# Comparison of Tax Credit Policies for Renewable Energy: Simulations on uncertainty models


**A Thesis submitted by**

**Ruihao Xie**


**In partial fulfillment of the requirements for the degree of**

**Master of Science**

**in**

**Economics**


**Tufts University**


**May 2016**

**Advisor: Professor Gilbert Metcalf**

# Abstract

Production tax credits (PTC) and investment tax credits (ITC) are two policies regulated by the U.S. government to stimulate renewable energy electricity generation. In this thesis, I constructed models on both the individual level and the aggregate level characterizing wind firms' reactions on electricity prices and tax credit policy statuses with uncertainty. Using estimated values of the parameters shown in models, I calculate trigger price lists of wind firms with different levels of production capacity. By running 1000-time simulations of stochastic processes contained in the model, I get expected values of two key measures following the Monte Carlo Method. Then I conduct comparisons between PTC and ITC on effectiveness and efficiency, and find ITC encourages more investment in wind energy, and costs less on each kilowatt-hour electricity stimulated than PTC does. In the end, I give several policy suggestions basing on comparison results and the sensitivity analysis.

# Acknowledgements

I am very grateful to my advisor, Professor Gilbert Metcalf, for his rigorous academic guidance and warm encouragement on my research project. Without his help, this thesis cannot be possibly conducted. I am also very grateful my second reader, Professor Ujjayant Chakravorty, for the comments he gave during my defense. Finally, I would like to thank my wife, Jiaxin Li, for her love and support.

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# 1. Introduction

The global warming issue is getting more and more public attention nowadays. According to Environmental Protection Agency[1], the electricity sector is the largest source of carbon dioxide emissions in the US. So to reduce carbon dioxide emissions in the electricity sector is an important task for the US in fighting against anthropogenic climate change. Responding to this situation in reality, President Obama unveiled the Clean Power Plan in August 2015, which aims to reduce the carbon dioxide emissions from electrical power generation by 32 percent within fifteen years relative to 2005 levels. This was proposed by the US Environmental Protection Agency, and also shows the determination of the US government in turning electricity industry more environmentally friendly.

One approach to lowering carbon dioxide emissions is to encourage more investment in clean energy electricity generation, such as wind and solar. In order to achieve this goal, the US government offers two kinds of tax credit policies in renewable energy field: a Production Tax Credit (PTC) and an Investment Tax Credit (ITC). If a wind turbine is eligible for the PTC, then the owner of this wind turbine will get a 2.3 cents tax credit for each kWh electricity produced by this wind turbine for the first 10 years of its operation. As for the ITC, the owner can receive tax credits of 30% of capital investment.

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[1] See Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2013 – Executive Summary <https://www3.epa.gov/climatechange/pdfs/usinventoryreport/US-GHG-Inventory-2015-Chapter-Executive-Summary.pdf >

After these tax credits were created, each policy has been applied to many states and industries, some of which are covered by both credits. Given both of these two policies are tax credits aiming at encouraging renewable energy for electricity and have co-existed for a couple of years, a reasonable question is which one of these two is better? Or in other words, which one is more effective in stimulating investments in renewable energy? If we can tell the advantage of one policy over another, it will provide the federal government meaningful guidance on the future policy tendency. The main task of this thesis is to answer this question.

In this analysis, I constructed models on the individual level and on the aggregate level, solved the models and ran simulations to get expected values of key measures using the Monte Carlo methods. Basing on the results I got, I conducted comparisons between the PTC and ITC in terms of their effectiveness and efficiency on stimulating investment in the renewable energy sector, and discussed results in different situations.

The effectiveness and efficiency of tax credit policies in the renewable energy sector has been discussed a lot in previous literature. However, the most distinguishing point of this analysis is that I include the uncertainty of policy status as well as electricity prices in a theoretical model, and find solutions to this model to study the investment decisions of renewable energy projects. The uncertainty of electricity price is obvious, for it always fluctuates over time. But the uncertainty of tax credit policy status is also a noticeable phenomenon related to this topic, and has very important influence in construction decisions for wind projects.

First, I constructed an individual level theoretical model characterizing conditions that a firm would follow when deciding to invest in a renewable energy project or not, when there are uncertainties in electricity price and tax credit policies. Mainly I adopted models constructed by Hassett and Metcalf (1999), and adjusted it to fit the scenario I am studying. After I get the solutions to the individual model, I extended it into aggregate level by bringing in production heterogeneity, and then found the market equilibrium condition and solved it.

Second, I estimated all the parameters and constant variables shown in my model by collecting data and running regressions. With these parameters, I calculated trigger price lists of wind projects with different production level.

Third, I run multiple simulations of stochastic processes in aggregate level model, and then record the measures of interest during each simulation. By taking an average of these measure values, I get the expected value of these measures following the Monte Carlo Method. Basing on these expected values, I compared effectiveness and efficiency of current PTC and ITC portfolios.

Finally, I ran analogous simulations and conduct comparisons in different scenarios. (1) I compared the effectiveness and efficiency of these two tax credit policies in a scenario where wind energy industry is better developed than in the original model, which means that wind turbine projects have already been fully planted in sites with high wind resources. (2) I compared trigger prices of wind projects with different values of electricity price growth trend and different values of policies' responsiveness to price levels.

Simulation results of the basic model show that the current ITC portfolio can stimulate more electricity produced from wind energy sector per dollar spent by the government than the current PTC portfolio does. So ITC is more efficient than PTC. Moreover, PTC can encourage more wind energy investment and cost the government less in total than ITC does, indicating the current ITC portfolio has more positive effects on encouraging wind energy investment than PTC does, and ITC is an economically better choice for the government.

But if the wind energy industry is well developed, simulation results show that both the ITC and the PTC are less efficient in stimulating electricity output from the wind energy industry than they are in the original model. However, ITC remains its comparative advantage over PTC in both perspectives of efficiency and effectiveness.

Additionally, from the sensitivity analysis on policies' responsiveness and electricity price trends, I found wind projects with different production level would react differently to the change of price trends under different values of policies' responsiveness.

The remainder of this thesis is organized as follows. I review related literature in the next section. The construction of theoretical models, in both individual level and aggregate level, is illustrated in section 3. Then in section 4, I show how I get estimation of parameters and constant variables shown in the models, and describe each step I take in simulations. Results of simulations are shown and analyzed in section 5. Section 6 shows sensitivity analysis on results from different simulation scenarios. Conclusions are provided in section 7.

## 2. Literature Review and Background Information

To start, let me provide some historical information on Production Tax Credit (PTC) and Investment Production Tax Credit (ITC) policies. PTC was first enacted in 1992, and initially expired in July 1999. Through the first start date to present, PTC has expired, been reenacted and extended several times. This frequent change of policy status is the source of policy uncertainty, and I characterize this uncertainty in my analytic model.

One point to notice here is that the tax credit policies were made retroactive after being renewed each time. However, wind project owners did not know that they would still get matched for tax credit benefits if they constructed wind projects when the policy was not in place. Therefore, when the firm owners are making investment decisions, they consider that they would not get tax credit benefits if they invested in the industry during the policy expiration periods, and this is one of my assumptions in this model.

As for the Investment Tax Credit, the policy history in renewable energy sector is shorter. Though ITC was first created in 1972[2], it was not until year 2005[3] that ITC has been applied to encourage investment for renewable energy sector, including wind and solar. It offered and still offers a 30% tax credit of capital investment for legitimate projects, but will decline gradually in several future years.

Along the history of investment and production tax credits, the status of policies have changed several times, which brings uncertainty into their expected future policy status.

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2 Taubman, Paul. "Investment Tax Credit, Once More, The." BC Indus. & Com. L. Rev. 14 (1972): 871.

3 See < http://www.ownenergy.net/knowledge-center/government-incentives/investment-tax-credit-itc >

Rational firms should consider this uncertainty of getting potential profits from tax credits, when they are making investment decisions. Therefore in this thesis, I construct models containing these thoughts and conduct a comparison between ITC and PTC.

The most important point of the models is that I take uncertainties of policies and electricity prices into consideration when I analyze this problem, and I mainly adopted the theoretical model constructed by Hassett and Metcalf (1999). In this paper, the authors build models on irreversibly investment under uncertainty. They construct option value models characterizing individual firms' decision when the firms face an uncertain investment tax credit and fluctuating product prices. I adopted this model to analyze individual firms' investment decisions on wind projects under uncertain Investment tax Credit. Basing on this model, I constructed the individual level model under uncertain PTC, and the aggregate level model characterizing reactions of the wind industry towards fluctuating policy status and electricity prices.

In this thesis, I analyze the influence of policy uncertainty on wind project investment decisions by constructing a theoretical model. However, there are many researchers who studied this topic in their papers. Barradale (2010) discussed the effects of policy uncertainty on investment decisions in wind energy sector from a practical perspective. She claims that the uncertainty of the renewal of PTC has discouraged wind plant investment. First, it is not the low credit amount of PTC that influences the shortage of investments in wind energy field, but the uncertainty of its return. In the periods when the renewal of PTC is uncertain, independent power producers (IPPs) pessimistically assume no PTC renewal, whereas utilities optimistically assume PTC renewal. This makes Power Purchase Agreements (PPAs), the long-term contract under which the electricity producers sell the power, difficult to negotiate, leading to a volatile pattern of the investments. Also, Wiser, Bolinger et al. (2007) summarizes the legislative history of the PTC. They provide their conclusion on the impacts of the uncertainty of PTC, including difficulty in rationally planning transmission expansion and a reduction in R&D expenses. Moreover, they also have mentioned the benefits of a long term PTC, which encourages growth in domestic wind turbine manufacturing. In my framework of analysis, this can be seen as construction of wind projects in lower wind resource areas. Grobman and Jeffrey (2002) investigate the manner in which policy uncertainty of PTC impacts investment in wind power. Their results show that the expectation of a potential PTC enactment may decrease the level of wind power investment due to the increased option value of waiting for the PTC. In contrast, the expectation of a potential PTC removal may increase the level of wind power investment as firms increase their rate of investment to take advantage of the PTC while it is in effect. And this is consistent with my analysis, for this effect is an underlying intuition in the theoretical model in this thesis. Moreover, there are some research projects studying investments in renewable energy under electricity price uncertainty. Fleten, Maribu et al. (2007) present optimal investment strategies in decentralized renewable power generation under electricity price uncertainty. Similar to studies on investment with uncertainty in energy policies, Yang, Blyth et al. (2007) use a real options model to analyze the effects of government climate policy uncertainty on private investors' decision-making in the power sector. More generally, there are many research papers focusing on influence of tax credit policy uncertainty on individual firms' investment decisions (Pawlina and Kort (2005), Bohm and Funke (2000), Bloom, Bond and Reenen (2007)). Many of these researches construct models that are extensions of the one from Hassett and Metcalf (1999). Hassett and Sullivan (2016) provide a solid summary about these literatures and illustrate the difference among the models in these papers.

The assumption that prices of Natural Gas for power follows Geometric Brownian Motion in my model is fundamental to my research. Basing on this assumption, I show that the electricity price faced by potential wind turbine project owners is also following a Geometric Brownian Motion, and then derived the solutions to the model. This assumption is based on many previous research projects on trends of fossil fuel prices. Shafiee and Topal (2010) summarize previous uses of Geometric Brownian Motion in predicting natural gas prices, showing the appropriateness of taking this approach to proxy natural gas price process. For example, Fleten, Maribu et al. (2007) take this approach in constructing models to analyze firms' decisions on investment. Pindyck in his book *Volatility in natural gas and oil markets* (2003) also mentions the approach treating the spot price of the natural gas following a geometric Brownian motion. Similarly researches have also been conducted on oil price trends. Postalli and Picchetti (2006) find that Geometric Brownian Motion can perform well as a proxy for the movement of oil prices based on a quantitative analysis.

Besides, many previous research projects conducted studies on effects of renewable energy encouragement policies. Comello and Reichelstein (2015) study the effects of ITC and gives an alternative way of phasing down ITC for Solar Energy. They argue that the present expected sudden phasing down of ITC from 30% to 10% causes a “cliff” of the cost in Solar Energy field, which would harm the industry. Lewis and Wiser (2007) examines the importance of national and sub-national policies in supporting the development of successful global wind turbine manufacturing companies.

Unlike researches focused on effects of one single policy, Aldy and Sweeny (2015) conducted an empirical study on comparing the stimulating effects of PTC and ITC. They exploit a natural experiment in which wind farm developers were unexpectedly given the opportunity to choose between these two options in order to estimate the differential impact of these subsidies on project productivity. And they found that wind farms choosing the capital subsidy produce 8.5 to 11 percent less electricity per unit of capacity than wind farms selecting the output subsidy and that this effect is driven by incentives generated by these subsidies rather than selection. However, their study focuses on the electricity output of wind projects legitimate to PTC and ITC. They studied how wind projects would operate after they are registered for PTC and ITC benefit. While in my study, I focus more on the entry of wind projects into the electricity market. For the convenience of studying, I assumed wind projects would operate in the same way under ITC and PTC. So I am studying this topic, the comparison between PTC and ITC, from a different perspective than Aldy and Sweeny’s.

# 3. Theoretical Model Part

To characterize investment decisions made by renewable energy industries corresponding to two types of tax credit policies with uncertainty (Production Tax Credit (PTC) and Investment Tax Credit (ITC)), I developed aggregate level and individual level models based on Hassett and Metcalf's (1999). In the following subsections, I show the derivation and remarkable results of these models.

## 3.1 Constant Return to Scale

Two main sources of renewable energy are wind energy and solar energy. Firms of these two industries share a common feature: they can be treated as constant return to scale production in a general analysis. Namely increasing input of capital investment (solar PV and windmill turbines) will not influence the quantity of raw resources allocated to each electricity generator. For example, the numbers of wind turbines and solar PVs constructed in a place do not affect wind strength and sunshine level, respectively, there. So the firms in renewable energy industry can be considered as that they are constant return to scale. This is a key feature in individual level investment decision analysis.

But in aggregate level, production shows heterogeneity among the whole industry, due to uneven natural resource allocations (in this case, wind and sunlight). I will discuss more about it in aggregate level analysis.

Considering firms in both industries are constant return to scale, I conduct studies on a particular fixed level of capital input can represent the characteristics of total investments. With this unit level investment given, firms are facing a present value maximization problem when they are deciding whether or not to undertake a fixed construction project. With uncertainty in exogenous electricity price and tax credit policies, option value models for investment decisions can be applied to analysis on firms' decisions on each of these potential projects.

My study focuses on analyzing the effects and efficiencies of PTC and ITC in wind industry. Given this similarity of wind and solar industry, all analysis on wind turbines and wind energy industry can be conducted analogously on solar PVs and solar energy industry respectively, but with different parameters. In this thesis, I am not doing this analysis for solar industry, which is a possible extension of this research project.

## 3.2 Individual Model for Firms' Decisions under PTC

### 3.2.1 Uncertainty of electricity prices

Profits of these investment projects come from two parts: generating electricity and getting tax credits subsidies. For the convenience of study, it is reasonable to assume a wind turbine can generate electricity for infinitely long time, for my study is based on a long period of time. There are three factors that determine profits of electricity sale: (1) wind turbines' generating power in a unit time period with a unit strength of wind ($\overline{q}$), (2) exogenous electricity price ($p_t$), and (3) natural wind resources in the place where this turbine is planted ($\delta$).

Given fossil fuel electricity generating firms have large share of electricity markets and that marginal costs of these firms are significantly higher than those of electricity firms using other sources, exogenous electricity price $p_t$ is mainly driven by volatile fossil fuel prices (i.e. natural gas and oil). As can be seen from natural gas price time trend and previous research (Shafiee and Topal (2010), Fleten, Maribu et al. and (2007) Postalli and Picchetti (2006)), fossil fuel prices are tending to follow a process close to Geometric Brownian Motions. So I assume $p_t$ to follow Geometric Brownian Motion, corresponding to the pattern of fossil fuel price volatilities:

(1) $$dp_t = \mu p_t dt + \sigma p_t dz_t$$

Here we use a continuous process model to represent the discrete electricity price changes for the convenience of mathematical analysis. Discrete variables in reality can be considered as discrete observations of a continuous underlying model. And I use month as the unit time in my analysis. So time period $t$ indicates that it is the $t^{th}$ month in the analysis.

### 3.2.2 Production Tax Credit Uncertainty

As mentioned in the review of previous studies on PTC, the profits available from PTC are uncertain, and there are two statuses of wind energy PTC: in place and not in place. Firms can and only can get benefits of production tax credits if turbines are connected to the grids when PTC is in place. For now the PTC offers 2.3₡ per kWh for electricity produced by wind power for the first 10 years of operation. For a single wind turbine, the amount of electricity it generates in a unit time can vary over time, because the strength of wind dose not stay the same. I use an average electricity output level $\delta \bullet \overline{q}$, such that the total electricity produced by a wind turbine at a place with wind blowing in one year is equivalent to electricity produced by a generator with a constant output level $\delta \bullet \overline{q}$ continuously producing for one year. As I mentioned in the literature review of the efficiency of renewable energy in literature review part, the maximum efficiency of wind turbines is only 59% of theoretical maximum time (24 hours per day). Therefore I set the highest wind resource factor $\delta$ equaling to 50% in my study, which is a little bit less efficient than the most possibly efficient wind turbines. So the maximum equivalent operating time is $\overline{q} \bullet \max\{\delta\} = 24 \times 0.5 = 12$ hours every day. Then the expected amount of electricity generated by this turbine in 10 years is determined by average natural wind strength in the place where this turbine is planted, which is denoted as $\delta$, And here the maximum value of $\delta$ is 0.5.

With a constant coefficient ($\overline{\Omega}$) containing working time, subsidy amount ($\overline{p}_{sub}$), discount factor ( $\rho$ ) and average unit time electricity generating power ( $\bar{q}$ ), present value of PTC profits ( $\bar{\pi}$ ) can be expressed as:

(2) $$\bar{\pi} = \sum_{t=1}^{120} \frac{1}{(1+\rho)^t} \times \bar{p}_{sub} \times \bar{q} \times \delta = \bar{\Omega}\bar{q}\delta$$

where $\rho$ is the constant exogenous monthly interest rate.

As in Hassett and Metcalf (1999), I characterize uncertain tax credit policy as a Poisson stochastic process, switching between getting the benefits of PTC ( $\pi_1$ ) and not ( $\pi_0$ ). However, expected profits at time t from PTC would be zero if PTC were not in place at that time point, meaning $\pi_0 = 0$ and $\pi_1 = \bar{\pi}$ . By creating a time variable $\Omega_t$ , the present value of profits ( $\pi_t$ ) from tax credit policy at time *t* equals $\bar{q}\delta \cdot \Omega_t$ . And $\Omega_t$ follows a Poisson stochastic process of the motion:

(3) $$d\Omega_t = \begin{cases} \bar{\Omega} & \lambda_{1t}dt \\ 0 & 1-\lambda_{1t}dt \quad \Omega_t = 0 \\ -\bar{\Omega} & \lambda_{0t}dt \\ 0 & 1-\lambda_{0t}dt \quad \Omega_t = \bar{\Omega} \end{cases}$$

Here $\lambda_{1t}$ and $\lambda_{0t}$ are related to electricity price in a linear format to make tax policies endogenous, demonstrating the covariance between policy response and firm profitability.

(4)

$$\begin{cases} \lambda_{1t} = \bar{\lambda}_1 - \alpha_1 p_t \\ \lambda_{0t} = \bar{\lambda}_0 + \alpha_0 p_t \end{cases}$$

where $\bar{\lambda}_1$, $\bar{\lambda}_0$ and $\alpha_1$, $\alpha_0$ are constant parameters to be estimated

Here $\bar{\lambda}_1$ and $\bar{\lambda}_0$ are the basic probability parameters, indicating the floor value and ceiling value (when $p_t = 0$) of probabilities that the policy status changing from enacted to not enacted and vice versa, respectively. While $\alpha_1$ and $\alpha_0$ are parameters standing for responsiveness to higher (or lower electricity prices). With both of them being positive, the tax credit policy is more likely to vanish with higher prices when the policy is in place, for the probability $\lambda_{1t}$ increases. Similarly, the tax credit policy is more likely to come into place with lower prices when the policy is not in place. I will discuss more about the values of $\alpha_1$ and $\alpha_0$ as well as their infects on comparison of two policies.

### 3.2.3 Option value maximum problem

The time *t* in equations above is the time when wind turbine is connected onto electricity grids. According to Baradale (2010), there is a time period required for construction between time points of firms' investment decision and connection to grids. This study focuses on the decisions of firms on investment over a long period of time, so the short time gap can be ignored in our analysis. Given wind turbines have almost no marginal cost in generating electricity (Logan, Jeffery and Kaplan (2008)). A firm needs to decide when to invest in a wind turbine project by solving the option value maximization problem:

(5) $$V(p_t) = \max_T E_t\left(\int_T^\infty p_s \bar{q}\delta \bullet e^{-\rho t} ds - \bar{F}e^{-\rho T} + \bar{q}\delta \bullet \Omega_T \bullet e^{-\rho T}\right)$$

where $\bar{F}$ is the constant present value of fixed cost of building a wind turbine.

As shown in Equation (5), the profit of an invested project is determined by three terms. Its revenue selling electricity it produces, its fixed cost and its benefits from tax credits. So the value of investment option of a project at time *t* is the present value of highest expected future profit at time *T*.

By solving this maximization problem (Hassett and Metcalf (1999)), there are two trigger prices, $p_0$ and $p_1$. Firms will always invest when electricity price $p_t$ is greater than $p_0$; will invest if PTC is in place when $p_t$ is between $p_1$ and $p_0$; will never invest when $p_t$ is less than $p_1$. Values of $p_1$ and $p_0$ are affected by parameters $\mu$, $\sigma$, $\bar{\lambda}_1$, $\bar{\lambda}_0$ and $\alpha_1$, $\alpha_0$.

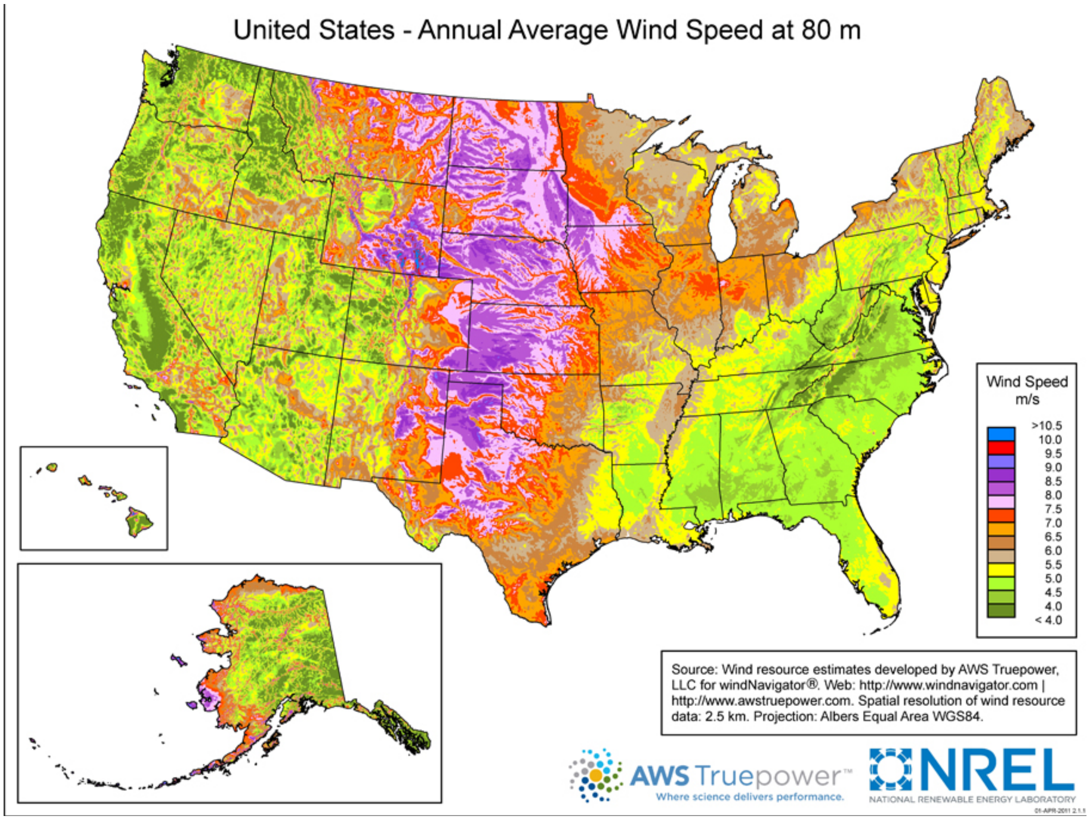
## 3.3 Aggregate Model

The previous model describes how wind firms' decisions on basic level investment are affected by the uncertainty of PTC. Now the question that I want to answer is: How does the whole industry in an aggregate level react to the uncertainty of tax credits? To solve this problem, I constructed a market equilibrium model to analyze this problem by adding production heterogeneity into firms.

### 3.3.1 Production heterogeneity

In an electricity market, assume there are sufficiently many sites with turbine construction potentials. As argued before, a given level of turbine can represent the characteristics of whole investments conducted by all firms, because the industry is constant return to scale. Also, given that the basic mechanic type of wind turbines is similar or same across states, one can assumed that there is only one type of turbine available for building. On all sites, an identical turbine could be constructed, with a constant fixed cost of construction ( $\bar{F}$ ) and the same average electricity generating power ( $\bar{q}$ ). I take wind turbine projects as unit objects of my analysis. Corporations and firms that have multiple wind turbines can be considered as an aggregation of several individual wind turbine projects. Decisions of investment on each turbine projects are still independent from each other. So the whole market of wind electricity can be simply considered as an aggregation of all wind turbine projects. The Figure 1 below shows allocations of wind resources in the United States.

Figure 1: Map of Annual Wind speed at 80-meter[4]




Considering different wind resources across states and regions, I assume there is production heterogeneity in electricity outputs of turbines. So that values of $\delta$ of all potential wind turbine projects are different from each other. The electricity output level (kwh electricity generated per unit of time) of turbines is determined as $\delta_m \bullet \bar{q}$ , where variable m is an index of potential construction sites in a strict construction priority order. Each value of m represents a potential project, and projects with higher value of m will be constructed earlier in the market. In other words, I am assuming that $\frac{d\delta_m}{dm} < 0$ .

To be more specific about the set-ups of this model, here we can see the factor $\delta$ as a

4 Source: http://apps2.eere.energy.gov/wind/windexchange/wind_maps.asp

general factor of production capacity level. It is possible that potential projects located in places with higher wind resources are constructed later in reality. It is partly because that the locations of these projects are too far away from high demand area and the transportation of electricity is too expensive. So the wind firms are less interested in building wind turbines in those places (i.e. Mountain area has far more wind resource than East coast does, while many wind turbines are operating in East coast area and mountain area has not been fully planted with wind turbines). But here I am taking all these factors represented by $\delta$ in a general way. All the high transporting costs of electricity can be considered as a decrease of the wind production level at that location. Then the order of construction can be simply seen as determined only by the value of $\delta$ in a general case. Also, wind resource allocation is more like a discrete distribution across the U.S., which makes this discrete mathematical model of distribution more close to reality.

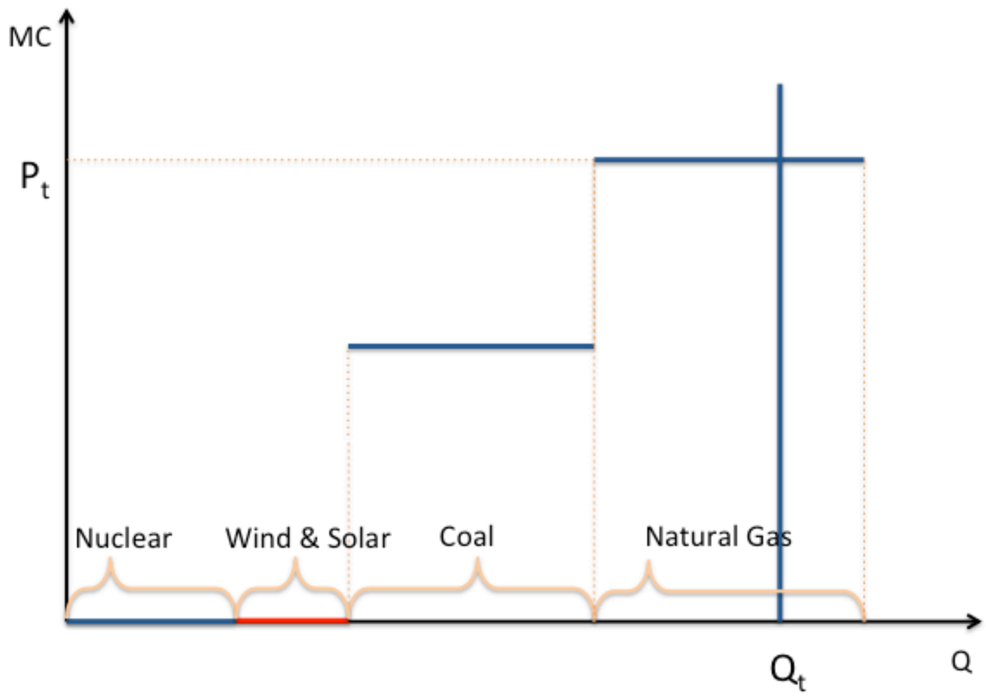
### 3.3.2 Demand and supply in electricity market

To characterize how the electricity price is determined in the market, we need to find expressions of both demand and supply in electricity market. Based on dispatching mechanism of electricity market, dispatching companies exogenously decide total electricity output. Also, considering the low elasticity of electricity demand, one can assume a fixed amount of electricity demand at each time point $t$ in an aggregate level analysis of electricity market. In the following analysis, I use $Q_t$, an exogenous time variable, to denote the total demand of electricity market.

Now I turn to the supply side in this market. As I have mentioned before, fixed costs occurring in constructing processes are the majority of costs in investing wind turbines. Once wind turbines are connected to grid, the marginal costs, which are maintaining costs during turbines' operation, are very low even close to zero. Traditional fossil fuel electricity companies are the main competitors of renewable energy generators in electricity market. Their marginal costs of electricity generating are higher than that of renewable energy firms and are mainly driven by the prices of fuels (e.g. oil and natural gas). Then for each sector of electricity production, I assume their marginal costs to be constant. Therefore, all electricity plants using the same resource have identical marginal costs determined by the resource price of their own sectors. By combining the marginal cost curves of renewable energy, fossil fuel energy industry of electricity generating, we can have a supply curve of electricity market in a shape of step functions, which is shown below in Figure 2.

Here $Q_t$ is the total amount of electricity generated by all energy sectors at time t. With $Q_t$ given, the highest marginal cost among all electricity-generating companies determine equilibrium price of electricity . In this case, it is the marginal cost of generators using natural gas in market. The point I am making here is that the total amount of wind (or solar) energy in the electricity market is not big enough to influence the determining elements of electricity price, which is natural gas price for electricity generation.

Figure 2: Step supply function and demand function




In this supply curve, I consider all electricity is sold in spot market, though renewable energy projects are often offered Power Purchasing Agreements (PPAs), and their electricity is not sold in spot market. I am making this assumption, because considering renewable energy electricity as sold in spot market makes no difference in outcomes when marginal costs of fossil fuel departments are determining the electricity price.

Additionally, I ignored components of other minority sources (e.g. hydraulic power). It is because their proportion of electricity supply and influence on equilibrium market price of electricity are too small to be taken into account.

Let the marginal cost function of natural gas generators at time t denoted as

(6) $$MC_t(Q_t) = p_t$$

Here $MC_t(Q_t)$ is the marginal cost function for natural gas sector, and it is a constant function at a given time point *t*. Since electricity firms are always generating electricity and have the highest marginal cost, $MC_t(Q_t)$ is determined by the fluctuating price of natural gas for power. According to previous analysis on processes of fossil fuel prices, I assume $MC_t(Q_t)$ follows Geometric Brownian motion, so that the electricity price $p_t$ also follows a Geometric Brownian Motion, as shown in the Equation (1) before.

Recall that electricity generated by each renewable energy firm located at m is $\delta_m \bullet \bar{q}$. Then at time t, there are $m_t$ wind electricity generators in the market, and electricity generated by wind sector can de denoted as $D(m_t)$:

(7) $$D(m_t) = \sum_{m=0}^{m_t} \delta_m \bar{q} dm$$

Now take a sum of both renewable and non-renewable energy sector electricity production. Since the total demand for electricity is a fixed constant given as $Q_t$, we have the equilibrium electricity market price at time *t*, which is $p_t$, determined by the following equation:

(8) $$p_t = L_t, \quad for \quad D(m_t) + Q_{Nuclear} + Q_{Coal} + Q_{NaturalGas} < Q_t$$

And this condition is always met in this model.

### 3.3.3 Equilibrium conditions

Since there are sufficiently many potential wind turbine projects waiting to enter market, wind firms are perfectly competitive and electricity price is exogenous to each firm. Production of each firm is too small to lead to an influential change in electricity output and price. Thus at equilibrium status at time $t$, assuming there are measure $m_t$ of firms producing electricity in the market, the firm locates at $m_t$ is indifferent between investing turbine construction and not doing so.

Based on previous analysis of individual level investment, the firm located at $m_t$ will invest at time $T$ so as to maximize the present value of this investment. Denote this maximum investment option value as $V_{mt}(p_t)$.

(9) $$V_{m_t}(p) = \max_{T} E\left(\int_T^{\infty} p_s \overline{q} \delta_{m_t} \bullet e^{-\rho s} ds - \overline{F} e^{-\rho T} + \overline{q} \delta_{m_t} \bullet \Omega_T \bullet e^{-\rho T}\right)$$

Then at equilibrium, $V_{mt}(p_t)$ should be equal to present value of expected profits generated by investing at time $t$. Thus we have the option value condition for this firm as follows:

(10) $$V_{m_t}(p_t) = E_t\left(\int_0^{\infty} p_s \overline{q} \delta_{m_t} \bullet e^{-\rho s}\, ds\right) - \overline{F} + \overline{q} \delta_{m_t} \bullet \Omega_0$$

Combine Equation (9) with Equation (11), we have the equilibrium condition for electricity at time t market as follows:

(11)
$$\begin{cases} p_t = L_t, \quad for \quad D(m_t) + Q_{Nuclear} + Q_{Coal} + Q_{NaturalGas} < Q_t \\ V_{m_t}(p_t) = E_t(\int_0^\infty p_s \overline{q} \delta_{m_t} \bullet e^{-\rho s} \, ds) - \overline{F} + \overline{q}\delta_{m_t} \bullet \Omega_0 \end{cases}$$

Given time point $t$, one can solve the system above and get a solution of $m_t$, denoted as $m_t$*. Thus one can find the output of electricity generation, in renewable sector and in total, and the equilibrium price of electricity at time $t$.

The intuition of this equation system is as following: In a non-equilibrium status, where profit for renewable energy firms to enter the market (constructing wind turbines and generating electricity) is at maximum level at this time point over all the time, potential wind firms will enter the market. Then the supply of electricity from renewable energy sector increases for a certain amount. A number of non-renewable firms, whose marginal costs are the highest among all, procuring the very amount of electricity will be crowded out. With firms entering the market following the order of $m$, production capability of potential wind firms ($\delta_m$) decreases, leading a shrink of investment option values at this time point. As a result, remaining projects' investment profits available at this time point finally go lower than the option value at another time point. Then investing immediately is no longer the strategy brings highest investment option values, and no firm would enter the market, which is the equilibrium status we get from the equation system above.

This model makes electricity price endogenous in aggregate level analysis, and shows the forces driven renewable energy firms entering and leaving the market. The equilibrium status resulted from this equation system follows the pattern:

For each time point $t$, there exists a corresponding value of the measure of wind projects, say $\bar{m}_t$, is determined by the value and history value of $\Omega_t$ and $L_t$, denoted as

(12) $$\bar{m}_t(\{L_r\},\{\Omega_r\};r\in(0,t])$$

The equilibrium value of the measure at time $t$, denoted as $\bar{m}_t^*$, is determined as

(13) $$\bar{m}_t^* = \max_{s\in(0,t]}\{\bar{m}_s\}$$

And the equilibrium electricity generating level of renewable energy sector in the market is $D(\bar{m}_t^*)$.

## 3.4 Individual and Aggregate Models under ITC

All the above is about derivation and analysis on models describing firms' and the industry's reaction to Production Tax Credit policies. What about Investment Tax Credit Policies? Analogous analysis can also be conducted in this case.

First, consider the individual model of firms' decision. Given all exogenous conditions same as they are in PTC analysis, the key difference between PTC and ITC is that PTC offers subsidies related to output quantities, whereas ITC provides subsidies proportional to investment amount. Assume this proportion is constant $w$, and then the profit that can be obtained by a firm from ITC is a constant

(14) $$\bar{\Theta} = w\bar{F}$$

where $\bar{F}$ is the fixed cost of constructing a wind turbine

Similar to what I did before in the PTC case, by creating a time variable $\Theta_t$, one can express the present profits gained by a firm from Investment Tax Credit policy at time *t*. $\Theta_t$ follows a Poisson stochastic process of the motion:

(15) $$d\Theta_t = \begin{cases} \bar{\Theta} & \eta_{1t}dt \\ 0 & 1-\eta_{1t}dt \quad \Theta_t = 0 \\ -\bar{\Theta} & \eta_{0t}dt \\ 0 & 1-\eta_{0t}dt \quad \Theta_t = \bar{\Theta} \end{cases}$$

Here $\eta_{1t}$ and $\eta_{0t}$ are related to electricity price in a linear format to make tax policies making endogenous, demonstrating the covariance between policy response and firm profitability.

(16) $$\begin{cases} \eta_{1t} = \bar{\eta}_1 - \beta_1 p_t \\ \eta_{0t} = \bar{\eta}_0 + \beta_0 p_t \end{cases}$$

where $\bar{\eta}_1$, $\bar{\eta}_0$ and $\beta_1$, $\beta_0$ are constant parameters

Then individual firms will need to solve the option value maximum problem to decide when to invest in a wind turbine project.

(17) $$V(p_t) = \max_T E_t\left(\int_T^\infty p_s \bar{q}\delta \bullet e^{-\rho t}ds - \bar{F}e^{-\rho T} + \Theta_t \bullet e^{-\rho T}\right)$$

It can be shown that results of this problem are analogous to those in the PTC case. There are two trigger prices, $p_0$ and $p_1$. Firms will always invest when electricity price $p_t$ is greater than $p_0$; will invest if PTC is in place when $p_t$ is between $p_1$ and $p_0$; will never invest when $p_t$ is less than $p_1$. Values of $p_1$ and $p_0$ are affected by parameters $\overline{\eta}_1$, $\overline{\eta}_0$ and $\beta_1$, $\beta_0$.

Based on this result, one derive the aggregate model problem for the electricity market as follows:

$$
(18) \qquad \begin{cases} p_t = L_t, \quad for \quad D(m_t) + Q_{Nuclear} + Q_{Coal} + Q_{NaturalGas} < Q_t \\ V_{m_t}(p_t) = E_t\left(\int_0^\infty p_s \overline{q} \delta_{m_t} \bullet e^{-\rho s}\, ds\right) - \overline{F} + \Theta_0 \end{cases}
$$

And at the equilibrium, the output level from renewable energy sector follows a same pattern as that in the PTC case.

# 4. Simulation

Following theoretical aggregate analysis, I then ran simulations to further analyze the efficiencies and effectiveness of PTC and ITC under this model framework. Using Monte Carlo methods, I estimated parameters appearing in the model, simulated processes of policy status and electricity prices over a period of time, and calculated expected values of two measures of interest: Wind projects investment increase and electricity stimulated per dollar of government expense. Through making comparison of these two measures reflecting policies' effectiveness and efficiencies, I am able to conduct a horse race between ITC and PTC on stimulating renewable energy investment. In this session, I fully illustrate each step I took to estimate parameters, run simulations and get these measures.

## 4.1. Estimating parameters

### 4.1.1 Parameters of electricity price process

First, I estimated the trend and variance of electricity process. In the introduction to aggregate models, I pointed out that the electricity price is collinearly related to natural gas price, making electricity price process follow Geometric Brownian Motion as $L_t$ does (as shown in Equation (19)). Divide both sides of Equation (19) with *p* and take an integral of both sides, we have an approximation of relationship between price *p* and time *t*, which is shown in Equation (20), where C is a constant and $\varepsilon_t$ is the error term at time *t*.

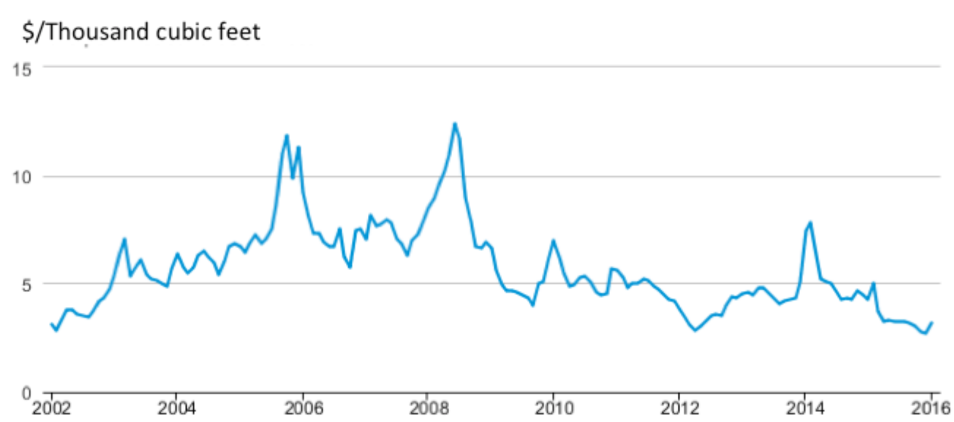
(19) $$dp_t = \mu p_t dt + \sigma p_t dz_t$$

$z_t$ in Equation (19) stands for the wiener process shown in the Geometric Brownian Motion

(20) $$\ln p_t = \mu t + C + \varepsilon_t$$

As discussed before, the electricity price is determined by the price of natural gas used in electricity generation. One can obtain the trend and variance of the Geometric Brownian Motion from a regression of natural gas price history over time. Figure 3 is a graph of real U.S. Natural Gas Electric Power Monthly Price history.

Figure 3: U.S. Natural Gas Electric Power Price, Monthly[5]




5 Source: http://www.eia.gov/opendata/qb.cfm?sdid=NG.N3045US3.M

Using data of historical natural gas prices, I ran a regression of the logarithm of natural gas prices on time. As we can see in Equation (21), the coefficient of $t$ is an approximation of $\mu$. The standard error in this regression is an approximated estimation of $\sigma$.

In the regression estimating $\mu$ and $\sigma$, I only used data of natural gas price history from year 2002 to 2010. It is because there was a dramatic continuous downward trend of natural gas prices starting at 2011. This shock is more of a reaction to the shock on global energy market[6], which is probably followed by a recovery of natural gas market in the future. But for now if we take this downward trend into consideration when estimating parameters, the estimate would be biased. Because this declining trend is the first half part of this fluctuation, and the probable recovery in the future has not been taken into account. So I take the period from year 2002 to 2010 and get estimates from the regression results shown in Table 1.

According to the regression results, I have estimations of $\mu = 0.00238$ and $\sigma = 0.2899$. And these are the values I am using for $\mu$ and $\sigma$ in following simulations. However, alternative estimates of $\mu$ and $\sigma$ are also possible in reality (i.e. estimates in regression on the whole period price process). I will conduct sensitivity analysis on other possible values of $\mu$ later in this paper.

6 See <http://www.usnews.com/news/blogs/rick-newman/2012/03/16/5-things-that-change-when-gas-prices-spi>

Table 1: Regression results

| | ln(price) |
|---|---|
| t | 0.0024 |
| | (0.0009)*** |
| Intercept | 1.6878 |
| | (0.0567)*** |
| $R^2$ | 0.062 |
| *N* | 108 |
| Standard Error | 0.29 |

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Standard errors in parentheses

### 4.1.2 Parameters of policy status process

In the discussion of theoretical model part, I characterized the policy status process as a Poisson process of two statuses. Now I need to estimate the value of $\bar{\lambda}_1$ and $\bar{\lambda}_0$, which are the ceiling and floor probabilities of PTC/ITC policy status changing from enacted to not in place and the other way around. According to the property of Poisson processes, the expected duration of PTC/ITC's lapse (and enactment) period equals to the inverse of $\bar{\lambda}_0$ (and $\bar{\lambda}_1$). So I estimated the values of these two parameters by inversing the expected duration of lapse (and enactment) period of policies. To get approximate expected values of average durations, I took averages of time length of sample periods. Records of PTC expiration and extensions are shown in Table 2 from Sherlock (2014)**.**

**Table 2. Renewable Electricity PTC Expirations and Extensions**

| Legislation | Date Enacted | PTC Eligibility Window | Lapse Before Extension? |
|---|---|---|---|
| Energy Policy Act of 1992 (P.L. 102-486) | 10/24/1992 | 1/1/1993 - 6/30/1999 (closed-loop biomass)<br>1/1/1994 – 6/30/1999 (wind) | — |
| Ticket to Work and Work Incentives Improvement Act of 1999 (P.L. 106-170) | 12/17/1999 | 7/1/1999 – 12/31/2001 | Yes<br>7/1/1999 – 12/17/1999 |
| Job Creation and Worker Assistance Act (P.L. 107-147) | 3/9/2002 | 1/1/2002 – 12/31/2003 | Yes<br>1/1/2002 – 3/9/2002 |
| Working Families and Tax Relief Act (P.L. 108-311) | 10/4/2004 | 1/1/2004 – 12/31/2005 | Yes<br>1/1/2004 – 10/4/2004 |
| The Energy Policy Act of 2005 (P.L. 109-58) | 8/8/2005 | 1/1/2006 – 12/31/2007 | No |
| The Tax Relief and Health Care Act of 2006 (P.L. 109-432) | 12/20/2006 | 1/1/2008 – 12/31/2008 | No |
| The Emergency Economic Stabilization Act of 2008 (P.L. 110-343) | 10/3/2008 | 1/1/2009 – 12/31/2010<br>10/3/2008 – 12/31/2011 (marine and hydrokinetic)<br>1/1/2009 – 12/31/2009 (wind) | No |
| The American Recovery and Reinvestment Act of 2009 (P.L. 111-5) | 2/17/2009 | 1/1/2011 – 12/31/2013<br>1/1/2010 – 12/31/2012 (wind) | No |
| The American Taxpayer Relief Act of 2012 (P.L. 112-240) | 1/2/2013 | 1/1/2013 – 12/31/2013 (wind) | No* |
| Tax Increase Prevention Act of 2014 (P.L. 113-295) | 12/19/2014 | 1/1/2014 – 12/31/2014 | Yes<br>1/1/2014 – 12/19/2014 |

**Source:** Information compiled by CRS using the Legislative Information System (LIS).

Sherlock (2014)

From this table, we can see there are four complete lapse and enactment periods. The following Table 3 shows calculated duration time lengths of the four laps and enactment periods, and the average time duration of PTC/ITC enactment and lapse are 34.25 and 7.25 (in months). Taking inverses of both average values, I have the estimate of initial parameter of status-changing probabilities, $\bar{\lambda}_0$ and $\bar{\lambda}_1$, equaling 0.029 and 0.138.

Table 3: PTC Enactment and Lapse Duration (in months)

| Enactment Period | Duration | Lapse Period | Duration |
|---|---|---|---|
| 10/1992-07/1999 | 80 | 07/1999-12/1999 | 6 |
| 12/1999-01/2002 | 24 | 01/2002-03/2002 | 2 |
| 03/2002-01/2004 | 22 | 01/2004-10/2004 | 9 |
| 12/2004-01/2014 | 111 | 01/2014-12/2014 | 12 |

One thing that we need to notice here is that the ITC (Investment Tax Credit) policy's enactment status changes in a different pattern from PTC's (Production Tax Credit). The Table 4 below shows effective values of the Investment Tax Credit for wind and solar industries by year.

Table 4: Values of Investment Tax Credit for wind and solar by year

| 12/31/16 | 12/31/17 | 12/31/18 | 12/31/19 | 12/31/20 | 12/31/21 | 12/31/22 | Future Years |
|---|---|---|---|---|---|---|---|
| 30% | 30% | 30% | 30% | 26% | 22% | 10% | 10% |

As we can see in Table 4, the Investment Tax Credit has been amended several times and will decrease gradually in the coming years, which is quite different from the pattern that PTC follows. Despite of the difference in reality, I assume the values of $\bar{\lambda}_1$ and $\bar{\lambda}_0$ are the same for these two policies in my analysis, because identical policy status changing probabilities make the comparison between two policies more straightforward and valuable: their statuses change following the same mechanism.

### 4.1.3 Discounting rate, fixed cost and tax credit coefficient

Then I need to estimate the discount rate $\rho$. Since a month is a unit of time in this analysis, I am using the average monthly discount rate. One possible way to get the estimation of this parameter is to take an average of U.S. in recent 10 years' interest rate as an approximation. But due to the impact of the financial crisis occurred in 2008, the interest rate experienced a dramatic shock in this time period, and the estimate would be biased if I take this approach. Given that a commonly used real intermediate discount rate between two periods in economics research is 0.06 (Warner and Pleeter (2001)), I take an annual discount rate of 0.06, which gives me a monthly discount rate equaling to 0.487%. I use this parameter in following calculation and estimations.

According to an EIA (Energy Information Administration) report[7], the overnight base cost of wind electricity generating facility is \$1850/kW. In this analysis, I consider all wind projects have the same generating power of 1kW. Basing on the constant return to scale property of wind industry I discussed before, this is a feasible and convenient assumption for this analysis. Thus the value of fixed cost ($\bar{F}$) of wind turbine projects equals \$1850.

The final parameters I need to estimate for this model are the tax credit coefficients. In this analysis, the ITC benefit for potential entering firms is a proportion of fixed cost

7 See < https://www.eia.gov/forecasts/aeo/assumptions/pdf/table_8.2.pdf >

($0.3\times\bar{F}$), for that the compensation proportion of ITC is 30%.

But what would that proportion of PTC be? First, the Production tax credit policy states that federal government credits 2.3₡ per kWh for electricity produced by wind power for the first 10 years of operation.

Equation (22) expresses the present value of this 10-year credit, at the time point when a wind turbine is connected on grid**.**

(21) $$PTC_m=\sum_{i=1}^{120}\frac{1}{(1+\rho)^i}\times\bar{p}_{sub}\times\bar{q}\times\delta_m$$

Here I use a discrete summation instead of an integral of continuous income to calculate the profits generated from PTC, because the payment in reality is more likely to be discretely paid at a sequence of regular time points. $\rho$ is the monthly discount rate, which is the monthly interest rate I estimated before. While $\bar{q}$ is the theoretical maximum amount of electricity produced by this single wind turbine in a unit length of time. Since I assume all wind turbines have the generating power of 1kW, I have $\bar{q}=24\times\frac{365}{12}=730$ kWh. But because of the instability of wind resources, a wind turbine can only operate a proportion of time. This proportion varies from turbine to turbine, and is denoted by $\delta$ here, consistent with the denotation we used before in the model part. As we discussed before, $\delta$ is an efficiency factor indicating the production heterogeneity of potential wind turbines at different locations.

With values of the discount rate and the fixed cost already estimated, I calculated the values of PTC profits as a function on the capacity level $\delta_m$. As the Equation (22) below shows, the PTC coefficient $\bar{\Omega}$ stands for the PTC profit as a proportion of the fixed cost for a wind turbine operating 730 hours a month. The value of $\bar{\Omega}$ is 0.823.

(22) $$PTC_m = 730 \times 0.023 \times \frac{1}{0.00487}(1-(\frac{1}{1.00487})^{120}) \bullet \delta_m = 1523.26 \bullet \delta_m$$
$$= 0.823 \times 1850 \bullet \delta_m = \bar{\Omega} \bullet \bar{F} \bullet \delta_m$$

According to Bertz (2014), the most efficient wind turbines can generate electricity equivalent to operating 59% of the theoretical maximum time over the course of a long period. I have assumed the highest efficiency among all potential wind projects is 0.50 in my analysis, which is a little lower than the most efficient turbine in reality. The reason why I made assumption is that I am assuming the wind projects with highest efficiency factors would have already entered the market, for there are wind turbines generating electricity before any encouraging tax credit policies come into effect. According to estimation from EWEA (The European Wind Energy Association)[8], a wind turbine will mostly generate electricity at an efficiency level of 24%. Therfore, I assume the range of $\delta_m$ covers from 0.5 to 0.1, with the typical efficiency level of 0.24 covered.

However, other distributions of $\delta_m$ are also possible and worth considering. I will propose an alternative distribution and make further analysis on it in the Sensitivity Analysis part.

8 See < http://www.ewea.org/wind-energy-basics/>

### 4.1.4 Summary of all parameter values

To summarize, Table 5 shows estimated values of all the parameters and constant variables that appear in the model. ITC can be expressed as a proportion to $\bar{F}$, same as $\bar{\Omega}$ for PTC. Additionally, the values of trigger prices calculated from these values are of the unit $/kWh.

Table 5: Values of constant variables and parameters

| Constant Variable | Value | Parameter | Value |
|---|---|---|---|
| $\bar{F}$ | $1,850 | $\rho$ | 0.00487 |
| $\bar{\Omega}$ | 0.823 | $\mu$ | 0.00238 |
| $\bar{\pi}$ | 0.3 | $\sigma$ | 0.2899 |
| $\bar{q}$ | 730kWh | $\bar{\lambda}_0$ | 0.029 |
| $\alpha_0$ and $\alpha_1$ | 0.1 | $\bar{\lambda}_1$ | 0.138 |

Then I arbitrarily pick $\alpha_0$ and $\alpha_1$ to be 0.1. I am picking this value to make sure that the electricity prices will not be too large or too small compared with the values of $\bar{\lambda}_0$ and $\bar{\lambda}_1$, so that the value of status changing properties make sense.

As for other parameters, they are just the values I estimated in previous part of this section. Thus, I have values of all initial parameters in my analysis. With all these initial parameters estimated, I ran multiple-time simulations to get a comparison on efficiency between PTC and ITC using Monte Carlo method. I will illustrate my simulations step by step in the following part of this section.

## 4.2 Production Heterogeneity and Trigger prices

The main goal of my research is to simulate the reaction of the wind energy industry towards electricity prices and policy states under uncertainty. Given the uneven wind resources allocation in the US, I assume there are many potential wind projects in the market with different level of production capacity. Then the trigger prices for each project will be different from others', and related to their own production capacities. Before I start simulations, I need to get the trigger prices for each project. So that with electricity price and policy status given at each time point, I can check which projects would have entered the market in this situation. Therefore reactions (entering project numbers and their production levels) of the market can be detected along the whole process period

To start, I assume that all potential projects follow a linear production distribution, as shown in Equation (23). The production capacity levels ( $\delta$ ) of each project are negatively correlated with their indexes ($m$), and there are 1000 potential projects in total. As we can see from the equation, capacity of the first project is 0.5, which is the highest capacity level. The values of $\delta$ start at 0.5 and decrease uniformly to 0.1. So the efficiency range of these projects covers from 50% to 10%. This is consistent with what I mentioned in the previous part of this section about the efficiency levels of wind turbines in reality. Here I describe the distribution of $\delta$ to be uniform arbitrarily, and I will discuss more distribution forms in Results part.

$$\delta(m) = 0.5 - \frac{m}{2500}, \quad m = 1,2,...,1000 \tag{23}$$

Since the production level $\delta(m)$ decreases as index $m$ increases, trigger prices for projects will rise as their index numbers rise. Since total amount of electricity produced by the wind sector is not big enough to affect equilibrium electricity prices with its changes, projects with higher indexes, and higher trigger prices, will enter market in a later time point.

Given that the amount of wind projects in operation will not affect the price process, the only difference among calculation of trigger prices for different projects is the change of production capacity. All other elements in this calculation, such as expected present value of electricity income and proportion of tax credit benefit, are of the same structure, making this calculation process less complicated.

As discussed before in the theoretical model section, trigger prices for a particular individual project are part of a solution to a system of six equations (see Appendix). This equation system consists of three value-matching conditions and their corresponding smooth pasting conditions. I use *Mathematica* to solve equation systems for all values of $\delta$. With all parameters have already been estimated, I use *Mathmatica* to numerically calculate trigger prices in the order of indexes, which is just the reserve order of production capacities.

Having estimated values of all parameters, I can get lists of trigger prices for different values of output capacity level in both cases of PTC and ITC. After I get these trigger prices, I run simulations and get the market reactions, which I will talk about more in the following part of this section.

## 4.3 Simulation Steps

In this subsection I introduce what are the steps of the simulation process I ran and how I got quantitative measures to compare stimulating effects and efficiencies of two policies.

To get comparable measures following Monte Carlo method, I need to run multiple simulations and take average values of measures as an approximation of expectation value. I use Matlab in this part of my thesis to run simulations and get values of comparable measures. Trigger price lists data, which are used in simulations and have already been calculated, are imported to Matlab from Mathematica.

### 4.3.1 Simulating stochastic processes

First, let me illustrate steps in a single simulation individually. At the start, I simulate a Geometric Brownian Motion process of electricity prices along the whole time period.

I set the total length of this time period to be 2400, with each step of 1. I am doing this to simulate a time period of 20 years, for the tax credit policies have come out of place for just about 20 years (23 years explicitly). Since I am having a month as the unit time length in my model, I have 240 unit time periods in the process. And for the accuracy of simulation, I decide to divide each month into 10 parts. Then there are 2400 periods in total.

With process step divided, I adjust the values of process trend and variance to make the process consistent to original model. Given the length of one step's time period is one tenth of the original, $\mu$, as the expected exponential increase rate, should be decreased to one tenth. As for $\sigma$, which is the standard deviation of this process, should be divided by the square root of 10 to correspond the time length change. So in this simulation, values of key parameters should be as follows:

$$\mu' = \mu / 10 = 0.000238,$$

$$\sigma' = \sigma / \sqrt{10} = 0.0917.$$

Then for the policy enactment status, I set a dummy variable $status_t$ that equals 1 if the policy is in place and equals 0 if not. At the start point, the policy is in operation. At each time point of simulation, it is possible for the policy status to change. The probability of policy changing is related to its current status and the price at that time point. To be specific, the probability follows equations as follows:

(24)
$$prob(changing) = \begin{cases} (\bar{\lambda}_1 - \alpha_1 p_t) \bullet dt, & status_{t-1} = 0 \\ (\bar{\lambda}_0 + \alpha_0 p_t) \bullet dt, & status_{t-1} = 1 \end{cases}$$

In this simulation, I am calculating a series of values of each variable at discrete time points, and the length of time lags is 1/10 of the unit time (a month). Therefore for this Poisson process, the *dt* part in Equation (24) equals 0.1 when I calculate the probability of policy status at each discrete time point. Values of $\bar{\lambda}_1$ and $\bar{\lambda}_0$ do not change. However, it is possible to have values of the right hand side greater than zero or less than zero for some particular values of electricity price. This will not happen in the continuous case, because *dt* is sufficiently small that none price values can make the probability to large or too small. Thus I adjust the expression of policy status change probability, which is Equation (25) below

(25)
$$prob(changing) = \begin{cases} \max\{0,\ (\bar{\lambda}_1 - \alpha_1 p_t) \bullet dt\}, & status_{t-1} = 0 \\ \min\{1,\ (\bar{\lambda}_0 + \alpha_0 p_t) \bullet dt\}, & status_{t-1} = 1 \end{cases}$$

At each time point in the simulation, I first check and record of how many new projects would have been constructed between this time point and the previous time point by comparing trigger prices with current price with policy status given. Then I simulate the outcome of policy status in the next time interval period, with probabilities calculated from Equation (25). The values of probabilities should be individually calculated at each time point, for the probability changes as the electricity price changes.

### 4.3.2 Measures generated during simulation process

The first measure of interest is the project number increase stimulated by tax credit policies. Following the steps discussed above, I have the increase of wind project numbers over the period. But tax credit polies are not the only force driving this increase. The fluctuation (mainly the increase) of electricity price also has contributed to stimulating investment in wind industry. To isolate the increase of projects number only stimulated by tax credits, I need to subtract the increase number caused by the rise of electricity price. So I checked and recorded the increased number of projects regardless of the existence of the tax credit policy. Basically, I compared the current electricity price with trigger prices under no PTC/ITC (the $p_0$ list). Then I recorded the wind project number increased in this situation without simulating the Poisson process of policy status. The first measure of interest is the project number increase stimulated by tax credit policies, which equals to the difference of the wind project increase number with and without the existence of tax credits. This measure shows the effectiveness of two policies. The more projects stimulated by a policy alone, the more effective this policy is. However, the expense on policies is not considered in the comparison on this measure.

This measure just shows an overall stimulating effectiveness of policies.

Then it comes to calculate the measure that can be used in the comparison on efficiencies between two policies. Following all the steps I have mentioned in previous part, I can simulate policy status processes and get the record of policy enactment status and the number of projects constructed at each time point. Since all projects are constructed in the order of from lower measure to higher project measure, I can also get the total production capacity increased at each time point basing on Equation (23).

I calculate a government expense efficiency ratio, $r_{EE}$, from the respect of electricity output. Equation (26) shows how this ratio is determined.

In Equation (26), $r_{EE}$ stands for the government expense efficiency ratio, *PV(Expense)* stands for the present value of all *Government Expense* spent on paying tax credits to legitimate projects (those connected onto grid when PTC is enacted), and *TEOI* stands for the *Total Electricity Output Increase* driven by tax credit policies. I will illustrate how I calculated values of these variables in the following part.

(26)
$$r_{EE} = \frac{TEOI}{PV(Expense)}$$

To get $r_{EE}$, I first need to get *PV(Expense)*. For ITC, it can be considered as a one-time payment for we consider projects are constructed overnight in our model. While for PTC, I considered it as a one-time payment also. Because I have already calculated present values of all payments in the total operation period, and express them as a lump sum present payment, the PTC parameter.

Then all payments can be considered as an immediate offer at the time point when projects are constructed. However, government expense should not equal to a simple summation of all these immediate payments over the simulation period. These payments are made at different time points, so a same amount payment can have different values because of discount of their values. Thus I just calculate the value of all payments at the final time point in this calculation, where t=2400 for simulation steps of a 1/10 month. Also, as described in the previous theoretical model part, the tax credits offered from PTC is related to the production capacity, while ITC is just a fixed amount with fixed cost given.

Taking all these into consideration, we can get the government expense expression for PTC and ITC as shown in Equation (27) and Equation (28)

(27) $$Expense_{PTC} = \sum_{t=1}^{2400} (status_t \times (\sum_{m=N(t)}^{N(t+1)} \delta(m) \bullet \bar{\Omega} \bullet (1+\rho)^{2400-t}))$$

(28) $$Expense_{ITC} = \sum_{t=1}^{2400} (status_t \times (N(t+1) - N(t)) \bullet \bar{\pi} \bullet (1+\rho)^{2400-t})$$

where *N(t)* stands for the number of projects in the market at time point *t*, while $\bar{\pi}$ and $\bar{\Omega}$ stand for values of ITC and PTC, as proportions of fixed cost, respectively.

Now I need to calculate the total electricity output increase (*TEOI*) stimulated by tax credit policies. Since I have history records of constructed projects and their production capacity level at each time point in both situations with and without the affects of PTC/ITC, I can get the total electricity output over the whole simulation period for both situations. Then I take the difference between them, which is the total electricity output amount increased due to the existence of tax credit policy with uncertainty. Here the electricity amounts I am calculating are compounded to the ending time point of this period, so as to reflect the time value of this electricity output increase.

(29) $$TEOI = \sum_{t=1}^{2400} \left( \sum_{m=N(t)}^{Npolicy(t)} \delta(m) \bullet \overline{q} \bullet (1+\rho)^{2400-t} \right)$$

After getting these two values, I can get the ratio $r_{EE}$ according to Equation (26). In each single simulation, I can get a value of $r_{EE}$. In thousand times of simulation I am running, I take record of each value I calculated, and then take an average of all these values.

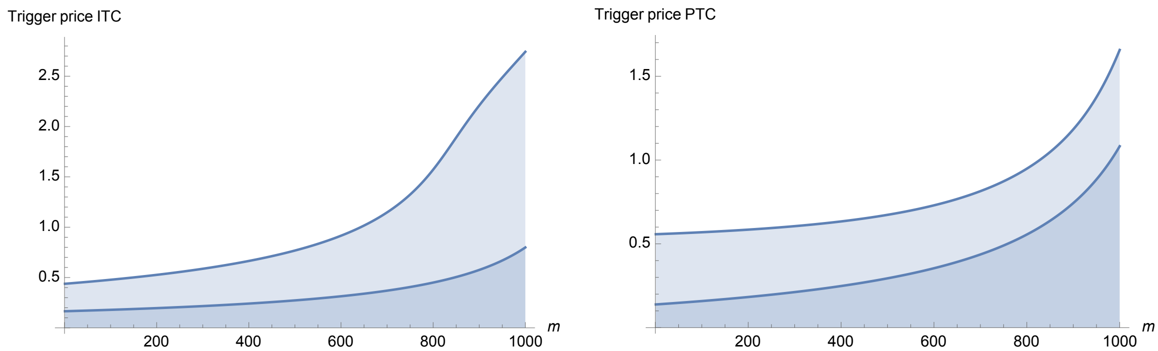
# 5. Results

In this section, I show some results obtained in the simulations I ran, and conduct comprehensive analysis. First I show lists trigger prices, and discussed the gap between two prices. Then there come the record of investment increase process, policy status process and the history of investment increase caused only by fluctuating prices, with which I isolated the investment increase stimulated only by policies. These are all simulation results in one singe simulation process. After 1000 simulations, I recorded the values of measures of interest in all simulations and proxies their expected values following the Monte Carlo Method. Then I conduct comparisons between PTC and ITC on these two measures.

## 5.1 Trigger prices

First, I obtained projects' trigger prices from solving equation systems generated in the theoretical model. The trigger price lists for projects with an output capacity distribution following Equation (23) (the linear capacity distribution) are shown in Figure 4 (trigger prices under ITC and PTC).

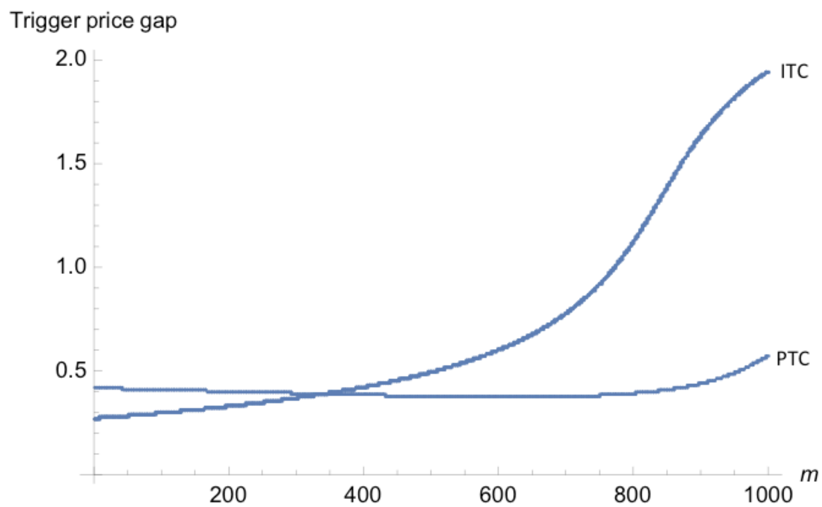
Figure 4: Trigger prices for firms facing ITC and PTC




The horizontal axis in these two graphs is project index, and the vertical axis is trigger prices ($\boldsymbol{p_0}$ and $\boldsymbol{p_1}$). As we can see from the graphs, projects with higher indexes have higher trigger prices than those with lower indexes, with PTC/ITC in place or not in place. Projects with higher indexes (lower production capacities, equivalently) will only be constructed when prices are sufficiently higher. And for each individual project, the trigger price is lower with credit policy in operation than when it is not. This implies that firms are willing to invest in a particular project with a lower price if tax credit policy is in operation, which is consistent to these policies' purpose of encouraging investment in wind industry.

When compare the trigger prices of two policies, one can see that $p_1$ of projects with high production capacity level (i.e. low value of $m$) are higher in ITC case than that in PTC case. This is because that PTC is more profitable than ITC to those projects, for PTC is related to the production level. So projects with high production capacity can expect more profits from PTC, which can compensate their benefit loos caused by entering the market with a relatively lower electricity price. That is why $p_1$ is lower for them with PTC than with ITC.

Figure 5: Trigger price gaps for firms facing PTC and ITC



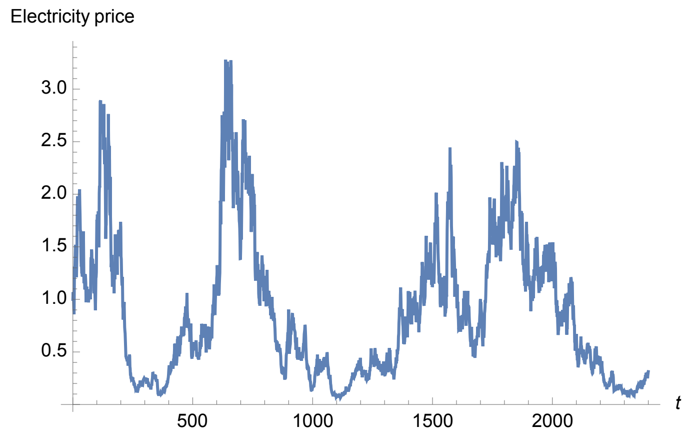

Out of the same reason, when the tax credit policy is not in place, projects with high production level are willing to wait and do not enter market until either PTC is back in place, or electricity price is sufficiently high so that the loss of not getting PTC can be compensated by selling electricity at a high price. This willingness to wait can be expressed by the gap between $p_1$ and $p_0$ . Figure 5 below shows the gap between two trigger prices for all projects under PTC and ITC. For projects with higher production level (lower index number), the gap under PTC is higher than that under ITC, indicating that PTC is more profitable for them. However, ITC is better than PTC for firms with lower production level and higher indexes. This provides a sense that PTC is a good encouragement for investment at high production level, but not so for low production capacity projects. I will discuss more about this feature in the following part of this thesis.

## 5.2 Results in a sample simulation process

After I got trigger price lists, I can run simulations following steps described in previous sections. As what I discussed before, both ITC and PTC benefits can be seen as lump sum profits, and the only difference between them is that one is related to fixed cost value and the other is related to production level. In this subsection, I am going to show the results I get in a single simulation in the case for ITC in the order of outputs, and I will illustrate how I get to move to each next step in a single simulation of these processes. Due to the similarity between PTC and ITC cases, I will only fully illustrate a single simulation process and show the results in it for the ITC case. Analogous results and steps can be implied for the simulations in PTC case.

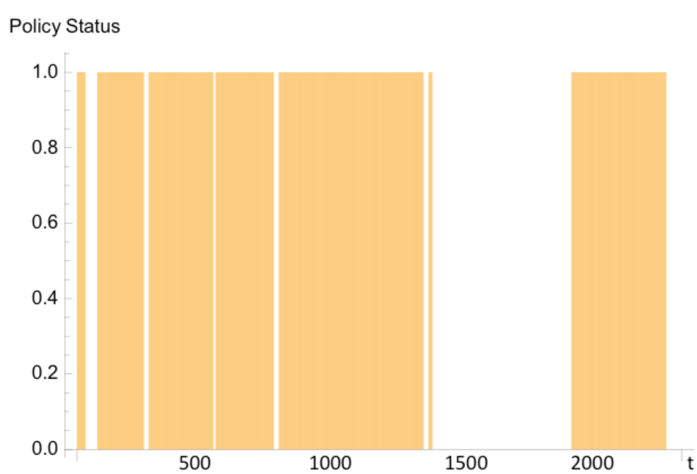
With all parameters estimated as described before, I first get a Geometric Brownian Motion process as the electricity price process, shown as Figure 6.

Figure 6: An Electricity Price Process (Geometric Brownian Motion)




Then based on the value of electricity prices at each time point, I simulate a policy status process. At each time point, I run a Bernoulli experiment following Equation (25) to represent the Poisson process of policy enactment status. The simulated status process I got corresponding to the electricity price process above is shown with a bar chart in Figure 7.

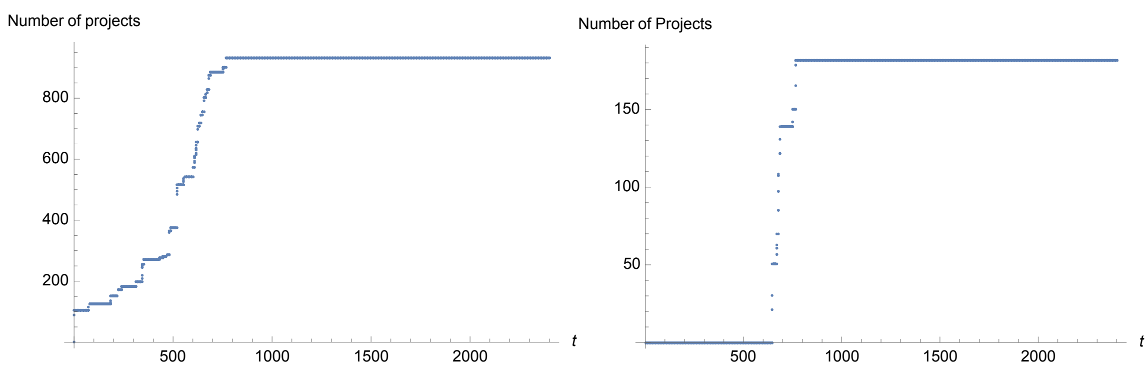
Figure 7: A Policy Status Process




The horizontal axis is time periods, and the vertical axis is policy enactment value. Solid bars (with value of dummy variable $status_t$ equal to 1) indicate the time periods when the PTC is in place, and the blanks stand for periods when PTC is not in place.

For now, these two processes can represent both a PTC case and an ITC case, because I have not get to the part that is different for two cases. In the following, I will take the ITC case as an example as I said before. Through checking the trigger price lists of ITC with electricity prices at each time point, one can get a record of numbers of projects constructed in market, which is shown in the left graph in Figure 8.

Figure 8: Numbers of projects in market with uncertain ITC




The left graph shows an increasing-in-step pattern of project numbers. Based on this number history, we can calculate the production capacity increase at each time point. This is because we have assumed the relationship between project index (*m*) and its production capacity ( $\delta$ ).

Overall, the left graph in Figure 8 shows the history of investment increase in wind energy sector with uncertain ITC policy. With the investment history recorded in the left graph in Figure 8, I can cross check investment increase and ITC status at each time point. So that I have the amount of government expense spent on paying ITC profits to legitimate projects (constructed when ITC is in place) at each time point, and then get the present value of total expense. As argued before, I still need to identify the increase of investment stimulated by the policy ITC alone to get the electricity efficiency ratio $r_{EE}$. Because the fluctuation of electricity price is also a force driving investment increase in the sector other than ITC policy.

In order to isolate the effects caused by ITC alone for both effectiveness measure and efficiency measure, I need to get a process of investment increase where ITC does not exist at all. With the same electricity price (Figure 6), I checked trigger price list without ITC with electricity prices at each time point to get the underlying investment increase driven by electricity price fluctuation. Under this circumstance, the number of projects in market will have a trend shown in the right graph of Figure 8.

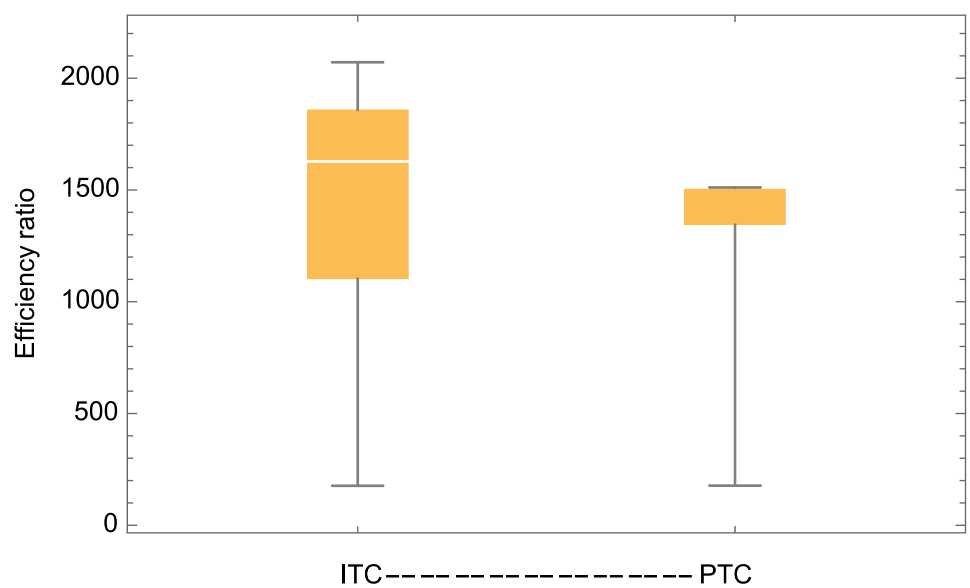
Analogously, I have information and history recorded of this price process. And then follow the instructions illustrated in Simulation section to get a ratio representing the effectiveness of ITC on stimulating investment. However, this is just one possible outcome I simulated. In order to get an approximate of expected value of this ratio, I need to run multiple time simulations and take an average, applying Mote Carlo Method.

## 5.3 Simulation results in 1000-time simulations

After running simulations as illustrated above for 1000 times for both PTC model and ITC model, I have simulation results history that can show us the pattern and effectiveness of how PTC and ITC policies are stimulating investment in wind energy industry. In this section, I will show the results I got in each category of simulations (PTC and ITC). Then, I conduct a comparison between the expected value of electricity efficiency ratio and total project number increase of these two policies.

As I mentioned before, I use *Matlab* running multiple time simulations and taking records of all values of ratios I get. The following Figure 9 contains two plots of all ratio values of $r_{EE}$ I got in 1000 simulations for PTC and ITC respectively.

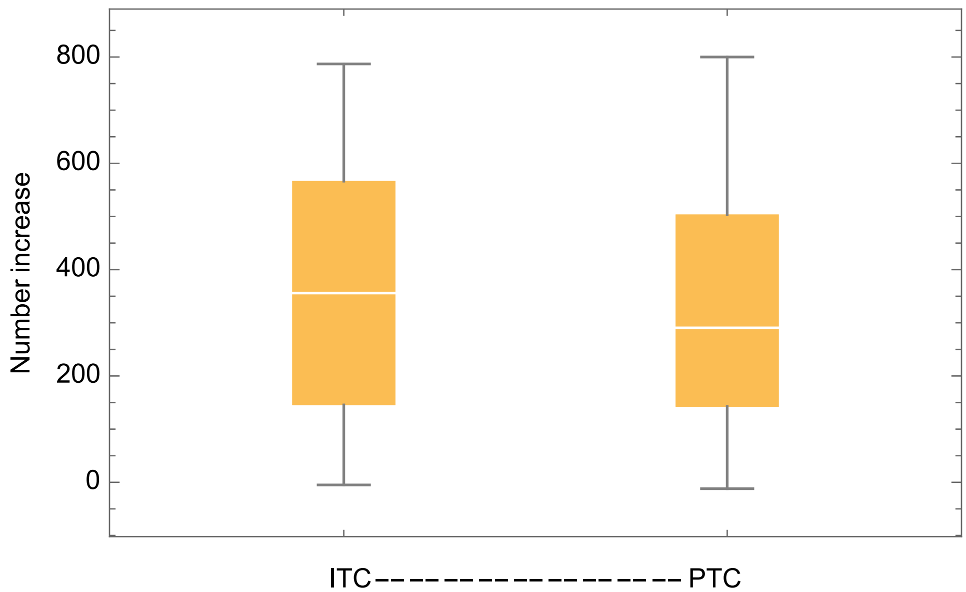
Figure 9: Ratio values for ITC and PTC



The average ratio value for ITC is 1475.23, while the average ratio for PTC is 1329.34. So on average, the expected value of “Electricity Efficiency” measure is higher for ITC than it is for PTC. Intuitively, it says that one dollar of government expense on ITC can stimulate investments in wind energy that generate more electricity than PTC can do in a period of 20 years. In particular, one dollar spent on ITC can stimulate 1475.23 kWh electricity generated in 20 years, while one dollar spent on PTC can only stimulate 1329.34 kWh Therefore, out of the consideration of a better expected-stimulating effect in renewable electricity market, ITC would be a better choice than PTC.

Another point need to notice from these graphs is that the ratio values for PTC is much more concentrated than ITC. Values of PTC ratios are extremely tending to gather at the maximum value, even almost form a solid line at the top, while values for ITC are more evenly distributed. This is because that $p_0$ for firms under PTC is too high, so that in most cases no firm would invest without the existence of PTC. In this circumstance, PTC is the only element driving investment of all the projects constructed over the experiment period. So that the electricity efficiency ratio $r_{EE}$ equals a fixed value, which is just the cap value shown in Figure 9 for PTC. Since this case happens very frequently in this 1000-time simulation process, the values of electricity efficiency ratio for PTC distribute intensively around the cap value.

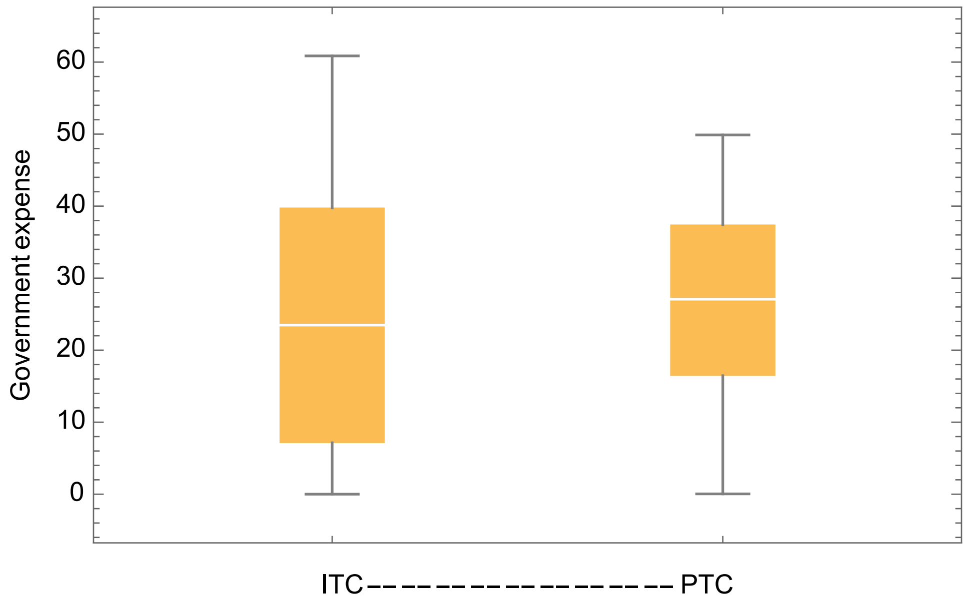
Figure 10: Project number increase for ITC and PTC




Moreover, if we choose the other measure on effectiveness to compare, the conclusion would be the same. Figure 10 shows the total number of wind projects stimulated by tax credit policies, ITC in left and PTC in right. The mean values of total project number increase for PTC is 325.26 and for ITC is 358.48. This indicates that ITC is stimulating more wind projects than PTC does, and overall is more effective in encouraging investment in wind energy. So in the perspective of total projects increase, ITC is still better than PTC.

Additionally, the expenditures of the government on tax credit policies are higher in the scenario where PTC takes place than in the one where ITC takes place. The government expense data in experiments for ITC and PTC are shown in Figure 11.

Figure 11: Government expenses on ITC and PTC




The mean value of government expenses over this 20-year period simulation is 24.37 for ITC and 26.48 for PTC (in billion dollars). So PTC costs more government spending than ITC does in a period of 20 years, showing ITC is more economic than PTC is. Combining this finding with the conclusion we get previously on the total project number increase, ITC is stimulating projects constructed in wind energy sector than PTC is, and costs less. This is consistent with the finding obtained from Figure 9: when stimulating the same amount of electricity from renewable sector, PTC is more expensive than ITC. Overall, the ITC is a better choice than PTC is for the government in stimulating wind energy investments.

# 6. Sensitivity Analysis

In the previous section, I showed and analyzed results I got from simulations basing on the standard theoretical model I developed. In this section, I conduct further analysis on two extensions of the model. First, I re-run the simulations with a different distribution of wind projects' output capacity. After comparing expected values of measures of interest, I found the PTC loses its advantage in the stimulation effectiveness over ITC. Second, I conducted sensitivity analysis of trigger prices with different values of $\mu$ and $\alpha$. Then I found that projects with different production levels are differently sensitive to the values of $\mu$ and $\alpha$.

## 6.1 Comparison in a well-developed wind industry

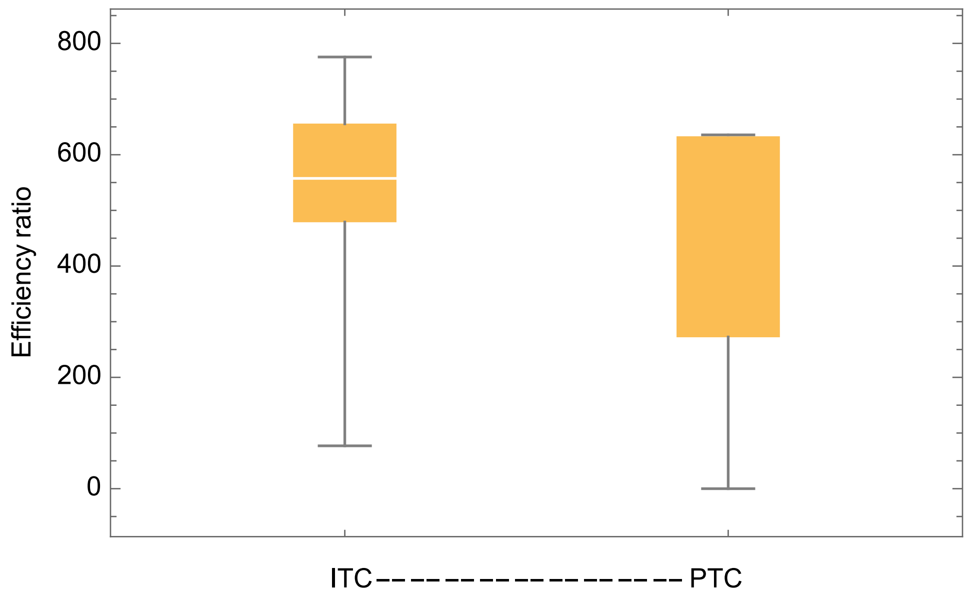
The conclusion I just showed is based on all parameters estimated from data in reality. remain the value levels that they are at for now. But what if the distribution of capacity level changes?

In the previous model, I assume that the capacity factor goes from 0.5 to 0.1, indicating the equivalent operating time goes from 0.5 to 0.1. I made this assumption because the theoretical maximum capacity of electricity generating is 0.59. What if the wind market has already been well developed, and the best position that a wind project can be constructed can only provide an equivalent operating time of 0.24? In this situation, where the wind industry is well-developed, what difference would show in simulation results? How would the conclusion of comparisons between PTC and ITC change?

I then change the distribution of $\delta$ by letting the equivalent operating time for potential wind projects go from 0.24 to 0.12, but still in a linear form for 1000 projects. Then I just followed each step of simulations I mentioned before, ran simulations for 1000 times and have the results recorded.

I got the electricity efficiency ratio simulation results shown in Figure 12. The mean value of ratios for PTC is 542.86, and for ITC it is 465.64, meaning that one dollar of the government expense spent on PTC and ITC can respectively stimulate 542.86 and 465.64 kWh electricity output from the wind industry. So both tax credit policies are less efficient than they are in the original model, indicating the encouraging effects of these two policies decline as the industry develops. However, ITC is still better than PTC from this perspective of efficiency, namely that the government can stimulate more electricity output with each dollar spent on ITC than spent on PTC.

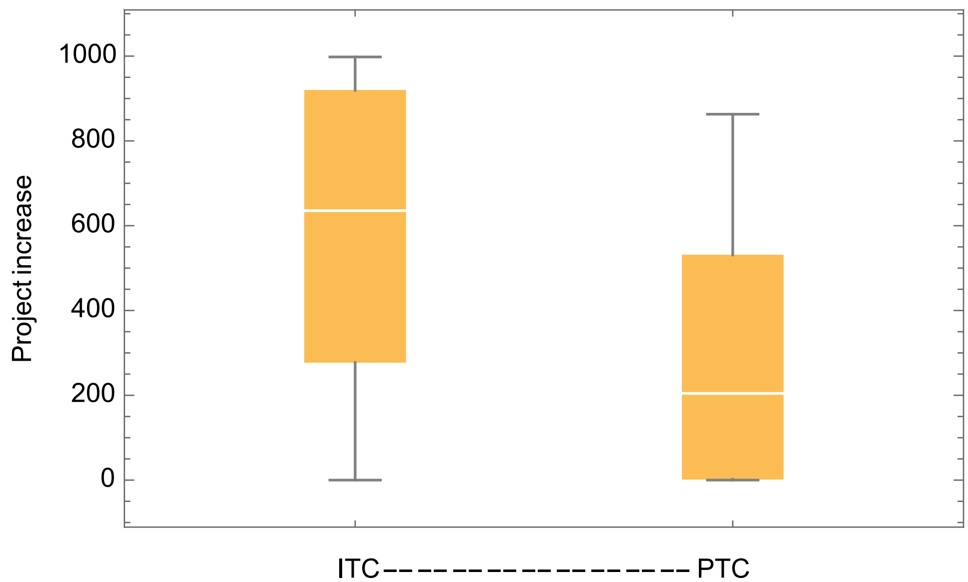
Figure 12: Ratio values for PTC and ITC with well-developed wind industry




Similarly, when it comes to the total number increase of wind projects, the comparison result is same as what I showed before. Figure 13 show the simulation results of total number increase of wind projects for ITC and PTC. The mean value of project number increase is 581.7 for ITC, and is 248.7 for PTC. This means that ITC is more effective than PTC from the perspective of total number of projects stimulated. So ITC remains its advantage over PTC on total project number increase when the market is more developed.

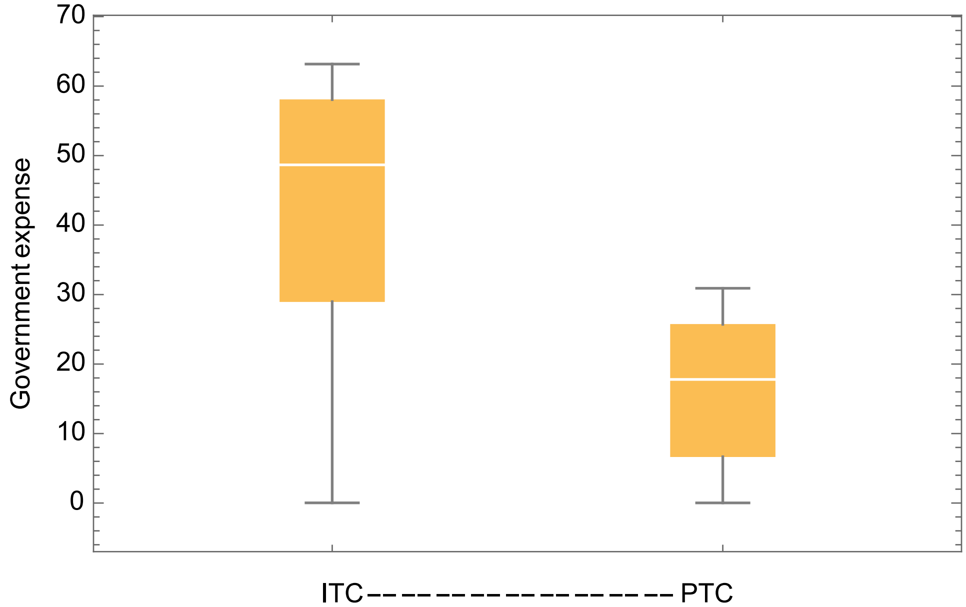
However, when comparing this case with the original model, the mean value of total project number increase caused by PTC is higher than the original value, indicating that ITC encourages more projects constructed in this case than it does in the original model. This is because the ITC is more profitable and attractive to the wind projects with lower production capacities, which are the majority of potential entering projects in a well-developed wind industry.

Figure 13: Project number increase for ITC and PTC with well-developed wind industry




Moreover, the expenditures on ITC are also higher than that on PTC, as shown in Figure 14. The mean value of government expense is 42.5 for ITC and 16.3 for PTC in billion dollars. This is mainly caused by two factors: 1) there are more projects constructed and eligible to credits under ITC than there are under PTC, 2) payments for PTC is related to the production capacities of wind projects while ITC is not, so the government pays less to these unproductive projects with PTC than it does with ITC.

Figure 11: Government expenses on ITC and PTC with well-developed wind industry




Combining this finding with what I showed before, I come up with a conclusion on the comparison between ITC and PTC:

First, if the wind industry is not well developed, then ITC is more efficient than PTC, for ITC can stimulate more electricity from renewable energy industries with each dollar spent. Basing on expected values of the electricity efficiency ratio measure, ITC is more efficient than PTC in stimulating wind energy electricity output. Namely, a government needs to spend more money with PTC than with ITC on stimulating each kWh electricity from the wind industry.

Moreover, when it comes to the overall effectiveness of stimulating investment in wind industry, ITC is still a better choice than PTC is. Because with current portfolios of PTC and ITC, there are more investment made under ITC than PTC. So PTC is more effective than ITC.

Second, even if the wind industry in an economy is well developed, ITC remains its advantage on effectiveness over PTC. Because ITC has expected values of both measures higher than those of PTC

This conclusion shows ITC is a always better choice, no matter how developed is the wind industry, than PTC is to encourage investment in wind energy for the government, from both perspectives of effectiveness and efficiency.

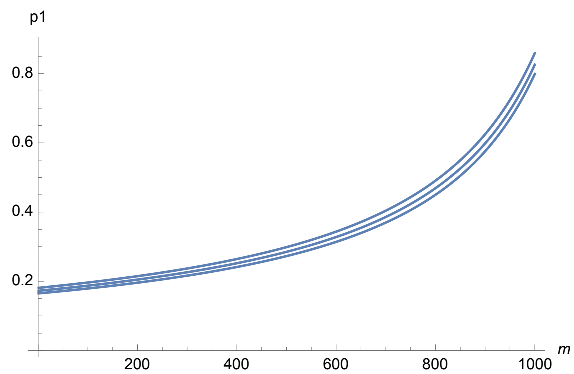
## 6.2 Sensitivity Analysis of trigger prices on policies' responsiveness

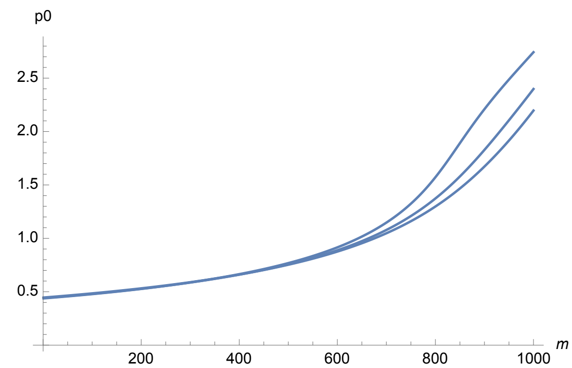
In this subsection, I conduct a sensitivity analysis on trigger prices of projects, in terms of how values of $\mu$ and $\alpha$ may influence wind projects' trigger prices. I only show the case of ITC in the following analysis and omit the analysis on PTC case for convenience, because analogous studies on PTC gives similar results and conclusions.

### 6.2.1 Interactions of trigger prices without ITC ($p_0$)

To study how are trigger prices of wind projects related to the electricity price trend $\mu$, I calculated trigger prices ($p_0$ and $p_1$) of wind projects with different values of $\mu$. I pick three values of $\mu$: 0.00238, the value I estimated before; -0.00262, the values estimated using the whole natural gas price data and 0. The two graphs in Figure 13 below show values of $p_0$ and $p_1$ respectively.

Figure 13: $p_0$ and $p_1$ of wind projects with different values of μ

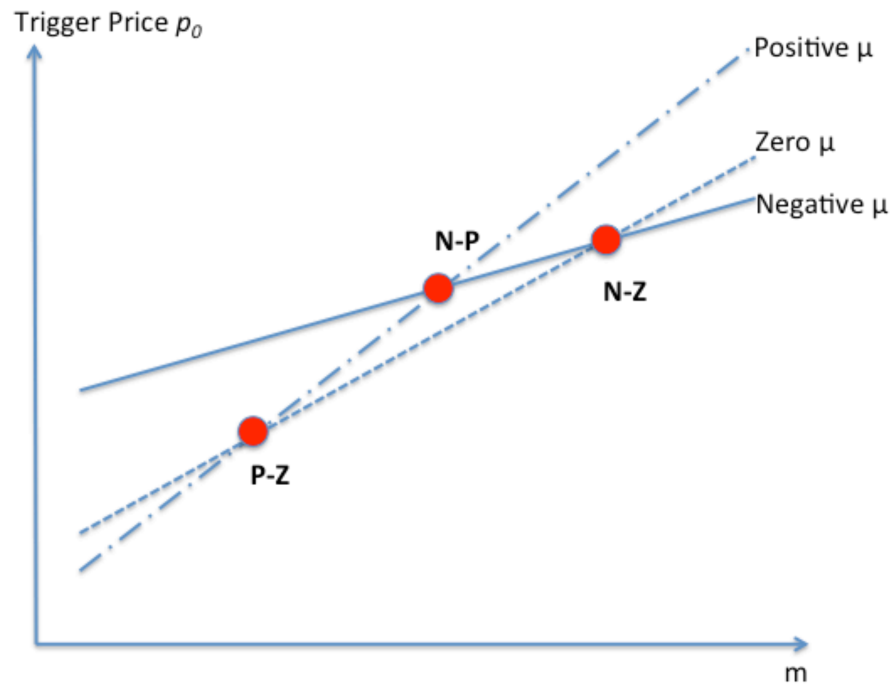



In both graphs of Figure 13, the horizontal axis is the index of wind projects, and the vertical axis is trigger price value. The three lines in the left figure represent values of $p_1$ of wind projects with three different values of $\mu$, and lines representing $p_0$ are shown in the graph in right.

The trigger prices are very close to each other, so it is difficult to see if the lines interact with each other. In fact, the three curves in the left graph are parallel with each other and do not interact. However, the three curves in the right graph interact each other at some point in the middle. Figure 14 shows the relative location relationship among these three curves by zooming in the graph and replacing the curves with symbolic lines.

Figure 14: Symbolic graph for the $p_0$ graph of Figure 13




The interaction points are noticed as PZ, NP and NZ, the corresponding values of horizontal axis of these points are 270, 343 and 420. These are the boundary index values that the relationship of $p_0$s changes. For example, for all projects with index lower than 270, its $p_0$ value gets highest with a positive μ, gets middle with a zero μ and gets lowest with a negative μ. So the interaction points are where the relationship of $p_0$ values with different μ changes.

### 6.2.2 Influence of α and μ on trigger prices

Though the $p_0$ curves interact, the $p_1$ curves are parallel to each other. What causes this difference in curves of $p_0$ and $p_1$? How do the locations of interactions change over different values of α and μ?

The reason lies in the possibility of getting tax credit benefits. Project owners can always get credit benefits when ITC is in place. Then the future revenue from selling electricity is the only factor that may influence expected profits of wind projects. As the value of μ decreases, the expected profit of selling electricity decreases. So the firms would like to wait for electricity price reaching a higher value before entering the market when the value of μ is lower, so as to get to a maximum profit from the investment. Then we can see that when ITC is in place, the trigger price $p_1$ value of each project gets highest with a positive μ, gets middle with a zero μ and gets lowest with a negative μ. As a result, we can see three parallel curves in the graph of $p_1$. I call this relationship *the revenue effect.*

However, there is another approach through which μ can influence trigger prices when ITC is not in place. Firms will not get the tax credit profit if their wind projects are constructed in the laps period of ITC. In this model, the probability of policy status changing is related to electricity prices. ITC is less likely to get re-enacted, as the electricity price gets higher. With a higher value of μ, the electricity grows more rapidly. As a result, the probability of ITC getting back in place is shrinking faster. Thus the wind projects would need to rely more on getting profits from selling electricity, so as to compensate the expected future loss of not getting ITC. Then we can see that the increase of value μ has a positive effect on $p_0$ through this approach. The higher the value of μ is, the higher the trigger price $p_0$ is. I call this relationship *the policy risk effect*.

This positive effect (*the policy risk effect*) offsets part of the negative effect (*the revenue effect*) that the increase of value μ has on trigger price $p_0$. Then the relative greater-less relationship of these two effects determines the total effect of increase of value μ has on trigger price $p_0$. If *the policy risk effect* is greater than *the revenue effect,* then $p_0$ increases as μ rises. Otherwise it is the other way around.

Since *the policy risk effect* is resulted from compensating profits lost with revenues of selling electricity, more productive projects are easier to accomplish this compensation and less influenced by this effect. This is why the order of $p_0$s with different values of μ remains the same as $p_1$s' for those projects with low indexes in Figure 14. They have relatively less *policy risk effect* than those with higher indexes (less productive).

Also, *the policy risk effect* is related to the probability of getting ITC back into place, then the higher the value of $\alpha_1$ is, the higher *the policy risk effect* is. To testify this deduction, I picked three values of $\alpha_1$: 0.08, 0.1 and 0.12. For each value of $\alpha_1$, I calculated trigger price $p_0$ of all projects with different values of μ, and found the interactions of three lines in each case. Table 6 shows results of these calculations.

Table 6: Horizontal axis values of interaction points with different α

| **α** | **P-Z** | **N-P** | **N-Z** |
|---|---|---|---|
| 0.08 | 460 | 525 | 586 |
| 0.1 | 270 | 343 | 420 |
| 0.12 | 73 | 161 | 254 |

According to Table 6, we can see that the interaction points move left when the value of $\alpha_1$ increases, indicating that more projects are having greater *policy risk effect* than *revenue effect.* This pattern verifies the deduction I previously mentioned: the higher the value of $\alpha_1$ is, the higher *the policy risk effect* is. Moreover, higher the value of $\alpha_1$ is, the more projects have greater *policy risk effect* than *revenue effect.* In this situation, more projects are having trigger price $p_0$ decreasing as the electricity price trend $\mu$ decreases. This suggests that by changing the responsiveness parameter $\alpha_1$ and $\alpha_0$, the government can change the relationship between firms' investment trigger prices and electricity price trend. This provides an approach to control the wind energy investment when the government is facing a slow increasing or even decreasing tendency of electricity prices. So that the government can stimulate investment in wind energy when the industry is driven weak by the decrease of electricity prices without taking the tax credit policy back into place.

# 7. Conclusion

In this thesis, I constructed models on both the individual level and the aggregate level characterizing wind firms' reactions on electricity prices and tax credit policy statuses with uncertainty. Then I estimated the values of all the parameters and constant variables shown in this model from real data. Using these parameter values, I get trigger price lists of wind firms with different levels of production capacity. By running 1000 times of simulations of stochastic processes contained in the model, I get expected values of two key measures following the Monte Carlo Method. Then I conducted comparisons between PTC and ITC on effectiveness and efficiency.

By comparing trigger prices, expected values of electricity efficiency ratio and total project number increase, I found that PTC is more profitable and attractive to firms with high production capacity than to those with low production capacities, while PTC is also more expensive for government in stimulating each unit of electricity output. Furthermore, ITC can drive more investment and cost less than PTC does in wind sector no matter how well the wind industry is developed. ITC is always more effective and efficient than PTC from either perspective. So my policy suggestion from my thesis is that: when a government wants to stimulate investments in wind sector electricity generation and has tax credit policies with uncertainty, then it should choose ITC rather than PTC as the encouragement tool.

Then I conducted sensitivity analysis on trigger prices with different values of electricity price trend and policies' responsiveness. I find that by controlling tax credit policies' responsiveness level towards electricity prices, the government can manipulate firms' preference on electricity price trends, so as to avoid the lack of investment in wind energy when the electricity price is not growing rapidly.

In conclusion, I analyzed and compared effectiveness and efficiency of the Investment Tax Credit and the Production Tax Credit. Basing on comparisons and sensitivity analysis, I give suggestions on government choosing policies to stimulate investment in wind energy industry. As for future study on related topics, adjusting the model and simulations shown in this thesis for analysis on solar energy industry is a possible extension of this study.

# Appendix

Following Hassett and Metcalf (1999), one can show that in the case of ITC, the trigger prices $p_1$ and $p_0$ for a wind project with index $m$ is determined by a system of 6 equations, including Equation (A1), (A2) and (A3) shown below.

(A1)

$$\frac{1}{\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1}[Bp_1^{\beta}-A(\bar{\lambda}_1-\alpha_1 p_1)\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma})]=$$

$$C_1[p_1^{\tau_1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_1(i)}\bullet p_1^{n+\tau_1})]+C_2[p_1^{\tau_2}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_2(i)}\bullet p_1^{n+\tau_2})]+\sum_{n=0}^{\infty}b_n p_1^n$$

(A2)

$$\frac{1}{\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1}[Bp_1^{\beta}+A(\bar{\lambda}_0+\alpha_0 p_1)\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma}))=\frac{p_1\delta(m)}{\rho-\mu}-(1-\bar{\pi})\bar{F}$$

(A3)

$$C_1[p_0^{\tau_1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_1(i)}\bullet p_0^{n+\tau_1})]+C_2[p_0^{\tau_2}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_2(i)}\bullet p_0^{n+\tau_2})]+\sum_{n=0}^{\infty}b_n p_0^n=\frac{p_0\delta(m)}{\rho-\mu}-(1-\bar{\pi})\bar{F}$$

where

$$\sigma^2\beta(\beta-1)/2+\mu\beta-\rho=0,\quad and \quad \beta>0;$$

$$\sigma^2\gamma(\gamma-1)/2+\mu\gamma-(\rho+\bar{\lambda}_1+\bar{\lambda}_0)=0,\quad and \quad \gamma>0;$$

$$\sigma^2\tau(\tau-1)/2+\mu\tau-(\rho+\bar{\lambda}_1)=0,\quad and \quad \tau_1>0>\tau_2;$$

$$\Phi(i)=\sigma^2(\gamma+i)(\gamma+i-1)/2+\mu(\gamma+i)-(\rho+\bar{\lambda}_1+\bar{\lambda}_0)$$

$$\Psi_j(i)=\sigma^2(\tau_j+i)(\tau_j+i-1)/2+\mu(\tau_j+i)-(\rho+\bar{\lambda}_1),\quad j=1,2$$

Then take derivative with respect to $p_1/\,p_0$ at both sides of Equation (A1), (A2) and (A3). Let the derivatives of both sides of each equation equal to each other. We can have another 3 equations, say (A1'), (A2') and (A3').

(A1')

$$\frac{1}{\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1}[\beta Bp_1^{\beta-1}-A(\bar{\lambda}_1-\alpha_1p_1)\bullet(\gamma p_1^{\gamma-1}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n(n+\gamma)}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma-1})-\alpha_1\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma})]-$$

$$\frac{\alpha_0-\alpha_1}{(\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1)^2}[Bp_1^{\beta}-A(\bar{\lambda}_1-\alpha_1p_1)\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma})]=$$

$$C_1[\tau_1p_1^{\tau_1-1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_1(i)}(n+\tau_1)\bullet p_1^{n+\tau_1-1})]+C_2[\tau_2p_1^{\tau_2-1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_2(i)}(n+\tau_2)\bullet p_1^{n+\tau_2-1})]+\sum_{n=1}^{\infty}b_np_1^{n-1}$$

(A2')

$$\frac{1}{\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1}[\beta Bp_1^{\beta-1}+A(\bar{\lambda}_0+\alpha_0p_1)\bullet(\gamma p_1^{\gamma-1}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n(n+\gamma)}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma-1})+\alpha_0\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma})]-$$

$$\frac{\alpha_0-\alpha_1}{(\bar{\lambda}_1+\bar{\lambda}_0+(\alpha_0-\alpha_1)p_1)^2}[Bp_1^{\beta}+A(\bar{\lambda}_0+\alpha_0p_1)\bullet(p_1^{\gamma}+\sum_{n=1}^{\infty}(\frac{(\alpha_0-\alpha_1)^n}{\prod_{i=1}^{n}\Phi(i)}\bullet p_1^{n+\gamma})]=\frac{\delta(m)}{\rho-\mu}$$

(A3')

$$C_1[\tau_1p_0^{\tau_1-1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_1(i)}(n+\tau_1)\bullet p_0^{n+\tau_1-1})]+C_2[\tau_2p_0^{\tau_2-1}+\sum_{n=1}^{\infty}(\frac{(-\alpha_1)^n}{\prod_{i=1}^{n}\Psi_2(i)}(n+\tau_2)\bullet p_0^{n+\tau_2-1})]+\sum_{n=1}^{\infty}b_np_0^{n-1}=\frac{\delta(m)}{\rho-\mu}$$

Therefore, there is an equation system of 6 equations: Equation (A1), (A2) and (A3); (A1'), (A2') and (A3'). There are 6 unknowns: $p_1$, $p_0$, $A$, $B$, $C_1$ and $C_2$. So the values of trigger prices $p_1$ and $p_0$ can be found.

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