Market and Non-market Policies for Renewable Energy Diffusion: A Unifying Framework and Empirical Evidence from China's Wind Power Sector

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ABSTRACT

We provide a comprehensive framework of analyzing the diffusion process of renewable technology, incorporating epidemic and pecuniary effects. Relying on a panel dataset consisting of information from 1207 CDM wind projects in thirty provinces over the period 2004-2011, we find strong evidence on the dominant role of the epidemic effect and new evidence on pecuniary effects that generate a diminishing marginal effect of profitability in inducing technology adoption. Our numerical simulation demonstrates that the 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 policy instruments to enhance the diffusion and adoption of clean technology. Price instruments should be complemented by a wide range of non-market instruments to address non-market barriers. Policy interventions should be taken using a systemic approach.

Keywords: Technology diffusion, Incentive policies, Renewable energy, Technological change

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INTRODUCTION

Increasing environmental and energy concerns can be addressed by accelerating technological change around the world. A technology can significantly impact an economy only if it is widely adopted by producers and accepted by consumers. Delays in deployment of low-carbon technologies could rule out the cost effectiveness of global climate policy (IEA 2015). Also, productivity growth has slowed down over the 2000s, partly owning to a slowdown in diffusion of global frontier innovations (Andrews et al. 2015). 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. Although China had almost no wind power capacity in 2001, the country has led the global wind market with the highest installed capacity since 2010. This seemingly accessible wind technology did not diffuse to all countries but rather showed two deployment paths in the past decade. While most countries have failed to ac-

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celerate wind technology diffusion, China's wind energy has been surging. How could China have kept the technology diffusion so rapidly? What are the quantitative effects of various driving forces?

The literature has identified two groups of driving forces behind technology diffusion. One group includes market-based forces. Certain economic instruments can provide financial incentives to potential technology adopters by correcting market failures, i.e. allowing the adopters to explicitly obtain social net benefits associated with renewable technologies. The other group of driving forces is non-market based from a systematic perspective. For example, a specific institutional and regulatory framework may induce technological change. A comprehensive theoretical and empirical framework is required to investigate market- and nonmarket-based forces of renewable technology diffusion to support decision making in the choice of policy instruments.

In this article, we provide such a framework by developing a theoretical model that considers both groups of driving forces in the technology diffusion literature. Then, we validate the model with historical data derived from 1207 Chinese wind projects in the Clean Development Mechanism (CDM)[1] over the period 2004-2011. Finally, we numerically simulate the pathways of optimal production subsidies for maximizing social welfare associated with the wind power sector in China.

I. BRIEF LITERATURE OF TECHNOLOGY DIFFUSION

Technology diffusion is the process of gradual adoption of a new technology by an economy as defined by the well-known Schumpeterian trilogy of technological change (Schumpeter, 1934). This process is generally analyzed within two theoretical frameworks: nonmarket intermediated (or epidemic) 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 to further rapid adoption. Earlier works used probability density functions and Bass models to develop the concept of information acquisition (Mansfield 1963; Bass 1969, 2004). Bass diffusion models are typically applied to consumer decision-making and less to firm decision-making. All these epidemic-type models specify an S-shaped diffusion curve.[2] Recently, this social contagion is also discussed as peer effects (Gordon et al. 2014; Manski 1993). With the help of a disaggregate dataset of daily residential solar-panel adoption in California, Bollinger and Gillingham (2012) estimate the magnitude of peer effects by allowing for better identification of the peer group.

The epidemic effect is likely to be systemic. A regulatory framework and national innovation system are important to provide a long-term view with clear milestones, reduce uncertainty and establish credibility. National systems of innovation (NSI) and regulatory instruments are key factors to shape and convey this epidemic effect. The concept of the NSI was developed successively by Freeman (1987), Lundvall (1992), Nelson (1993), and Metcalfe (1995). Their definitions of the

1. 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. Almost all Chinese wind projects declared over the period of 2004-2011 have responded to the CDM.

2. The number of adopters will increase over time while the adoption process is accelerated initially and then decelerated until the satiation point is reached.

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. A windfarm project lifecycle often involves multi-stakeholder cooperation.[3] The interactions of these institutions will be crucial to determining the speed of wind technology deployment. Ru et al. (2012) provide a good review on China's wind technology innovation pathways, as well as policy and market frameworks at different stages of its maturity.[4] Mandatory requirements, obligation schemes or voluntary approaches can also help strengthen this epidemic effect. The Chinese government did encourage electricity generators to include a minimum share of clean energy in their output mix, even though these goals were not often associated with a penalty in case of non-compliance.[5]

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 profitability driven effects are identified in the literature: rank effect, stock effect and order effect (Karshenas and Stoneman 1993; Geroski 2000; Hoppe 2002).[6]

The *rank effect* models, also known as Probit models, rank firms in terms of the benefit from technology adoption, mostly determined by firm's heterogeneous 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-theoretical 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 (Karshenas and Stoneman 1993). 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

3. Bank, equity investor, utility, grid operator, civil and electrical works contractor, turbine supplier, and land owner are listed among key institutions.

4. In Ru et al. (2012), the development of China's wind energy sector is divided into four stages: (1) early R&D activities pushed by the government (1970s–1996), (2) imitative innovation based on technology imports (1997–2003), (3) cooperative innovation including collaborative design and joint venture (2004–2007), and (4) indigenous innovation based on enterprise internationalization and R&D globalization (2008–present).

5. Under the Medium to Long-Term Renewable Energy Plan in 2007, generators with over 5 GW of capacity were required to reach specified capacity targets for non-hydro renewables: 3% by 2010 and 8% by 2020. However, there appeared to be no penalty for non-compliance: half of the companies missed their 2010 mandatory market share targets. (Retrieved from http://www.theenergycollective.com/michael-davidson/279091/transforming-china-s-grid-sustaining-renewable-energy-push)

6. A complete description of epidemic, rank, order and stock effects can be found in Karshenas and Stoneman (1993). Reminder that both order and stock effects are derived from the game-theoretical models and suggest a negative impact of previous adoption on future adopter decisions. However, the causes of the negative impact are different. Stock effects come from the output market, whilst order effects focus on the first mover advantage. From the theoretical modelling perspective, the stock effects could be identified in a one-period model, but the order effects must be analyzed in an intertemporal model. Yet distinguishing empirically between these effects is extremely difficult if not impossible with available data (see, for example, Karshenas and Stoneman 1993).

return than low-order adopters (Karshenas and Stoneman 1993). The order effect is usually related to the first-movers that can obtain prime geographic sites or preempt the pool of skilled labor. High-order adopters can face less competition and gain greater benefits, therefore their decisions affect the adoption dates of low-order adopters (Fudenberg and Tirole 1985). However, it is worth noting that later adopters can potentially benefit from improved performance and reduced cost of a technology as second-mover advantages (Rosenberg 1976; Hoppe 2000).

In the context of China's renewable energy sector, the order effects relate to first-mover advantage through control of a number of resources. Early adopters may benefit from the most favourable land and wind conditions. They may receive a higher feed-in tariff because a periodic tariff degression is expected to be implemented by the regulator. They can also receive carbon revenue through the CDM. Early adopters can access to the locations with a higher emission baseline enabling to claim more carbon credits. In a regulated electricity market, the stock effects generated through the output market may be less pronounced unless the variation in electricity sale prices is contained by a long-term feed-in tariff agreement. However, grid integration may still raise a serious concern due to the intermittency and non-dispatchable nature of wind energy. In fact, the Chinese grid constraint resulted in an abandon of a significant part of wind electricity. This could trigger the expectation on revenue loss of the wind investors. 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.

The theory cannot predict the role of precedent adoption unambiguously, with stock and order effects having a negative impact and epidemic effects by contrast a positive one (Karshenas and Stoneman 1993). The net impact of precedent adoption on later adopter behavior must be treated as an empirical question. This article contributes to the literature from the perspective of theoretical method and analysis scope. The majority of literature on technology diffusion involves industrial and financial sectors.[7] Explicit modelling renewable energy diffusion is less common.

Previous empirical analysis has been inconclusive. Existing literature is unanimous in finding that adoption decision is positively correlated with firm size and epidemic effect.[8] On the contrary, evidence on stock and order effects is mixed. Depending on the characteristics of technology and output market structure, Mulligan and Llinares (2003) and Hannan and McDowell (1987) find opposite impact of precedent adoption in the technology diffusion process, although their competitive models do not attempt to distinguish the order and stock effects. The results of Karshenas and Stoneman (1993) and Colombo and Mosconi (1995) lend little support to the existence of stock and order effects, whilst those of Gourlay and Pentecost (2002) and Kerr and Newell (2003) support the negative impact of order effects and stock effects respectively.

The existing studies have used a hazard function to study the probability of technology adoption. In the real-world market, utility-scale renewable energy investment may be highly dominated by a couple of utility groups. A project company is often affiliated with its parent group, thus the project company may have little impact on investment decision and project scale.[9] There-

7. Karshenas and Stoneman (1993) study the spread of computer numerically controlled machine tools in the UK engineering industry. Gourlay and Pentecost (2002) investigates the diffusion of automated teller machines in the UK financial sector. Colombo and Mosconi (1995) concentrate on the diffusion of flexible automation production and design/engineering technologies in the Italian metal working industry. Mulligan and Llinares (2003) analyse the diffusion of high-speed detachable chairlifts in the US ski industry. Hannan and McDowell (1987) study the adoption of automatic teller machines by US banking firms. Kerr and Newell (2003) study the U.S. petroleum industry's phasedown of lead in gasoline.

8. One exception is Kerr and Newell (2003) that rejects the existence of epidemic effect.

9. Given the fairly homogeneous wind technology, wind resources availability and administrative process; most of explanatory variables have a limited effect on the project scale (installed capacity per project). Moreover, the vast majority

fore, 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). It is not possible to separate the epidemic effects from stock and order effects, because the existing stock of adopters enters the estimating equation via the stock and order effects. In order to investigate the epidemic effect, the time dependence of the baseline hazard is separately tested, as the epidemic hazard is absorbed into the baseline hazard. In addition, cost variable is often highly correlated with stock variable; the inability to precisely estimate the stock effects is not surprising.

II. THEORETICAL MODEL

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 duration 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 strong epidemic effect and also the stock and order effects have different implications on the profitability of investments. We also numerically demonstrate that to what extent an optimal renewable subsidy will be affected by these market and nonmarket effects.

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. New adoption of a renewable energy technology at any time $t \geq 0$ can be represented by newly installed capacity at time t,

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

where 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

of wind projects in China fall within the range of 49-50 MW in order to benefit from a simplified administrative procedure (wind projects of less than 50 MW are subject to the approval of the provincial authority instead of the central government). For these reasons, it is appropriate to construct a province-level panel dataset to study the policy impact at an aggregated level.

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

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.

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

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.

If we assume that the maximal market potential for energy installation (Q^{max}) is large and the functions in the above three equations are continuous with respect to time t, then we obtain (the proof is detailed in Annex 1[10])

$$Q_t \cong \frac{1}{1-\gamma} e^{\gamma \cdot \left(t - \frac{QS_t}{Q^{max}} \right) + b \cdot NPV_t} \tag{4}$$

We will utilize this equation to decompose the profitability effect into rank, stock and order effects and test the magnitude of these effects. The double log form of Eq. 4 is

$$\text{Model A:} \qquad ln(Q_t) \cong \gamma \cdot t - \frac{\gamma}{Q^{max}} QS_t + b \cdot NPV_t + \beta \tag{5}$$

where β is a constant including the effect of all missing variables besides one component of $\frac{1}{1-\gamma}$.

Eq. 5 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 γ. In previous studies, the driving forces behind the epidemic effect are generally summarized as information acquisition, which can only occur over time. In this sense, the epidemic effect is related to the endogenous forces that grow with time duration. Hence, the epidemic effect captures all effects of non-price driving forces that evolve over time.

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 adopters increases and also that later adopters will make less gains than earlier adopters. Therefore, we expect this coefficient to be negative. The coefficient of NPV_t may capture 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 (NPV_t) by discounting future cash flows in comparison to an alternative investment with

10. Available at http://folk.uio.no/taoyuaw/Liu_Wei_2015Annex.pdf

equivalent risk-return conditions, assuming full information and rational behavior among investors. Consequently, 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, policy makers have implemented feed-in-tariff and carbon pricing policies in order to create favorable conditions for investors in renewable energy technology. NPV_t can be calculated by

$$NPV_t = -C_t^{Invest} + \sum_{n=1}^{T} \frac{(FIT_t + P_t^{CO2} \cdot \pi^{emission}) \cdot yield - C_t^{Operation}}{(1+i)^n} \tag{6}$$

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 CO_2 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. 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 purchasing 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 degression 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. 5, we will estimate two other regression models:

$$\text{Model B:} \quad ln(Q_t) \cong \gamma \cdot t - \frac{\gamma}{Q^{max}} QS_t + b \cdot NPV_t + c \cdot NPV_t^2 + \beta \tag{7}$$

$$\text{Model C:} \quad ln(Q_t) \cong \gamma \cdot t + b \cdot NPV_t + c \cdot NPV_t^2 + \beta \tag{8}$$

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 what extent the impact of QS_t on Q_t is partially captured by NPV_t. We check the robustness of the empirical results derived from models A, B and C.

III. DATA

Models A, B and C are estimated using a panel of provincial 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),

Table 1: Summary Statistics

Variable	Unit	Mean	Std. Dev	Min	Max
New installed capacity (Qt)	MW	5.205	1.376	2.610	8.502
NPV	CNY/KW	0.696	1.203	−3.412	7.254
Cumulative capacity	MW	1113.699	2287.368	0	17303.78
Time duration	Year	3.5	2.296	0	7
Capital costs (CNY2010)	1000 CNY/kW	8.13	1.04	6.11	11.3
FIT price (CNY2010)	CNY/Kwh	0.49	0.08	0.36	0.74
Plant load factor	%	0.2372	0.2589	0.1669	0.3631
Emission factor of the electricity system	Ton CO2/Kwh	0.9492	0.092	0.6789	1.1376

Source: Own calculation. CNY represents Chinese Yuan.

as of the end of 2011. The CDM project participants were required to submit a Project Design Document (PDD) that aims to demonstrate the project additionality[11] and emission reductions. Since nearly all the wind projects in China have participated in 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 (Liu 2014). For a minor of wind projects that are implemented without the CDM support, the projects are mostly identified as recipient of special government funding or foreign aid.[12]

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 of a project 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 a wind project is considered to be 20 years. The discount rate for calculating the NPV is assumed to be 8% according to the common practice in the Chinese market. [13]

As stated in a vast majority of PDDs, the expected price of Certified Emissions Reduction (CER) credit is assumed to be 100 Chinese Yuan (CNY)/ton CO_2, 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' 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.

11. The CDM rests fundamentally on the concept of additionality—the proposed project would not have occurred in the absence of CDM support.

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

13. *Economic & Technical Assessment and Indicators for Construction Project (Version 3)* National Development & Reform Committee and the Ministry of Construction, 2006.

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[a]
F-test value (Model)	11.61***	11.86***	14.04***
F-test value (provincial effects)	7.05***	6.02***	10.03***

Source: Own estimation.

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

[a] The lagged cumulative capacity variable reduces the number of observations to 117, while the removal of this variable makes our number of observation increase to 144.

The starting date of a CDM project activity is the earliest date at which either the implementation, 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.[14] 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.

IV. EMPIRICAL ANALYSIS AND DISCUSSION

We use fixed effect models to estimate Models A, B and C. Each province has its own unobserved characteristics, notably associated with wind resource endowment, energy 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 estimation results are showed in Table 2. 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 in all the three models are statistically significant, indicating that one additional year may lead to an increase of newly installed capacity by around 40%. This indicates the presence of epidemic effect, i.e., the annually installed capacity of renewable energy shows positive time duration dependence. 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 0.38-0.45. This finding is consistent with our intuition. China's leapfrog in wind energy

14. 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.

occurred when relatively mature wind technology was already widely used in developed countries, leading to significantly decreasing marginal cost reduction of technology deployment and 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 NPV_t is insignificant in Model A, but becomes significant and relatively stable in the other two models, where the quadratic term of 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 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.[15] 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 adopters increases.[16] 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 (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. In Model A, the coefficient on cumulative capacity QS_t(representing stock effects) is found to be statistically significant. 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 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. A3 in the annex 1). 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.

Although the estimated coefficient of cumulative capacity QS_t is significant in Model A, where the quadratic term of NPV_t is absent, it becomes insignificant in Model B, where the quadratic term is present. This indicates that a large part of the effect of QS_t has been captured by the quadratic

15. 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.

16. 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.

term of 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 effect of QS_t on newly installed capacity is actually channeled through the project profitability. As noted by Karshenas and Stoneman (1993), the insignificance of cumulative capacity variable may not necessarily indicate the total absence of stock effects and may alternatively be captured by the time-varying baseline hazard. If this is the case, then removing the variable of cumulative capacity would lead to an increase in the estimated coefficient for the time. However, as shown by the estimates of Model C, a decrease in the coefficient for the time occurs with the omission of QS_t since the quadratic term of NPV_t becomes economically and significantly more important.

V. 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. Assume that policy makers aim to set up a time path of subsidies that maximize the discounted present value of net social benefits. There are two streams of the benefits from wind technology adoption. One involves the avoided external environmental costs from fossil-fuel electricity replaced by wind electricity. The other stream takes the form of customer benefits from the policy-induced learning effects received by wind electricity consumers. Hence, the policy makers need to solve a dynamic optimization problem expressed by

$$\max_{S_t} W(S_t) = \sum\nolimits_{t=1}^{T} \frac{Q_t(S_t) \cdot \{C^{ext} \cdot yield + CB_t(S_t, QS_t) - S_t \cdot yield\}}{(1+r)^t} \tag{9}$$

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 benefits 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 CO_2/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. The FIT price is represented by the average feed-in tariff in the wind power sector and the benchmark electricity price is calculated as the average electricity price generated from fossil sources.

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. The details of the calculation are in Annex 2.[17]

17. Available at http://folk.uio.no/taoyuaw/Liu_Wei_2015Annex.pdf

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 $\gamma = 0.38$ and $\gamma = 0.05$, respectively. The FIT subsidy and lifetime of the wind projects are assumed to last for 20 years in China's context. It is worth noting that based on our empirical results, we added the quadratic term of NPV in Eq. 1 to better simulate stock and order effects in the demand function.

The wind projects yield 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 SO_2, NO_x, Particulates, and also includes the climate damage caused by CO_2 emissions. The environment benefits associated with CO_2 emissions are estimated at a price of 20 EUR per ton CO_{2e}. The costs of other pollutants are based on specific Chinese values. According to Zhu et al. (2008), the total environmental benefits are estimated to be 0.0254 EUR per kWh, i.e., 0.27 CNY per kWh with an exchange rate of 10.75 CNY/EUR 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 CO_2 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 in Annex 2) is estimated to be 0.066, which leads to a learning rate of 4.4% (Yao et al. 2015). 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.

Due to market and/or resource constraints, each technology may confront a maximum production or capacity limit. China's Meteorological Administration (CMA) estimates 2,380 GW of onshore wind power potential, equivalent to 4,800 TWh/yr at a 23% average capacity factor (CMA, 2006). A more recent study points out the same magnitude for China's wind power resources (He and Kammen 2014). Consistent with the experience in developed countries, we assume that in medium-term, China's wind energy can technically reach 20% of national electricity supply (Wiser et al. 2011), which is forecasted to be 9,300 TWh in 2030 (IRENA 2014). Given an average capacity factor of 23%, the technical maximum of on-shore wind installed capacity is translated into about 920 GW. Thus, Q^{max} is estimated to be approximately 50 GW on a yearly basis over the period of 2011-2030 in China.

The key parameters used in our simulation are displayed in Table 3.

To highlight the crucial role of the epidemic effect, below we compare the optimal social welfare, annually installed wind capacity, environmental benefits, customer benefits and subsidy cost between two cases: one assuming the epidemic effect in the past decade continues until 2030 ($\gamma = 0.38$) and the other assuming a much smaller epidemic effect ($\gamma = 0.05$).

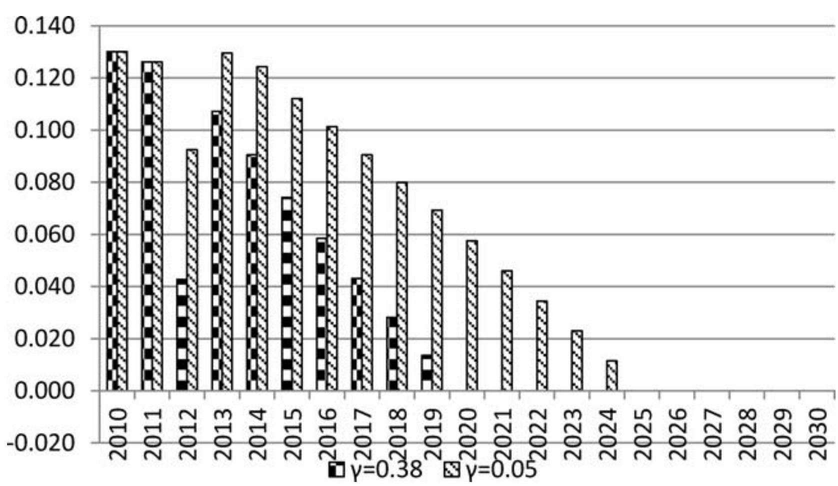
The optimal social welfare is much larger with the large epidemic effect, double of that with the small epidemic effect. By contrast, the present value of total subsidies required with the large epidemic effect is 10% below that with the small epidemic effect. The evolution of different components of social welfare is shown in Annex 3.[18] Meanwhile, the optimal subsidy is phased out earlier with the large epidemic effect, 5 years ahead of the small epidemic effect case (Fig. 1). The

18. Available at http://folk.uio.no/taoyuaw/Liu_Wei_2015Annex.pdf

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 CO_{2e}
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 (in 2009)	7840	
Coefficient of NPV	0.35	
Coefficient of NPV^2	−0.05	
Parameter of the epidemic effect γ	0.38 or 0.05	

Figure 1: Optimal Subsidy of Newly Installed Capacity

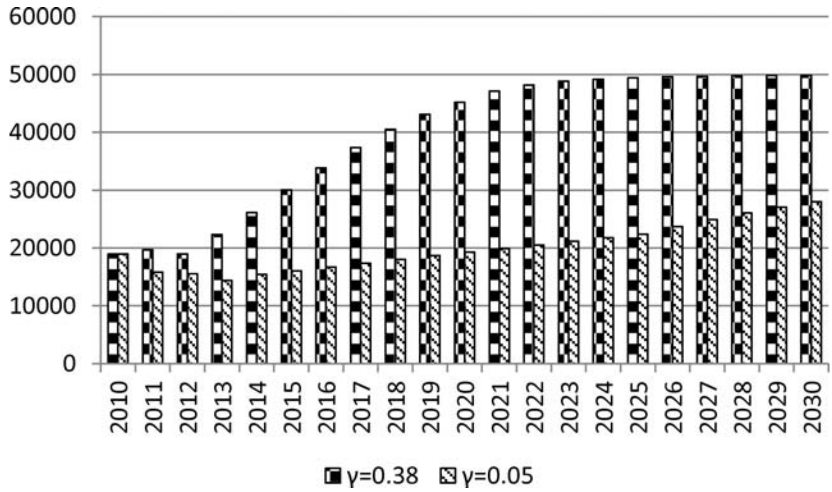


cumulative installed capacity in the large epidemic effect case in 2030 is double of that in the small epidemic effect case (Fig. 2). Hence, the society can benefit considerably if current epidemic effect continues although it is almost impossible.

VI. CONCLUSION

In this article, we develop a theoretical model that incorporates market and nonmarket effects in technology diffusion. With a panel data of China's CDM wind energy sector, the model

Figure 2: Annually Installed Wind Capacity (Unit = MW)



is used to 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 the 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 instruments to induce technology diffusion. 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.

The empirical part of our work could be extended by considering a wider range of technologies and we can apply the approach to other countries. It may also be useful to compare the origins of the epidemic effect in different national innovation contexts.

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