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Is Research and Development Investment Influencing Co_2 Emissions in China

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Abstract: China is one of the world's greatest consumers of energy. As a result of the negative environmental effects of fossil fuel-based power generation, the government has lately made investments in the commercialization and deployment of various RE sources. This study utilizes a Black-Scholes-Merton model, this model is a system dynamics approach. In addition, from 2018 to 2035, researchers will look at the interconnections of uncertainty elements as well as the effects of the probability of default on carbon dioxide emission reduction amounts and renewable energy output. The results indicate that Research & Development investments in marine energy have a 2.60% high default risk, and waste energy usage has a major drop in carbon dioxide emissions 46.85 B kgCO_2. The results are showing that the probability of default of the Research & Development investment mitigates when the uncertainty of R&D amount, price of a unit, and renewable energy production amount increases. In short, results are showing that the probability of default of the research & development investment does not significantly affect by the unhazardous investment rate.

1. Introduction

As we know ecological influences of carbon secretion generated from the consumption of fossil fuels continue to increase in the whole world day by day. A large number of developed nations have heavily invested in the technologies of clean energy to increase the maximum consumption of clean sources of energy (Kim et al., 2014). China's total primary energy (Renewable Energy) supply was 3.51% in 2013. To achieve the goal of 7.7% renewable energy in 2035, the government of China has launched an R&D

investment plan. The basic purpose of this Research & Development investment plan is to promote the renewable energy technology (Kim et al., 2012).

Because of the initial and major investment of funds the specific time duration required for the implementation of Research & Development (R&D) technology, this investment would be beneficial for the government of China to attain the potential target. The government of China can adjust more efficient and significant strategies for the fundamental financial predictions (Ryu and Byeon., 2011). For technological assessment in the renewable energy industry, discounted cash flow methodologies and contingent valuation methods are most typically utilized. Further, no other method is suitable for the evaluation of long-term Research & Development technology (Jeon et al., 2015). Furthermore, in the performance of the default prediction model, several research took into account unobserved systematic risk variables. There are various studies that make use of empirical data to determine the degree of accuracy of the Black Scholes Merton model, which may be found here. The empirical findings from these past studies suggest that the Black Scholes Merton model sufficiently calculates the probability of default (PD) in firms (Jeon et al., 2015).

Although to estimate the probability of default of Research & Development (R&D) investments none of above mentioned studies employ the option pricing model. On the other hand, several studies do effective use of the option pricing model to assess the significance of high-tech investment in the sector of clean energy. In past, some empirical studies effectively used the option-pricing model because of the capital size, while there are few other studies that inspect the advantages of clean energy. Furthermore, few studies conclude the proper types of clean energy sources, and some other studies scrutinize the suitable time span and capacity of RE sources. The majority of relevant earlier research have concentrated their attention only on the uncertainty aspect of energy pricing, while renewable energy investment factor eliminated (Leland., 2004; Bruche and Aguado., 2010; Chara and Purnanandam., 2010; Da and Gao., 2010; Li and Miu., 2010; Vassalou and Xing., 2004; Kadan and Swinkels., 2008; Lando and Nielsen., 2010).

Besides that, several research takes into account the unobserved systematic risk variables in the model's performance as well (Koopman *et al.*, 2008; Duffie *et al.*, 2009; Qi *et al.*, 2014; Azizpour *et al.*, 2018). However, the majority of this research only addresses the increasing effects of unobserved-systematic hazard variables on default prediction skills. Several research, use actual data to inspect the precision of the Black Scholes Merton based prediction model (Hillegeist., 2004; Du and Suo., 2007; Reisz and Perlich., 2007; Agarwal and Taffler., 2008; Bharath and Shumway., 2008; Wu *et al.*, 2010; Charitou *et al.*, 2013; Doumpas *et al.*, 2015; Afik *et al.*, 2016). The empirical research findings demonstrate that the BSM model accurately predicts a firm's PD (Kealhofer., 2003).

This model isn't used in any of the aforementioned research, but it has been used in other studies to evaluate the probability of default of the expenditures of research and development in the RE production. Few past studies employ the option pricing model to analyze the viability of the RE investment because of the large initial investment (Venetsanos *al et.*, 2002; Lee., 2002; Jang *et al.*, 2013; Zhang *et al.*, 2014; Wesseh and Lin., 2016). While, research on the advantages of RE are being conducted at the same time (Davis and Owens., 2003; Siddiqui et ., 2007; Lin and Wesseh., 2013; Wesseh and Lin., 2015). Furthermore, numerous studies establish the appropriate sorts of renewable energy sources, while others investigate the appropriate time and capacity of renewable energy sources (Kimbaroglu et al., 2008; Siddiqui and Fleten., 2010; Reuter et al., 2012; Kjaerland., 2007; Fleten et al., 2007; Backman et al., 2008; Boomsma et al., 2012; Cesena et al., 2013). Many studies just look at the price of energy as an uncertainty component in the assessment process of renewable energy investments, but not the interactions between numerous uncertainties.

The real-option technique is used to assess project investment, according to the relevant prior research (60 %), research and development (7%), and policy effects (33%) in the project of clean energy. While HE, SE, WE, and BE are the core factors of the project of clean energy. For instance, the black scholes merton model is a suitable technique to evaluate the probability of default (PD) and Research & Development technology investment in the project of RE in China. Even though a study has been carried out to determine the significance of PD for R&D technology investment, a study has been carried out to investigate the influence of the likelihood of default as part of the RE technology assessment method.

A real option-pricing model and a system dynamics model are employed to examine the effect of research and development expenditures in the RE industry in the China. Using BSM to forecast PD for renewable energy R&D expenditures, this research also examines how PD for R&D investments affects particular goal values for carbon dioxide emission reductions. To meet 2035's carbon dioxide emissions reduction objective, environmental regulators may use the findings of this research to better allocate funding for technological development and R&D expenditures.

2. Data sources and methodology

The present study does utilize the BSM model to evaluate the probability of default (PD) of research & development technology investment in marine photovoltaic energy, biomass energy, wind energy, marine energy, and waste energy in the China. Estimation through the BSM model is suitable in the China for above mentioned five types of renewable energy technology. An appropriate approach for analysis is SD approach, and this approach is developed by the BSM model. Further, the BSM model is employed to analyze the effect of uncertainty factors on the probability of default (PD) of research and development technological investments in the sector of RE.

3. Black-Scholes-Merton default-Prediction model

BSM model relies on the implication of the option pricing model, this model estimates the probability of default (PD) of any firm. At the period of debt maturity, it also measures the possibility that the face value of a firm's total liabilities is greater than the total assets market value of the firm. To evaluate the research and development investment value, the BSM model has been highly adopted model. Further, this study is the pioneer study that applies a pricing model named the option pricing model to evaluate the probability of default (PD) of the research & development investment in the sector of RE. For the estimation of the probability of default (PD), this study used the famous option-pricing model. The asset value of the firm follows Geometric Brownian Motion, the probability of a firm defaulting only at the time of maturity. According to the BSM model, B is showing the valuation of the European call option and this valuation is estimated by using the below-mentioned first three equations.

$$B = SN(b_1) - Ke^{-rt}M(b_2) \qquad (1)$$

$$b_1 = \frac{1}{\beta\sqrt{T}}\left\{ln\left(\frac{S}{K}\right)+\left(r+\frac{\beta^2}{2}\right)T\right\} \qquad (2)$$

$$b_2 = \frac{1}{\beta\sqrt{T}}\left\{ln\left(\frac{S}{K}\right)+\left(r-\frac{\beta^2}{2}\right)T\right\} \qquad (3)$$

$$PD = M\left[-\frac{1}{\beta\sqrt{T}}\left\{ln\left(\frac{S}{K}\right)+\left(r-\frac{\beta^2}{2}\right)T\right\}\right] \qquad (4)$$

K = strike value of the model

S = underlying value of the model

T = time of maturity

β = volatility in the value

r = interest rate without any risk

M(b) = cumulative standard normal function of the model

4. System-Dynamics Model

The system dynamics model is a multifaceted system that uses auxiliary variable flows, feedback, and stock. The basic purpose of this approach is to acknowledge the "time varying behavior" of a system at the same time, to analyze the impact of an independent value on a particular dependent value. Because of these qualities, the present study is allowed to feign the Black Schole Merton model by using a system dynamics method to compute the probability of default (PD) of the research and development technology investment in the sector of RE.

5. Casual-Loop diagram

The Causal-loop consists of two loops: balancing loop and reinforcement loops which are directly used by a particular variable to affect the other variables, whether this influence is positive or negative. The present study developed the research and development technology investment's default-prediction model. The model is showing that the increased value of research and development investment resultantly increases the production amount of green energy and default probability of R&D investment. While it reduces the value of R&D technology. The increased production amount of renewables increases the sales of renewables and carbon emissions reduction amount. The increased sales of renewables reduce the default probability of research and development investment. In contrast, the increased sales of RE increase the value of R&D technology which is opposed to the default probability of R&D investment. Moreover, the increased carbon emissions reduction amount increases the renewable energy production, while the carbon emissions reduction amount is positively influenced by the carbon emissions target.

Table 1

Energy Forms	**K in Million Dollars**	**S in Million Dollars**	**B in Percentage**	**R in Percentage**	**T in Years**
Biomass	9.20	2.20	43.50	2.70	20 years
Marine	1.35	0.1773	43.50	2.70	20 years
Photovoltaic	3.62	1.35	43.50	2.70	20 years
Waste	21.9	10.40	43.50	2.70	20 years
Wind	21.99	1.05	43.50	2.70	20 years

6. Stock and flow

The cause and effect relationship of 32 variables. These four level 32 variables are developed by employing the (SD) developmental tool of vensim. The estimated inflation rate is 2.74% from 2018 to 2035. The sale of renewable energy production is intended by multiplying the unit price of RE by the amount of RE produced.

Table 2

Energy	Unit Price ($)/kWh
Maine Energy	0.125
Waste Energy	0.127
Biomass Energy	0.127
Wind Energy	0.139
Photovoltaic Energy	0.200

This Kinetic energy is converted into mechanical power by turbines, which are a primary source of wind energy. The photovoltaic energy source is solar cells and these solar cells convert the photons into electrons. Ocean waves and tides together with Kinetic energy generates the marine energy. Biomass energy is generated from the uses of some organic materials such as waste of animal, crop, wood, and plant waste. Non-recyclable waste conversion into fuel, electricity, and heat generates the waste energy. It is expected that when renewables is generated then carbon emission production can be reduced from fossil based electricity.

RE production multiplying by the value of 0.47722 kg CO_2/kWh of the carbon emission density of the energy is showing the expected reduction of carbon emission. On the other hand, RE production multiplying by the (PD) of research and developmental investment is showing a predictably disappointed reduction in CO_2 and this reduction is the cause of failure in research and development investment in the sector of RE. Expected carbon emission reduction subtracting from the expected unsatisfied carbon emission reduction is showing the total carbon emission amount.

Reduced emissions of carbon dioxide are a top priority for China's government by 25.9% or 219.9M CO_2 equivalent tons (MOLIT). The government of China further take some corrective actions and assigned a 26.9% carbon emission reduction target to the sector of energy, which means the energy sector will be helpful to reduce carbon emission (CE).

Table 2 CE reduction target values

Energy	Biomass	Marine	Photovoltaic	Wind	Waste
Proportion (%)	1.2	7.8	14.3	18.5	18.2
CE (MT CO_2)	0.05	0.34	0.66	0.87	0.82

Table 2 is showing proportionate (%) and million ton CO_2 values of each type of energy. The carbon emission for each renewables is measured as 0.05 Million tons of carbon emissions for biomass, 0.34 Million tons of carbon emissions for marine energy, 0.66 Million tons for carbon emissions for photovoltaic energy, 0.87 Million tons for carbon emissions for wind energy, and 0.82 Million tons for carbon emissions for waste energy. Carbon emission target values compared with carbon emission reduction amount show the carbon emission surplus amounts and carbon emission predicted reduction amount.

The five renewables' research and development investment values are determined using yearly sales and annual research and development investment levels from 2018 to 2035 in Equations 1-3. The research and development technology worth is represented by the difference amongst the projected advantages of research and development expenditure and the adjusted research and development investment amount. The predictable benefits of the study are considered to be the product sales of RE. Over this, adjusted research and development investment amount committed by the two factors, such as the chance of the risk happening and concession by the interest rate, which is risk free. Equation 4 is used to estimate the probability of default (PD) of the research and development investment.

7. Model Validation

The available data collected from the period of 2018 to 2035. As well as, the study follows the annual RE production amount from the period of 2018 to 2035. The present study also likens the reference data with simulated results. The simulated yearly results of the research and development investment amount are also highlighted in this research. According to this, wind energy investment decreased on average 0.02 percent from 21.99M dollars in 2018 to 14.54M dollars in 2035. The planned execution of R&D investment shows that the aggregate production of wind energy improved on average 16.97 percent from 7.62B in 2018 to 56.16B kWh in 2035.

Table 3 (a): Annual renewable energy production

Year	Biomass	Marine	Photovoltaic	Wind	Waste
2018 (M$)	17.07	1.49	6.90	7.62	82.35
2035 (M$)	26.13	2.53	27.96	56.16	108.18

Table 3 (b): Annual R&D investment amount

Year	Biomass	Marine	Photovoltaic	Wind	Waste
2018 (M$)	9.18	1.36	3.64	22.27	22.90
2035 (M$)	12.27	1.36	3.64	14.54	4.54

Table 3 (a) indicates the annual RE production and annual research and development investment amount. The amount of annual clean energy production is probably 17.07 for biomass, 1.49 for marine, 6.90 for photovoltaic, 7.62 for wind, and 82.35 for waste in 2018. As well as, it also indicated that the expected RE production in 2035 would be 26.13 for biomass, 2.53 for marine, 27.96 for photovoltaic, 56.16 for wind, and 108.18 for waste.

8. Results and Discussion

The present study estimates the PD of research and developmental investment in the above mentioned five types of renewables by employing the default developed prediction model, the present research also investigates the effect of the PD on the CO_2 reduction amount in the country of the China. Further, to check the impact of uncertainty factors, this study conducts a parameter sensitivity. Uncertainty factors are investment amount, unit price, and production of renewables. While this study also investigates the impact of RE production on the targeted carbon dioxide emission mitigation amount. Further, this study used Morte Carlo simulation to highlights the relationship between risk-free interest rates on the probability of default of RE investment.

Table 4

Energy	Minimum	Maximum	Mean	Median	Standard Deviation
Biomass	0.51	2.07	0.91	0.78	0.44
Marine	0.73	5.05	2.64	2.02	1.35
Photovoltaic	0.05	0.91	0.26	0.15	0.25
Wind	0.33	9.85	2.58	1.11	2.89
Waste	0.02	0.69	0.26	0.19	0.21

Table 4 indicates the default probabilities of RE from 2018 to 2035 in percentage. Some statistical values of five types of renewables are tabulated in above mentioned table 4. The mean value of biomass is (0.91), marine (2.64), photovoltaic (0.26), wind (2.58) and waste is (0.26). It is very important to discuss the mean values of marine energy and wind energy have the highest mean values. On the other hand, biomass energy, photovoltaic energy, and wind energy have relatively the lowest mean values. Wind energy has high variability of investment in the China.

Annual R&D investment has an inverse association with the PD of the investment. Planned annual research and development investment gradually decreases the PD of the investment. Results show the large capital amount in the technologies of the renewable energy. Further, the probability of default of RE sources annually decreases without a decrease in marine energy.

9. Carbon dioxide emissions mitigation

The present study analyses the expected carbon emission reduction from the effect of the probability of default of the R&D investment. Non-renewable energy that is replaced with sources of clean energy is said to be carbon emission reduction amount. To explore the impact of the probability of default (PD) of the research and development investment on CE mitigated amount, the resulting study uses the zero value of the probability of default (PD). At the point where PD value is zero the expected average reduction is 15.60B kg of carbon emissions for wind energy, 8.89B kg of carbon emissions for photovoltaic energy, 0.79B kg of carbon emissions for marine energy, 47.05B kg of carbon emissions for waste energy, and 10.5B kg of carbon emissions for biomass energy from 2018 to 2035. The default probability contained in the established default prediction model reduced the amount of carbon emission reduction.

The results are showing with the probability of default, for wind energy average expected reduction in the energy sector is 0.77B kg of carbon emissions, 8.87B kg of carbon emissions is for photovoltaic energy, 46.90B kg of carbon emissions for waste energy, and 10.40B kg of carbon emissions for biomass energy between 2018 to 2035. Further, the expected reduction in energy industry is from 2018 to 2035, 92.40B kg of carbon emissions for biomass energy, 21.83B kg of carbon emissions for marine energy, 21.81B kg of carbon emissions for photovoltaic energy, 11.33B kg of carbon emission for waste energy, and 207.54B kg of carbon emission for wind energy.

10. Sensitivity analysis for results

The present research analyses the uncertainty factors and these uncertainty factors are RE production, investment, and unit price. Further, analyses the incremental rate influence on the probability of default of the research and development technology investment. An increase from 5 percent to 20 percent was analyzed with the help of a sensitivity analysis.

Table 5: Unit price relationship with a default probability

Rate of Increase	Biomass	Marine	Photovoltaic	Wind	Waste
5%	0.90	2.62	0.26	2.57	0.26
10%	0.89	2.59	0.26	2.56	0.26
15%	0.89	2.57	0.26	2.55	0.25
20%	0.88	2.55	0.26	2.53	0.25

Table 5 represents the incremental increase in rates of the five renewable energies. Sales of renewable energy have a negative relation with the PD of research and development investment. In terms of price, this study takes the sales of renewables and an upsurge in the unit price of the clean energy decreases the PD of the research and development investment of renewables except for photovoltaic energy. Further, outcomes show that uncertainty of unit price no more affected photovoltaic energy because photovoltaic energy has a constant amount of research and development investment.

A 5% increase in unit price is showing 9.8% to 0.3% change in the probability of default of research and development investment for wind energy, from 0.90% to 0.05% for photovoltaic energy, from 3.27% to 1.16% for marine energy, from 1.60% to 0.85% for biomass energy and from 0.68% to 0.02% for waste energy from the period of 2018 to **2035.**

Table 6: Amount of investment relationship with a default probability

Rate of Increase	Biomass	Marine	Wind	Photovoltaic	Waste

5%	0.89	2.53	2.56	0.26	0.25
10%	0.87	2.41	2.53	0.26	0.25
15%	0.84	2.29	2.52	0.26	0.24
20%	0.82	2.15	2.49	0.26	0.24

This study investigates the uncertain investment amount and change in the values of PD at different increasing rates (5% to 20%). For this purpose, this study tabulated the average probability of default values in table 6. Each investment reflects a similar trend that is already shown in the case of unit price. Further, the photovoltaic form of energy has not been significantly influenced by investment uncertainty.

Table 7: Production of RE relationship with a default probability

Rate of Increase	Biomass	Marine	Waste	Wind	Photovoltaic
5%	0.90	2.64	0.26	2.52	0.25
10%	0.89	2.63	0.26	2.41	0.25
15%	0.88	2.62	0.25	2.35	0.24
20%	0.86	2.61	0.25	2.28	0.23

This study analyses the renewable energy production's uncertain amount and change in the values of PD at a different increasing rate, and all these values are tabulated in table 7. The results are showing that renewable energy production has a similar trend that has already been shown in unit price and investment. But the average probability of default of photovoltaic has changed from 0.24% to 0.22% at a 5% to 20% increasing rate. Results also indicate that if the amount of RE increases then it is possible to reduce the failure chance of research and development investment.

The results are showing the change in default probabilities and this change occurred with an increasing rate of 5% in renewable energy production. Between 2018 to 2035 the probability of default of research and development investment are changed from 9.80% to 0.26% for wind, 0.90% to 0.05% for photovoltaic energy, 3.27% to 1.17% for marine energy, 1.71% to 0.80% for biomass energy and 0.68% to 0.02% for waste energy.

Table 8: Renewable energy production impact on carbon emission

Increase rate	Biomass	Marine	Photovoltaic	Wind	Waste
5%	10.06	0.7392	8.88	15.96	46.46
10%	10.16	0.7438	9.33	17.21	46.81

15%	10.30	0.7476	9.86	18.56	47.23
20%	10.45	0.7512	10.30	19.96	47.60

This study examined how CE reduction amounts are affected by the change in renewable energy production. Table 8 shows the average amount of carbon emission decrease, which ranges from 5% to 20%. According to the findings, there is a negative relationship between the quantity of carbon emissions decrease and renewable energy generation. Because a decrease in the amount of CE reduction increases the amounts of renewable energy production. The above-tabulated values also indicate that waste energy has the significant carbon emission reduction as well as, the marine has smallest.

The CE reduction amounts gradually increases from 2.95B kg CO_2 to 29.07 kg CO_2 for wind energy, from 3.02B kg of carbon emission to 13.92 kg of carbon emission for photovoltaic energy, from 670.5M kg of carbon emission to 850M kg of carbon emission for marine energy, from 7.8B kg of carbon emission to 12.05 kg of carbon emission for biomass energy, and from 39.22B kg of carbon emission to 52.14 kg of carbon emission for waste energy.

The PD values of photovoltaic energy decrease, while initially, the default values are between 0.40% and 1.2%. The PD values of wind energy also gradually decrease and initially, default values are between 5.65% and 12.2%. The PD values of marine energy are between 0.74% and 5%. In the case of biomass energy, the values of PD stay in the range from 0.75% and 2.3% in 2018 and 0.373% to 3.0% after 2018. For waste energy, PD's are in the range between 0.30% and 0.78% in 2018 and the PD's are gradually decreasing. Monte Carlo simulation results indicate that uncertainty in the values of the risk free interest rate has a large and significant impact on waste energy as well as, smallest on the photovoltaic energy.

10. Conclusion and limitations

The Chinese government intends to invest in the research and development of renewable energy technology in order to promote the use and commercialization of diverse renewable energy sources. However, this work uses an SD method to construct a default prediction model based on the BSM model, which calculates the probability of default (PD) of R&D expenditures and the influence of uncertainty variables on the PD and the carbon dioxide reduction aim of the Research and Development investments.

A comparison of five potential renewable energy sources, including wind, solar, marine, biomass, and trash in this research shows that the Chinese government has a keen interest in all of them. Wind energy (2.58%) and marine energy (2.64%) have the highest default risks, while wind energy (15.96 billion kilograms of CO_2) and waste energy (46.46 billion kilograms of CO_2) have the highest carbon dioxide emissions reduction amounts, according to this research. Using these statistics as guidance, researchers propose photovoltaic energy as the best renewable energy source since it has the lowest PD of the five options studied, while also lowering carbon dioxide emissions enough. China should also be mindful of undertaking R&D expenditures in the wind and marine energy because of the significant default risk.

Using this model as a starting point, it is possible to create different kinds of default prediction models that take into account the relationships between R&D technology investment uncertainty variables. Using the input-output framework provided by this paper, a default-prediction model can be developed whose PD can be calculated for R&D expenditures made at a particular investment level and for renewable energy generation at a given level.

Only sales from renewable energy generation are used to calculate the predicted returns on R&D investment in this research, which is a shortcoming. This study's estimated PD may thus be considered as a minimum value for the PDs associated with R&D expenditures in the renewable energy industry generally. Because interest rate, risk premium, and maturity time aren't included in the BSM model, the authors propose to use alternative option models in future research to enhance the created default-prediction model.

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