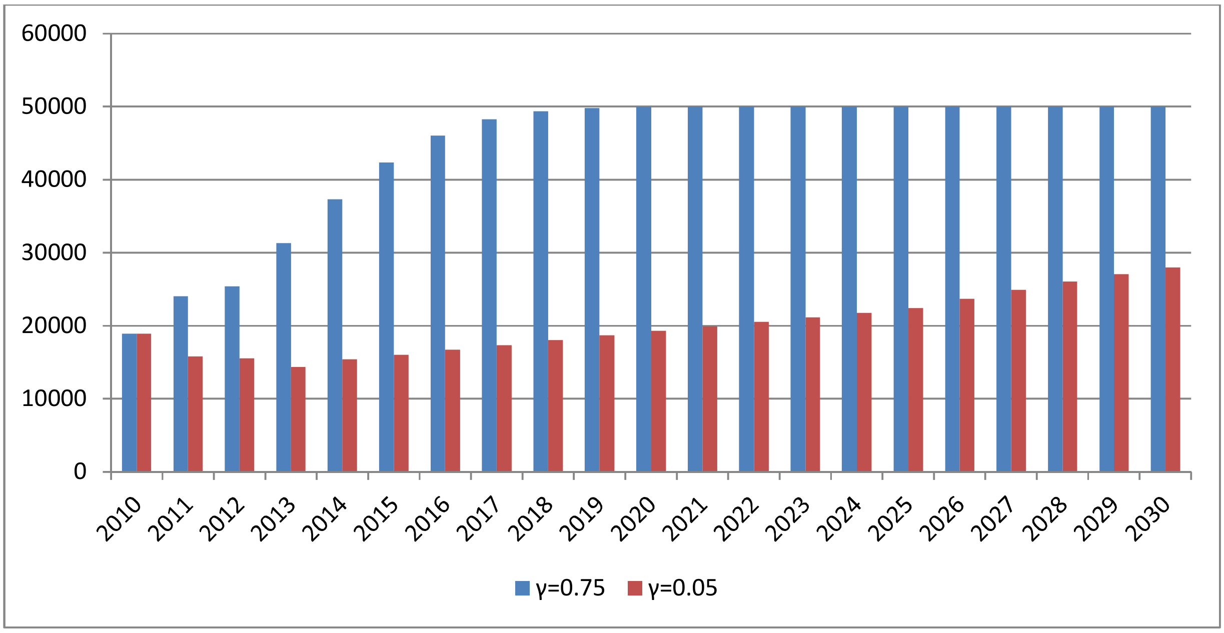


Figure 2. Environmental benefits, customer benefits and subsidy costs (γ =0.75, Unit=billion RMB)

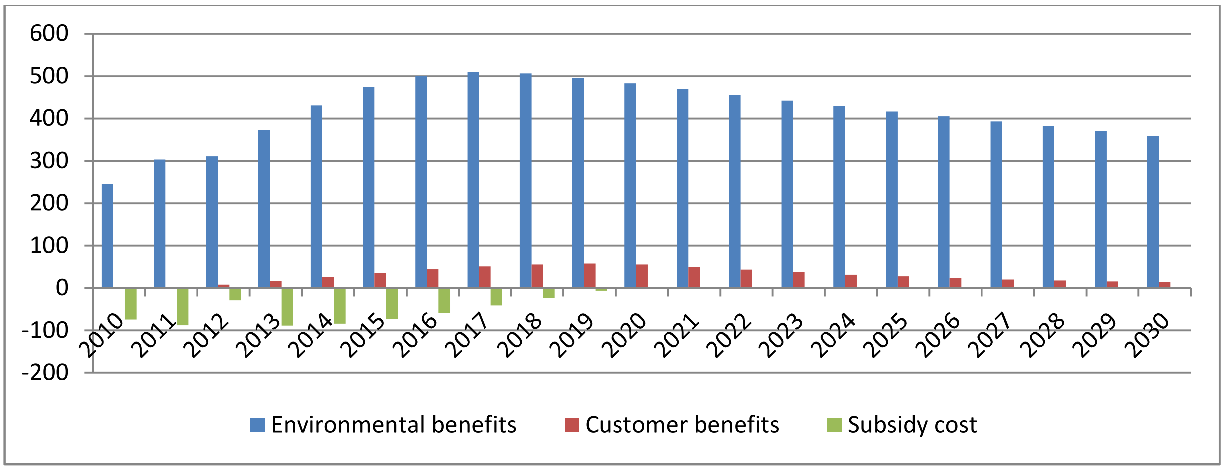


Figure 3. Environmental benefits, customer benefits and subsidy costs (γ =0.05, Unit=billion RMB)

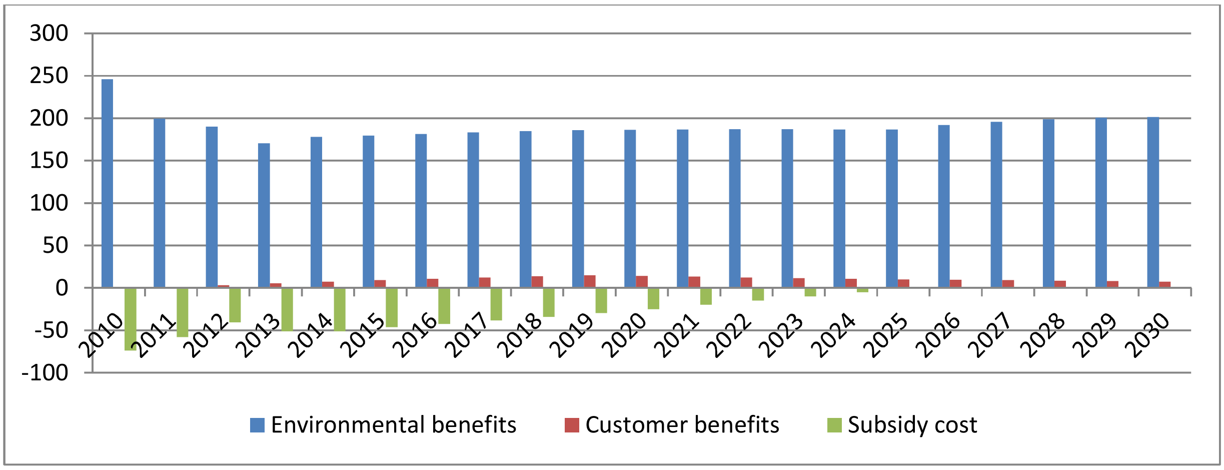
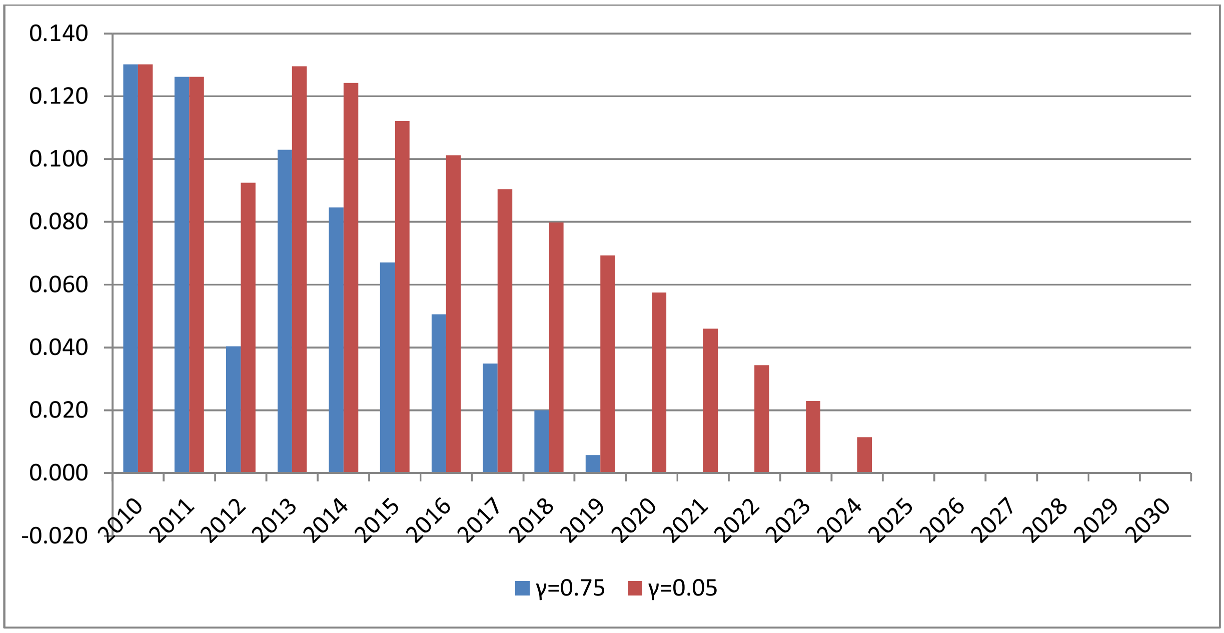


Figure 4. Optimal subsidy of newly installed capacity



7. Conclusion

In this article, we develop a theoretical model which incorporates market and nonmarket effects in technology diffusion. With a panel data of China's wind energy sector, the model is used to test for and estimate the magnitude of epidemic, stock, order and rank effects. Our model can be generalized to any geographical context with rich renewable resources endowment, because we assume that relative to the early adoption, the market potential of renewable energy endowment is large enough to derive a reduced form of the empirical model. Thus, we do not need to compile a dataset on the complete life cycle of technology diffusion to undertake empirical research on diffusion of new technologies.

We find that the epidemic effect may significantly influence the pattern of renewable technology diffusion. In the case of China's wind power diffusion, the evidence shows that the epidemic effect outweighs the profitability effect. This implies that policy instruments can internalize positive (learning-by-doing) and negative (carbon emissions) externalities to obtain an overall effect on adoption that is greater than their direct effects, since the new adopters induce others to adopt as well. The cumulative impact of subsidies in forms of feed-in-tariff or carbon price will be significantly greater than their immediate impact. Our simulation further demonstrates that such epidemic effect can play a quantitatively important role in the spread of renewable energy technology and markedly enhance the optimal social welfare.

This finding has important policy implications on choosing two most commonly used instruments to induce technology diffusion - information provision and subsidies. Our study suggests that the epidemic effect is not derived from the traditional market failure-based policy perspective. It may be largely reflected in the absorptive capacity, user-innovator interaction, and institutional cooperation. Understanding the sources of this epidemic effect may change the justification of choosing policy instruments. With a traditional market failure approach, policy intervention always aims to internalize externalities. However, with a systemic approach of a national innovation system, such policies may have a set of different goals, such as facilitating the knowledge creation and exchange, achieving institutional coordination not provided by the market, or increasing the cognitive capacity of firms.

In the context of renewable energy market, we suggest that this information effect is more likely to be formed and conveyed within a technology diffusion system: network of agents interacting in a technology area under a particular institutional infrastructure for the purpose of generating, diffusing and using technology (Jacob et al. 2004). The policy makers need to strengthen this technology diffusion system together with existing subsidies.

We also provide empirical evidence on the existence of stock and order effects on renewable technology diffusion. Depending on the national context and regulatory characteristics of the electricity market, the stock and order effects may not necessarily reduce the expected profitability of marginal adoption of renewable technology. However, we find that the profitability of wind investment has a decreasing marginal effect to encourage newly installed capacity.

Based only on the wind power sector in China, the empirical part of our work could be extended by considering more a wider range of technologies and in yet other countries with the help of a richer panel dataset. It may be also of great help to compare the origins of the epidemic effect in different national innovation contexts.

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