THREE ESSAYS ON RENEWABLE PORTFOLIO STANDARDS

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

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This dissertation is dedicated to my beloved wife Arin Kwon

supporting me with love and sacrifice.

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THREE ESSAYS ON RENEWABLE PORTFOLIO STANDARDS

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ABSTRACT

The first essay investigates the technical efficiencies of South Korean solar photovoltaic (PV) power plants by type: ground-mounted PV (GPV) and rooftop PV (BPV). The two-step stochastic frontier analysis (SFA) of the true-random effects model is used to capture heterogeneity. In the results, the first-order input parameters are positive and significant, satisfying the monotonicity condition for valid production functions, except for the daily sunshine hours. The average technical efficiency (TE) scores for BPV and GPV are 0.995 and 0.991, respectively, it can be concluded that there is no evidence that many plants of these types are significantly lagging behind the most efficient producers of the type. The estimates of mean technology gap ratio (TGR) values are very close to 1, and the meta-technology efficiency (MTE) scores are 0.991 for the BPV and 0.985 for the GPV. There is a small difference in TEs, TGRs, and input use.

The second essay examines how the Renewable Portfolio Standards (RPS) policy influences the decision-making process of manufacturers regarding the choice between staying in their current country or relocating to a foreign country in response to initiatives such as RE100. Three-stage game is considered in which three player groups participate: the social net benefit maximizing government sets the RPS target in the first stage, the profit maximizing RPS obligors (utilities) makes decisions regarding the amount of

renewable electricity they will provide in the second stage, and the profit maximizing firms supplying RE100 companies determine to remain in their current country or relocate to another country offering cheaper renewable electricity in the third stage. The findings indicate that a rational government will choose a target share that maintains employment as long as it brings a non-negative net benefit. Moreover, there exists a range where between domestic and foreign renewable energy prices to determine domestic production, even when domestic prices are higher. By increasing the price of non-renewable electricity, it is possible to subsidize renewable electricity depending on cost transparency. The exogenous variables determine the subgame perfect equilibrium.

The third essay investigates the impact of RPS policies on total primary crop acreage in the United States. Our empirical framework is based on the premise that acreage is influenced by climatic factors, farmers' crop management practices, and land allocation decisions, while considering input and expected production prices. We extend the framework to incorporate the influence of renewable electricity policy (RPS) and other agricultural policy (CRP). The coefficients of the composite price index are positively related to acreage, while the coefficients of the fertilizer price index exhibit a negative relationship. The estimated output price elasticities range from 0.297 to 0.329, and the elasticities from the models considering electricity market characteristics show similar magnitudes, approximately 0.30. The RPS electricity supply target is found to significantly reduce acreage, although the actual magnitude of reduction is relatively modest, estimated at around 24 to 26 acres per 1000 MWh. Crop acreage changes by target level of renewable electricity is similar to STRATA's data, however it can be seen as overestimated based on the National Renewable Energy Laboratory (NREL)'s data.

TECHNICAL EFFICIENCY AND TECHNOLOGICAL GAPS BETWEEN ROOFTOP AND GROUND-MOUNTED SOLAR PHOTOVOLATAIC PLANTS IN SOUTH KOREA

1. Introduction

In many countries there are significant concerns about the emission of greenhouse gases and microparticles associated with traditional fossil fuel generation, especially coal-fired power generation. To mitigate climate change and to secure sustainable energy, the renewable energy such as solar power and wind power, has been emerging as an alternative to address climate problems and energy demands. Various policies have been implemented to promote the deployment of renewable energy, such as feed-in-tariffs (FIT), feed-in premiums (FIP), and supply targets as well as mandated supply. According to REN21's report of 2021, the most used policies are supply targets, with 33 countries including Australia, Greece, South Korea, the United Kingdom, and the United States having implemented Renewable Portfolio Standards (RPS) nationally or sub-nationally.[1]

An RPS typically increases the proportion of renewable electricity supplied by imposing mandatory obligations. This policy requires electricity suppliers to obtain a certain percentage of their electricity from renewable sources to meet RPS obligations. Compliance can be proved by Renewable Energy Certificates (RECs) which can be acquired by generation of renewable electricity or purchasing RECs in the market. RECs are issued when renewable energy electricity is produced at a certain level adjusted where required based on production method.

[1] Renewables 2021 Global Status Report

In the RPS system, renewable electricity producers sell their electricity and RECs in electricity markets and REC markets, respectively. It is a more market-oriented policy than the Feed-in Systems (FIT and FIP) with the tariffs or premium reflecting the additional cost of renewable energy production. In the electricity market, the renewable electricity producers compete as electricity producers with coal-fired plant companies or nuclear power plant companies to sell their electricity. In the REC market, they can sell RECs to obligors who must demonstrate compliance with their RPS obligations. Therefore, the renewable electricity producers can achieve their revenue from RECs sales to offset the costs associated with renewable energy supplies.

Prior to 2000 in South Korea, a lack of economic feasibility for renewable energy compared to traditional energy sources, especially nuclear power, hampered the development of the industry. To address this challenge and to encourage the production of renewable electricity, South Korea adapted FIT in early 2000s. Implementing FIT presented several challenges, in particular the determination of the proper level of tariffs, and the government budget sources on the tariffs.[2]

In 2012, the South Korean government adapted the RPS system instead of FIT to overcome the problems of FIT. To foster competitive and balanced renewable electricity market among the different technologies, differentiated RECs are assigned to different technologies. In the case of solar photovoltaic power (PV), the differentiated RECs are assigned by installed capacity and type of installation. As of 2022, installed solar PV

[2] Many countries that implemented FIT use tariffs that directly reflect the difference in electricity rates, but in South Korea, the difference was subsidized by the Electric Power Industry Basis Fund. The fund not only supports the deployment of renewable energy, but also supports power demand management projects, power source development promotion projects, and power support projects for residents of islands and remote areas. However, due to tariffs that caused excessive windfalls, there was a boom in construction of renewable energy power plants, and budget problems for funds to be used for other projects emerged (Lee and Cho, 2017).

capacity accounts for 15% of total capacity, with capacity increasing to 19 times that of 10 years ago.

As we stated above, RECs are issued based on the capacity and types of installation, and PVs installed on the rooftop are guaranteed higher REC weights than PVs installed on the ground. One reason for this is that South Korea has a small land area compared to its population, so the installation of PV on existing structures is favored. The purpose of this paper is to study the technical efficiency and technological gaps of rooftop and ground-mounted solar PV plants in South Korea using a stochastic meta-frontier model. For this topic, the research questions follow: Is there a difference in technical efficiency between rooftop PV and ground-mounted PV after the implementation of RPS in South Korea? How do these types of power plants differ from meta-technology, and what factors affect their technology efficiency?

The remainder of this paper is organized as follows: Section 2 review previous literature related to methodologies and renewable energy, especially solar PV. In Section 3 the theoretical model and outline of the empirical model is explained, and the empirical model is described in Section 4. Section 5 provides an overview of PV plant structures in South Korea under the RPS policy, highlighting typical differences. In Section 6, the dataset and variables used in the production function will be described. The empirical estimations and results are presented in Section 7, and conclusions will be followed in Section 8.

2. Literature review

Farrell (1957) introduced the concept of (Farrell) technical efficiency (TE) to measure productivity efficiency. It is a measure of how well an entity utilizes its inputs to produce output compared to the best-performing entity in the observed dataset. The concept of technical efficiency had been developed by Charnes, Cooper, and Rhodes (1978) who introduced data envelopment analysis (DEA), a non-parametric mathematical technique. From DEA, the relative efficiency of multiple entities or decision-making units (DMUs) is evaluated.

Aigner et al. (1977) and Meeusen and van den Broeck (1977) introduced stochastic frontier analysis (SFA). In SFA, both the observed output and the unobserved random factors are considered in the production function of a firm or entity to capture inefficiencies which allow deviations from the maximum attainable output. SFA enables the identification of inefficiencies, the evaluation of performance relative to the production frontier, and the determination of factors that contribute to inefficiency. Also, Greene introduced true-fix and true-random effect models to capture heterogeneity for different groups (Greene 2005a, 2005b) with SFA.

The concept of the meta-production function is advocated by Hayami (1969), Hayami and Ruttan (1970, 1971). It was applied to SFA by researchers such as Battese and Rao (2002), Battese et al. (2004), and O'Donnell et al. (2008), and developed to meta-frontier analysis. It can break down the causes of inefficiency into operational inefficiency and uncontrollable production environment factors (Honma and Hu, 2018). Meta-frontier analysis allows the heterogeneity by estimating separate each group frontier, representing a unique production possibility for each group. Then, these frontiers are compared to a meta-frontier, which represents the optimal achievable frontier across all groups, given the available technologies and resources.

Huang et al. (2014) introduced a two-step stochastic frontier approach for estimating TE scores in firms belonging to different groups that adopt different technologies. The difference between the work of Battese et al. (2004) and O'Donnell et al. (2008) is that they formulate and apply a stochastic frontier analysis model to estimate the meta-frontier in the second step instead of linear programming. Alem et al. (2018) developed Huang et al.'s method by applying the model devised by Greene (2005a, 2005b).

Sueyoshi and Goto (2014) conducted a comparative analysis of the technical efficiency of PV power plants in Germany and the US. They used cross-sectional data and applied the DEA method with a radial model. The inputs considered were insolation, average annual sunshine, photovoltaic modules, and land area, while the outputs included installed capacity and annual power generation. The study found that PV power plants in Germany operated more efficiently than those in the US, which was attributed to the FIT policy.

Cucchiella and Gastaldi (2013) assessed the efficiency of photovoltaic technology in Italy using cross-sectional data. They employed Data DEA under both constant return to scale (CRS) and variable return to scale (VRS) assumptions. The inputs included renewable power plant capacity, solar irradiation, investment cost, and management cost, while the outputs consisted of avoided CO_2 emissions and energy intensity. The study identified the most and least efficient regions and provided a detailed analysis of the results.

Jung (2011) presented an efficiency evaluation method for FIT in the private solar power plant sector in Jeonnam Province, South Korea. The study used cross-sectional data and applied an output-oriented DEA under both CRS and VRS assumptions. The inputs considered were total project cost, construction unit price, plant area, personnel, and installed capacity, while the output was annual power generation. The study revealed that 59% of the examined PV plants had an efficiency below 0.050.

You, Fang, Wang, and Fang (2018) compared the environmental efficiency of 118 PV plants in China using cross-sectional data. They employed an output-oriented DEA under VRS assumption. The inputs considered were insolation, annual sunshine duration, and covering area, while the outputs included installed capacity, annual electricity generation, CO_2 emission reduction, and coal saving. The study revealed a wide range of inefficiencies among the PV plants, with variations in performance across different economic zones. Rooftop PV plants were found to have the highest efficiencies among the four types of PV plants due to minimal power loss.

Table 1 Literature reviews on the renewable energy and solar PV plants

Study	Objective	Location	Model	Inputs	Outputs
Sueyoshi and Goto (2014)	Technical efficiency of PV power plants in Germany and the U.S.	Germany / The U.S.	Input- and Output-oriented DEA under VRS for alternative	1. Insolation (kWh/m^2/day) 2. Average annual sunshine (hours) 3. Photovoltaic modules (# of modules) 4. Land area (m^2)	1. Installed capacity (MWp) 2. Annual power generation (GWh)
Cucchiella and Gastaldi (2013)	Efficiency of photovoltaic technology	Italy	DEA under CRS and VRS	1. Renewable power plant capacity (MWh) 2. Solar irradiation (kWh/m2) 3. Investment cost (€/MWh) 4. Management cost (€/MWh)	1. Avoided CO2 emission (CO2/MWh) 2. Energy intensity (tep/M€)

Jung (2011)	Efficiency of private solar power plants	Jeonnam Province, South Korea	Output-oriented DEA under CRS and VRS	1. Total project cost (KRW) 2. Construction unit price (KRW) 3. Plant area (m^2) 4. Personnel (person) 5. Installed capacity (kW)	Annual power generation (kWh)
You et al. (2018)	Environmental efficiency of PV plants	China	Output-oriented DEA under VRS	1. Insolation (MJ/m^2) 2. Annual sunshine duration (hours) 3. Covering area (m^2)	1. Installed capacity (W) 2. Annual electricity generation (kWh) 3. CO2 emission reduction (t) 4. Coal saving (t)
This study	Technical efficiency and technological gap	South Korea	Output-oriented Stochastic meta-frontier	Insolation ($kWh/m^2/day$) Average annual sunshine (hours) Photovoltaic modules (# of modules) Land area (m^2)	Annual power generation (GWh)

Source: Author's summarization

3. Theoretical model

The previous studies used DEA that assumes the strict disposability, which implies that the DMU can control all inputs or outputs. In the analysis to examine TE of solar PV plants with yearly data, DEA does not satisfy the strict disposability because some or all inputs cannot be controlled by DMU. When the PV plant is installed, it is reasonable to assume that the land area and capacity (or number of modules) are fixed. Moreover, there are several advantages to use SFA: firstly, the parameters are estimated by maximum likelihood method, the usual statistical inferences can be conducted rather than simulations or bootstrapping. Secondly, the stochastic meta-frontier analysis can estimate the technology gaps by treating them as a conventional one-sided error term (Huang et al., 2014).

The approach of Alem et al. (2018) is followed which used the two-step SFA of Huang et al. (2014) and adapted the true-random effects model of Greene's (2005b) to capture heterogeneity.

A single output general stochastic production frontier model is given by:

$$y_{it} = f(x_{it}, \beta)e^{(v_{it} - u_{it})} \tag{1}$$

where y_{it} is the output scalar produced by plant *i* at time, x_{it} is a input vector for the plant *i* at time *t*, , v_{it} is the stochastic noise error term of plant *i* at time *t*, and u_{it} is the technical inefficiency of plant *i* at time *t*, where *i* = 1, 2, …, *N* and *t* = 1, 2, …, *T*. β is a unknown parameter vector to be estimated by SFA.

Both v_{it} and u_{it} are assumed to be independently and identically distributed (iid) with variances σ_v^2 and σ_u^2, respectively. This model assumes that all plants use the same production function in the same environment.

Since it is assumed that there are differences in generation between two (*k*) types of PV plants, we can estimate group stochastic frontiers for each type as follows:

$$y_{it}^k = f^k\left(x_{it}^k, \beta^k\right) e^{(v_{it}^k - u_{it}^k)} \quad i = 1, 2, \ldots, N(k) \tag{2}$$

where y_{it}^k denotes the output, x_{it}^k is the input vector, v_{it}^k is the stochastic error term, and u_{it}^k is the technical inefficiency for plant *i* of the *k*th type at time *t*. β^k is a unknown parameter vector for the *k*th type. u_{it}^k and u_{it}^k are assumed to be iid and follow normal distribution and half normal distribution, respectively ($v_{it}^k \sim N(0, \sigma_{vk}^2)$ and $u_{it}^k \sim N^+\left(0, \sigma_{vk}^2(z_{it}^k)\right)$), where z_{it}^k is environment determinants for inefficiency or production. Parameters are estimated using the 'true' random-effect model of Greene (2005b) to account for the plant effect (unobserved heterogeneity) within the type.

The TE of the i^{th} plant relative to the type k frontier can be calculated, as:

$$TE_{it}^{k} = \frac{y_{it}^{k}}{f^{k}\left(f_{it}^{k}, \beta^{k}\right)} = \frac{f^{k}\left(f_{it}^{k}, \beta^{k}\right) e^{\left(-u_{it}^{k}\right)}}{f^{k}\left(f_{it}^{k}, \beta^{k}\right)} = e^{\left(-u_{it}^{k}\right)} \tag{3}$$

where TE_{it}^{k} is a technical efficiency of the individual plant i relative to the k^{th} group frontier. For the estimation of the stochastic meta-frontier function, we follow the approach of Huang et al. (2014). In step 2, we specify the follow SFA:

$$\hat{f}\left(x_{it}^{k}, \beta^{k}\right) = f^{M}\left(x_{it}^{k}, \beta\right) e^{\left(v_{it}^{M} - u_{it}^{M}\right)} \tag{4}$$

where the $\hat{f}\left(x_{it}^{k}, \beta^{k}\right)$ are the predictions from the group frontier from step 1 in (2). It means a vector for the entire sample consists of individual vectors of a group frontier predictions. Like the models above, v_{it}^{M} is the error term, and u_{it}^{M} is the technical inefficiency. They are assumed to be iid, and distributed as $v_{it}^{M} \sim N(0, \sigma_{vM}^{2})$, and $u_{it}^{M} \sim N^{+}\left(0, \sigma_{uM}^{2}\right)$, respectively. Also, β is a vector of unknown parameters to be estimated for the meta-frontier.

At a given input level x_{it}^{k}, the observed output y_{it}^{k} of the i^{th} plant relative to the meta-frontier consists of three components, $y_{it}^{k}/f^{M}(x_{it}^{k}, \beta) = TGR_{it}^{k} \times TE_{it}^{k} \times e^{v_{it}^{M}}$, where $TGR_{it}^{k} = f^{k}(x_{it}^{k}, \beta^{k})/f^{M}(x_{it}^{k}, \beta)$ is technological gap ratio, $TE_{it}^{k} = f^{k}(x_{it}^{k}, \beta^{k})e^{\left(-u_{it}^{k}\right)}/f^{k}(x_{it}^{k}, \beta^{k}) = e^{-u_{it}^{k}}$ is the plant's technical efficiency, and $e^{v_{it}^{M}} = y_{it}/f^{M}(x_{it}^{k}, \beta^{k})e^{-u_{it}^{k}}$ is the random noise component.

Then, the two-step approach to estimate the meta-frontier consists of two SFA regressions:

$$\ln y_{it}^k = f^k\left(x_{it}^k, \beta^k\right) + v_{it}^k - u_{it}^k, \quad i = 1, 2, \ldots, N_k; t = 1, 2, \ldots, T \tag{5}$$

$$\ln \hat{f}^k\left(x_{it}^k, \beta^k\right) = f^M(x_{it}^k, \beta) + v_{it}^M - u_{it}^M, \quad \forall i,\ t \quad k = 1, 2 \tag{6}$$

where $\ln \hat{f}^M\left(x_{it}^k, \beta^k\right)$ is the estimate of the type-specific frontier Equation (5). Since the estimates $\ln \hat{f}^M\left(x_{it}^k, \beta^k\right)$ are type specific, regression (5) estimated *K* times, one for each region (*k* = 1, 2). These output estimates from two regions are then pooled to estimate (6).

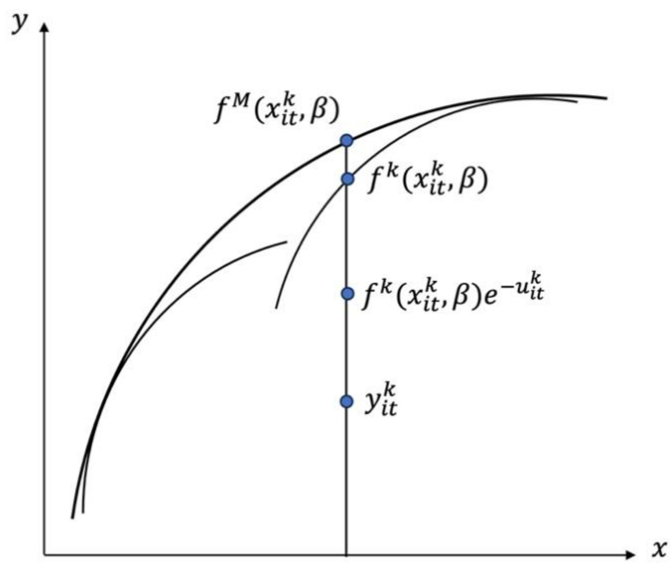


Figure 1 Meta-frontier production model

Source: Adapted from Huang et al. (2014), p.243

Since the meta-frontier should be larger than or equal to the group-specific frontier, the estimated Technological gap ratio must be less than or equal to unity:

$$T\hat{G}R_{it}^k = \hat{E}\left(\left(e^{-u_{it}^M} | \hat{\epsilon}_{it}^M\right)\right) \leq 1 \tag{7}$$

where $\hat{\epsilon}_{it}^M = \ln \hat{f}^k\left(x_{it}^k, \beta^k\right) - \ln \hat{f}^M(x_{it}, \beta)$ are the estimated composite residuals of (6). The technology gap ratio (TGR) is the expected value of $e^{-u_{it}^M}$ given the estimated composite residuals. The multiplication of estimated of the TGR in Equation (7) and the individual plant's estimated TE in equation (3) indicates the TE of the *i*th plant to the meta-frontier, that is, $M\hat{T}E_{it}^{k} = T\hat{G}R_{it}^{k} \times T\hat{E}_{it}^{k}$.

4. Empirical model

The second-order flexible translog (TL) function was estimated. The type *k* frontier (5) is specified as:

$$\begin{aligned} \ln y_{it}^{k} = \beta_0^k + \textstyle\sum_{j=1}^{4} \beta_j^k \ln x_{jit} + \frac{1}{2}\sum_{j=1}^{4} \beta_{jj}^k \left(\ln x_{jit}\right)^2 + \sum_{j=1}^{4}\sum_{l=2}^{4} \beta_{jl}^k \ln x_{jit} \ln x_{lit} \\ + \beta_t^k t + \tfrac{1}{2}\beta_{tt}^k + \textstyle\sum_{j=1}^{4} \beta_{jt}^k \ln x_{jit} t + \theta_i^k + v_{it}^k - u_{it}^k \end{aligned} \tag{8}$$

where y_{it} is a vector of outputs, x_{jit} is a vector of inputs $(j = 1, 2, \ldots, J)$ by plants $(i = 1, 2, \ldots, N)$ over time $(t = 1, 2, \ldots, T)$, and all the βs, and θ^k are parameters to be estimated. The error term v_{it} allows random measurement error, and it is symmetrical and is assumed to follow the assumptions, $v_{it} \overset{\text{iid}}{\sim} N(0, \sigma_v^2)$ and $v_{it} \perp u_{it}$. u_{it}^k is specified as $u_{it}^k \sim N^+(0, \sigma_{uk}^2(z_{it}^k))$, and θ_i^k is a plant-specific component for capturing time-invariant unobserved heterogeneity, which is assumed to have an iid normal distribution. The trend variable, *t*, is introduced to capture the effect of technological change. The same estimation model is used to estimate (6), but the dependent variable in (8) is replaced by $\ln \hat{f}^k \left(x_{it}^k, \beta^k\right)$.

All data for the TL model are described as deviations from their sample means, which allow us to interpret the first-order parameters directly as partial production elasticities at the geometric means (Coelli et al. 2005). We set the trend variable as zero in the year 2013 and normalize all other variables by dividing each variable by its mean value before calculating logarithms.

5. Korea RPS and Solar PV plants

To understand South Korea's RPS system, it is good to know the particular features of the electricity market in South Korea. In liberalized electricity markets like the United States and the United Kingdom, RPS obligations are imposed on the utilities because they will try to source the lowest cost renewable electricity when purchasing power from the various power generators. Renewable electricity producers can either sell electricity and RECs to utilities or sell electricity to power consumers and RECs on the REC market.

However, in South Korea, Korea Electric Power Corporation (KEPCO) is a legally guaranteed monopolistic electricity supplier in the retail market and is responsible for both transmission and distribution. As it is a monopolist in retail market, it acts as a monopsonist in the wholesale electricity market. Systematically, there is the possibility of an unfair wholesale market when KEPCO buys RECs if it is assigned as the only obligor. Because of this problem, the South Korean government assigned RPS obligations to power generation companies with installed capacity of 500 MW or more. This is a unique feature of South Korean RPS.

Another feature is that most of RPS obligations are allocated to the subsidiaries of KEPCO that were a part of KEPCO, when it was in charge of the power generation in the past. Other than those entities, some private power companies are assigned as RPS obligors as well. With the exception of private power companies that can adjust manpower and financial resources according to business needs, most of the RPS obligors have the possibility that their business may be constrained in various forms. Since these are public corporations, their management is evaluated by the government every year and are constrained by various restrictions on their budget and manpower management. Therefore, it is not easy for companies to allocate the desired amount of manpower to the new renewable energy projects based on their own judgment. It may be difficult to construct and operate small projects by themselves unless those projects are themselves part of large-scale projects.

Korea's RPS is a system that mandates power companies to obtain a specified percentage of their total electricity generation from renewable sources. It was introduced in 2012 to substitute FIT, and the legislation set an annual target ratio as 10% renewable electricity in the electricity supply in 2022. RPS obligors are expanded from 12 in 2012 to 23 in 2021. The lower enforcement decree specified the obligation ratio for each year. During that time the decree underwent five revisions, and the recent obligation ratio in 2030 was extended to 25%. The latest decree shows that targets have fallen (Table 2).

Table 2 RPS obligation revisions and target ratio

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Enact	2	2.5	3	3.5	4	5	6	7	8	9	10	10	10	10	10	10	10	10	10
1st 3.30.15	2	2.2	3	3	3.5	4	4.5	5	6	7	8	9	10	10	10	10	10	10	10
2nd 12.5.16	2	2.2	3	3	3.5	4	5	6	7	8	9	10	10	10	10	10	10	10	10
3rd 9.29.20	2	2.2	3	3	3.5	4	5	6	7	9	10	10	10	10	10	10	10	10	10
4th 1.4.22	2	2.2	3	3	3.5	4	5	6	7	9	12.5	14.5	17	20.5	25	25	25	25	25
5th 4.11.23	2	2.2	3	3	3.5	4	5	6	7	9	12.5	13	13.5	14	15	17	19	22.5	25

Source: Korean Law Information Center, Ministry of Government Legislation

As we stated before, the RPS brings revenue to renewable electricity producers in two main ways - revenue from electricity sales and revenue from RECs sales. Since both electricity and RECs are traded in their respective markets, the RPS is market-oriented policy. One of the reasons why the government uses a market mechanism is that RPS also induces competition among renewable energy sources. If the government were to weight RECs equally, competition would be on the basis of cost regardless of renewable energy sources. However, the South Korean government imposes differentiated RECs weights not only to compete between renewable energy sources but also to promote a specific source which is not secured economic feasibility now but its development is needed to meet some policy goals.[3]

Table 3 REC weights of solar PV

Location	Installed Capacity	Previous	Current (July, 2021)
General land (GPV)	< 100 kW	1.2	1.2
	100 kW – 3000 kW	1.0	1.0
	> 3000 kW	0.7	0.8
Rooftop or installation on other facilities (BPV)	< 100 kW	1.5	1.5
	100 kW – 3000 kW	1.5	1.5
	> 3000 kW	1.5	1.5
Floating PV	< 100 kW	1.5	1.6
	100 kW – 3000 kW	1.5	1.4
	> 3000 kW	1.5	1.2
Forest	any	0.7	0.5
Self consumption	any	1.0	1.0

Source: MOTIE press/announcement

In South Korea, the total mandatory supply is determined by the RPS mandatory supply ratio set year by year, and the technology preference is determined by the REC weights. Table 3 shows that the differentiated REC weights of solar PV by size and

[3] South Korean government allowed temporarily to ESS-linked solar PV to promote the development of the battery industry.

installation locations. The actual RECs are issued per 1 MWh by multiplying the weight assigned to each type. Installed capacity is classified into less than 100kW, 100~3000kW, and more than 3000kW, and the installation site is divided into general land, forest, facilities such as buildings, and water.

First, looking at the weighs by the installed capacity, the largest weight is assigned to solar power plants of less than 100 kW, and the smallest weight is given to PV plants exceeding 3000 kW across all types, except BPV. This seems promote the deployment of small-scale solar power plants that are relatively easy to install. From these figures BPV has the highest REC weights compared to the GPV. These types of weights suggest that installation on existing facilities is recommended, even if the construction difficulty and cost are higher than installation on general land that occupy a relatively large land area. Clearly, we can find that solar PVs installed in forests are assigned the lowest weight regardless of the installed capacity. It may be that this reflects the concerns about environmental, landscape damages.

Finally, South Korea's solar REC weight does not consider technical factors such as whether the panels are tracking or fixed, but only considers the installation location and related technologies and costs. Since the REC weight selection is determined by increasing or decreasing the weight according to the cost of installation, BPV is allocated a higher weight than GPV to encourage capacity installed on the structures.

6. Data

The data used for our empirical analysis is plant-level unbalanced panel data for 2013-2018, with 8,273 observations from 3,000 solar plants where 1,500 are ground-mounted PVs (GPV) and 1,500 are rooftop PVs (BPV) from random sampling. The data source is the New and Renewable Energy Center, Korea Energy Agency, collected annually when RECs are issued for renewable electricity producers. A summary of the output and input variables is shown in Table 4.

Table 4 Descriptive Statistics of PV plants

	Unit	Total	BPV	GPV
Output variable				
Annual generation	kWh	225,014.5	173,607	293,239.1
		(546,084)	(427,988)	(665,435.9)
Input variables				
Land area	m^2	2,245.2	1,372.4	3.403.6
		(7,019.9)	(5,770.1)	(8,255.6)
Number of modules	count	581.9	466.3	735.3
		(1,437.5)	(1,167.0)	(1,720.7)
Daily insolation	kW/m^2	3.784	3.764	3.811
		(0.155)	(0.151)	(0.155)
Daily sunshine hours	hour	6.389	6.416	6.352
		(0.516)	(0.551)	(0.464)
Plant-specific environmental variables				
Age of plant	year	2.040	2.180	1.853
		(1.092)	(1.139)	(0.997)
Regional Dummy variables				
Central East (1 = Yes / 0 = No)		0.056	0.047	0.067
		(0.230)	(0.213)	(0.250)
Central West (1 = Yes / 0 = No)		0.308	0.334	0.274
		(0.462)	(0.472)	(0.446)
South East (1 = Yes / 0 = No)		0.106	0.133	0.070
		(0.308)	(0.340)	(0.255)
South West (1 = Yes / 0 = No)		0.520	0.482	0.570
		(0.500)	(0.500)	(0.495)
Jeju (1 = Yes / 0 = No)		0.011	0.004	0.019
		(0.102)	(0.062)	(0.138)
Observations		8,273	4,718	3,555

Standard deviations in the parenthesis

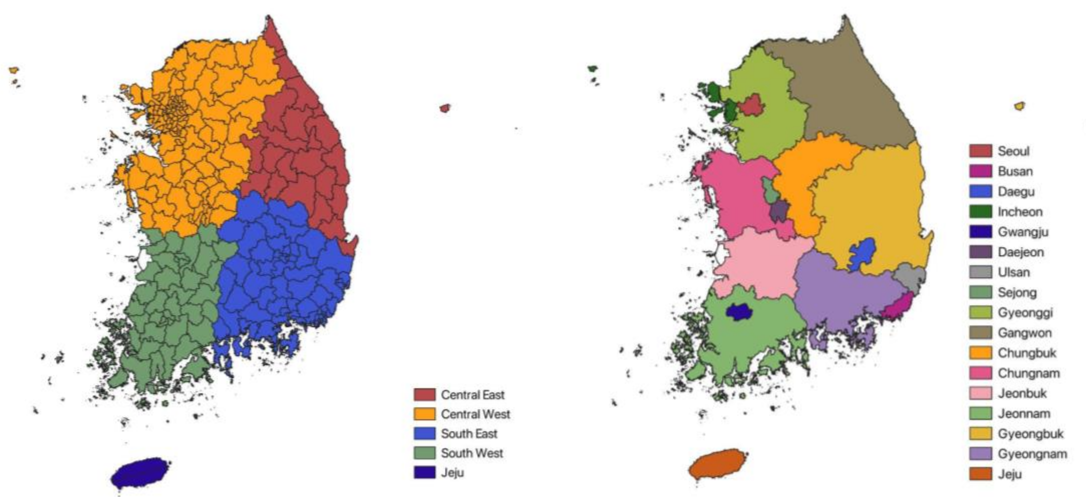
The data used for this analysis contain one output variable and four input variables. Output (y) is electricity generation, and it is measured in kWh. The TL production function in the empirical model (8) is specified using the four input variables described next.

Land (x_1) is defined as the area of the address of the solar power plant is installed and the unit is square meters. KNREC's data does not include power plant area data. However, the address of the power plant is included. To secure the area data, the area of the address is checked on the website SEE:REAL provided by the Korea Land and Housing Corporation. GPVs do not make a big difference even if they use the area of the address. However, there is a difference between the area of the address and the solar installation area of BPV. For rooftop solar power, roof surface area data is used. The number of modules (x_2) is determined by dividing the overall installed capacity by the capacity of each individual module in the KRNEC data and rounding up to the nearest whole number. Daily insolation (x_3) is the total amount of solar radiation energy received per 1 square meter over a given day, and it is measured in kilowatt-hours per square meter (kWh/m^2). Daily insolation data are provided by the Korea Institute of Energy Research, consisting of 291,924 grids (1 km^2) across South Korea. It is not possible to measure plant input as accurately as solar radiation data directly measured at individual plants, but it provides plant-specific data that is closest to reality among existing data. Comparing the latitude and longitude data of individual plants with the latitude and longitude of the grid of insolation data, the data of the nearest grid is used as the insolation of the plant.

Daily sunshine hours (x_4) is the number of hours in a day during which sunlight is received at a specific location. It is a measurement of the duration or amount of time that the sun is visible and directly illuminating the Earth's surface. Unlike temperature, rainfall, etc., it was difficult to find data on the hours of sunshine measured by city, county, or district. However, as Sueyoshi and Goto (2014) used it as an important input, it is necessary to use data from the closest location. The Korea Meteorological Administration measures the hours of sunshine in 95 meteorological stations. Among the available data, it is thought that the Korea Meteorological Agency data provides accurate information throughout the country, and the closest meteorological zone for each individual plant is identified and used as the sunshine time data.

In the analysis, both plant-specific or z-variables are included. Solar PV systems generate electricity by converting sunlight directly into electrical energy. Solar panels, composed of multiple solar cells made of semiconductor materials like silicon, absorb photons from sunlight, exciting electrons and creating an electric current. In general, photovoltaic power generation is known to have a degradation rate from about 0.5% per year (Jordan et al., 2016) to less than 1% per year (NREL). Based on this information, the plant-specific z-variables considered for plant-level efficiency consist of plant's age (z_1) measured as the number of years plant has been operated. All things being equal, solar power generation should decrease with increasing age. On the other hand, in terms of power plant operation, increasing the age of a power plant means that operational experience is accumulated. It indicates that immediate and quick response to various failures and various phenomena is possible than before. Therefore, age will be the result of a combination of declining original characteristics and increasing experiential factors.

Another feature is the installation area (z_2 - z_6). In agriculture, the area in which a farm is located is an important factor in capturing the unexplained characteristics of an individual farm. The meta-frontier stochastic analysis also establishes and analyzes that different technologies are used by region (Huang, 2014; Alem et al., 2018). Although this regional division is meaningful and important in itself, this study treats the region as a factor that determines the characteristics of a plant other than input because it is of interest to understand the difference by type of installation location. It is divided into 5 regional regions and a dummy variable is created and analyzed. Regional classification follows the regions classified according to climate and environmental conditions by Moon (1996). Regional classification is made as shown in Figure 2 (a) below.



(a) Regions by environment (b) Administrative District

Figure 2 Regional categorization by environment

Source: Author's categorization based on Moon (1996)

7. Results and discussion

In order to test the goodness-of-fit between Cobb-Douglas model and translog model, we conducted the likelihood ratio (LR) test for all SF models each type and pooled data. The results reject the null hypothesis of a simplification of the TL to Cobb-Douglas functional form. Therefore, TL functional form retained, and the results from SF and meta-frontier model using TL functional form are presented.

Table 5 Estimates for the parameters of the TL stochastic frontier model by type, for the pooled data model, and for the meta-frontier

	BPV	GPV	Pooled data	Meta-frontier
Elasticities				
x_1 (Number of modules)	0.970***	0.873***	0.924***	0.906***
	(0.008)	(0.012)	(0.007)	(0.000)
x_2 (Land area)	0.018*	0.135***	0.091***	0.089***
	(0.007)	(0.011)	(0.006)	(0.000)
x_3 (Daily insolation)	1.078***	0.770***	0.967***	0.934***
	(0.097)	(0.088)	(0.063)	(0.005)
x_4 (Daily sunshine hours)	-0.034	0.060	-0.020	-0.002
	(0.037)	(0.047)	(0.027)	(0.002)
t (Time trend)	-0.005	0.014***	0.003	0.002***
	(0.004)	(0.004)	(0.003)	(0.000)
t^2 (Time trend)	-0.001	-0.005***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Plant-specific environmental variables				
z_1 (Age)	1.679***	1.414***	1.332***	
	(0.196)	(0.114)	(0.113)	
z_2 (region Central East)	-22.790***	-1.542	-4.864	
	(1.598)	(1.662)	(2.681)	
z_3 (region Central West)	-6.401***	-0.735	-2.006*	
	(1.332)	(1.319)	(0.834)	
z_4 (region South East)	-6.128***	1.030	-1.762*	
	(1.180)	(0.836)	(0.810)	
z_5 (region South West)	-4.174***	0.315	-1.081	
	(0.839)	(0.762)	(0.722)	
Observations	4,718	3,555	8,273	8,273
Number of Plants	1,500	1,500	3,500	3,000

Note: Robust standard errors in parentheses.
*** 1% level, ** 5% level, * 10% level

Table 5 presents the estimation results of the true random effects model for different types of photovoltaic, the pooled data model, as well as meta-frontier model. In all cases, the model demonstrates positive and significant first-order parameters, satisfying the monotonicity condition for valid production functions, except for the daily sunshine hours. Among the models considered, the coefficient of the stochastic frontier (SF) for daily insolation is the highest, indicating that changes in daily insolation have a more pronounced impact on power generation compared to other inputs.

Examining the individual input elasticities, the number of modules (x_1) exhibits the second-largest elasticity across all models (excluding GPV, where it is the most elastic), and all show high statistical significance. The module elasticity is 0.970 for BPV and 0.873 for GPV. Among the GPV elasticity estimates, the number of modules has the greatest influence on power generation. The estimated elasticity for land input (x_2) is 0.018 for BPV and 0.135 for GPV, showing statistical significance at the 1% and 10% levels, respectively, in all models except BPV. Daily insolation (x_3) has an elasticity of 1.078 for BPV and 0.770 for GPV. It is observed that daily insolation has the most substantial impact on BPV compared to the partial elasticities of other inputs. A 1% increase in daily insolation for BPV leads to an approximate 1.078% increase in power generation. Daily sunshine hours (x_4) only show a positive value in GPV, and its statistical significance is not observed across all regions. The first three inputs were based on actual plant data or geographically close approximations, whereas the daily sunshine hours utilized values measured at 95 weather stations, leading to a lack of reflection of plant-specific differences.

Technological change (TC) represents the productivity changes resulting from the adoption of new production practices. The first-order coefficients of the time-trend variable provide estimates of the average annual rate of TC (Alem et al, 2018). In the case of BPV, the first-order coefficient is negative but not statistically significant. However, for GPV and the meta-frontier model, the coefficient is positive and statistically significant. Additionally, the parameters associated with the time-squared variable (t^2) are negative and significant for all models except BPV. This suggests that the rate of TC increased at a decreasing rate over the period covered by the data, as shown in Table 5. The presence of a positive first-order coefficient can be attributed to advancements in module efficiency or technological developments. Conversely, the negative secondary coefficient can be explained by the fact that sites with favorable solar radiation and location conditions are typically developed earlier, while sites with less favorable conditions are developed later.

The lower section of Table 5 presents estimates of plant-specific and regional environmental variables affecting technological inefficiency. Age has a consistent negative impact on TE across all types, as indicated by positive and statistically significant parameter estimates for inefficiencies of this variable. These results confirm that there are degradations of PV panels in both BPV and GPV.[4]

Regional dummies are based on Jeju Island and are compared to other regions. The results show that BPV significantly increases TE in regions other than Jeju. This suggests that BPV is less efficient in Jeju compared to other regions. On the other hand, for GPV, the central regions are found to be more efficient than Jeju, while the southern regions are less efficient. However, statistically, there is no significant difference between GPV in these regions and Jeju. Environmental condition, especially strong wind is a possibility because BPV in Jeju island has lower TE compared to other region. Jeju island is more frequently affected by strong winds such as typhoons and the infrastructure on the rooftops are exposed by harsh environmental conditions.

In Table 6, the average TE score for BPV is 0.995, indicating that these plants achieve 99.5% of the maximum possible output given the inputs used. This means that, on average, the plants have a potential to increase their production by approximately

[4] NREL (2018) provides information about the degradation rate of solar panel is 0.5% per year.

0.5% to reach technical efficiency. The average TE scores for GPV is 0.991, indicating that the plants potentially can be increased their production by 0.9%. Therefore, it can be concluded that there is no evidence that many plants of these types are significantly lagging behind the most efficient producers of their types.

Table 6 Technical efficiency and technology gap ratio estimates

	BPV	GPV	All types
TEs to the typical frontier (*TE_{it}*)			Pooled
Mean	0.995	0.991	0.992
Std. Dev.	0.008	0.010	0.009
Minimum	0.843	0.836	0.851
Maximum	1.000	0.999	0.999
Technology gap ratio (TGR)			
Mean	0.997	0.993	
Std. Dev.	0.003	0.016	
Minimum	0.954	0.321	
Maximum	1.000	1.000	
Tes to the meta-frontier (*MTE_{it}*)			Meta
Mean	0.991	0.985	0.988
Std. Dev.	0.008	0.019	0.014
Minimum	0.843	0.320	0.320
Maximum	0.999	0.998	0.999

The estimates of the mean TGR value of BPV and GPV are very close to 1. A TGR value of 1 indicates that the typical frontier closely aligns with the meta-frontier. BPV types have a slightly higher TGR value (0.997) compared to GPV, suggesting that BPV are slightly closer to the meta-frontier than those of GPV, but the amount of difference is negligible. The TGR values range up to 1.00 for both types, indicating that some plants are already achieving the maximum generation predicted by the meta-production function given the current technology.

The average TE scores for the group frontier model (TE_{it}) and the meta-frontier model (MTE_{it}) are very similar, as indicated by the TGR estimates close to 1 in Table 6. For the 2013-2018 period, the MTE_{it} scores are 0.991 for the BPV and 0.985 for the GPV.

This implies that BPV is more efficient than GPV with respect to the meta-frontier production function. However, from an economic point of view, there is little difference between the two types.

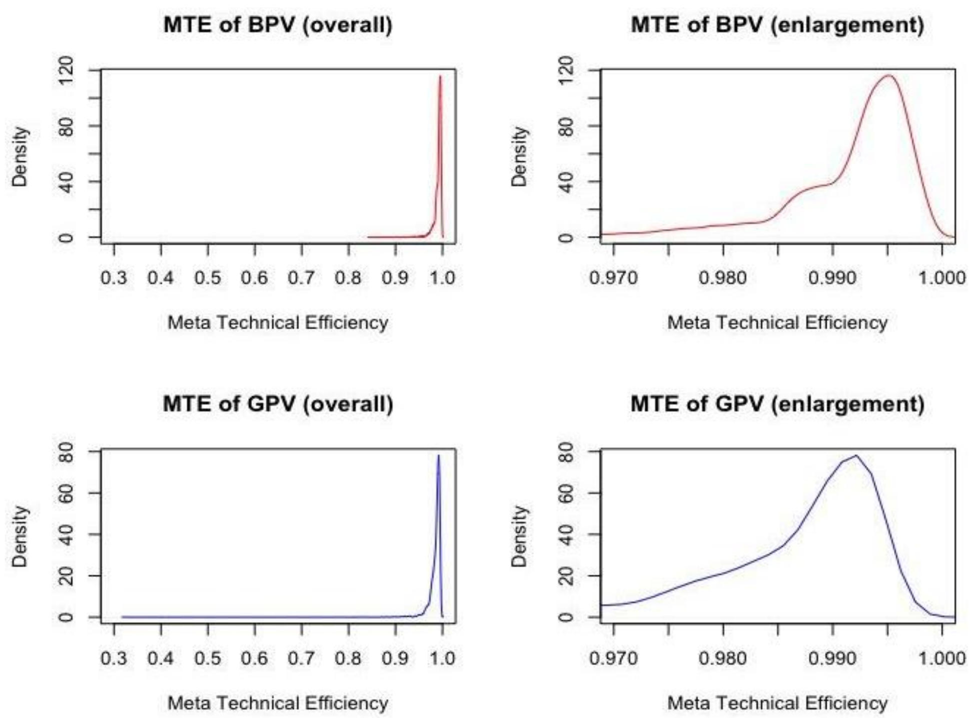


Figure 3 TEs to the meta-frontier

Source: Author's calculation

Some tests are needed to judge whether BPV and GPV are using heterogeneous production frontiers. We conduct the Kolmogorov-Smirnov test and t-test for the MTE of both types, the test results mean that the distribution of BPV and GPV are heterogeneous. Statistically, MTE scores of BPV and GPV are different however the difference is negligible in terms of economic significance.

8. Conclusions

The objective of this paper is to compare TE for BPV and GPV in South Korea using a stochastic meta-frontier approach. More specifically, it is checked whether there is a difference between BPV and GPV in terms of MTE and which factors can affect the efficiency. The results of the analysis show that TE scores and TGRs are very close to 1. The estimated average TE score are 0.995 for the BPV and 0.991 for the GPV. The results suggest that the two types of PV plants use available technology in the group sub-optimally. That is, there are some plants which produce less electricity from the inputs they use or use more inputs to produce the same level of electricity, when compared to the best-performing plants in their group.

The age of the plants had a negative impact on TE in all types, and the regional effect was only statistically significant for BPV. The estimated average TGR values were very close to 1, and there were no significant differences between types. A TGR value of 1 indicates that the frontier of a specific type aligns with the meta-frontier. Comparing all types, GPV had the lower average MTE scores than BPV and this implies that BPV more efficiently generate than GPV. However, the difference is very small in economic point of view.

A priori expectations were that there would be slightly larger differences in TE and TGR among different PV plant types, reflecting the technological variations between them in Korea. Solar power plants in South Korea are still considered relatively expensive compared to other conventional power sources. While the RPS system promotes renewable energy generation and provides economic incentives through REC sales, uncertainties exist as both electricity and REC sales follow market mechanisms.

Therefore, it is crucial to minimize factors that cause inefficiency to ensure economic viability, regardless of the type and installation location. Thus, assuming a shared underlying technology across types appears to be reasonable.

Throughout the course of this study, several limitations were encountered. Firstly, it was challenging to determine the exact area of solar installations as the competent authorities did not provide comprehensive information. Some local governments provided area data, but it was not available in most cases. Secondly, there were instances where the actual plant location and the address of the power generation company were mixed up. Thirdly, appropriate inputs needed to be selected and suitable data secured for the research methodology. This study borrowed input and output data from Sueyoshi and Goto (2014), which used average values over a specific period. Their study focused on identifying average power generation amounts by selecting locations from a long-term perspective. However, this study used annual measurement data for the installed plants, which differed from Sueyoshi and Goto's (2014) approach. In their study, power generation facility capacity and power generation constituted the output. Although this study considered land and module counts in combination with power generation, it did not exclude facility capacity as it is necessary to secure the power generation amount. When conducting stochastic meta-frontier analysis for multiple outputs, calculations based on specific gravity for a particular output do not make sense in this context. Data that have a significant impact on evaluating the productivity of installed power generation facilities, such as variable costs related to manpower operation or labor costs, may be more appropriate. However, separate aggregated data for these factors was not available, limiting their inclusion in the analysis.

Lastly, regarding company characteristics and capacity, the study identified whether a company was public or private. However, data for private companies were not utilized as it was challenging to determine if a public company had the actual characteristics of a public company based on share investments. Additionally, while the development of large-capacity power plants is progressing, the data obtained had limited representation of such plants, with over 90% of power plants being small-scale facilities of less than 100 kW. This reflected group and regional characteristics and posed challenges in considering capacity.

In this study, it was observed that BPV and GPV were mostly operated in a manner close to best practice, and each technology was found to be near the meta-frontier. It was concluded that BPV is a favorable option for expansion, given concerns in Korea about limited land area, reduction of farmland, landscape damage, and deforestation.

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APPENDIX A. Regions by environment

Table 7 Classification of counties by environment

Region	Province	County
Central East	Gangwon	Donghae, Gangneung, Goseong, Jeongseon, Pyeongchang, Samcheok, Sokcho, Taebaek
	Gyeongbuk	Andong, Bonghwa, Cheongsong, Gumi, Mungyeong, Pohang, Sangju, Uiseong, Uljin, Yecheon, Yeongdeok, Yeongju, Yeongyang
Central West	Chungbuk	Boeun, Cheongju, Chungju, Damyang, Eumseong, Goesan, Jecheon, Jeungpyeong, Jincheon, Okcheon, Yeongdong
	Chungnam	Asan, Boryeong, Buyeo, Cheonan, Cheongyang, Dangjin, Geumsan, Gongju, Hongseong, Nonsan, Seocheon, Seosan, Taean, Yesan
	Daejeon	Daejeon
	Gangwon	Cheolwon, Chuncheon, Hoengseong, Hongcheon, Hwacheon, Inje, Wonju, Yangju, Yeongwol
	Gyeongbuk	Gimcheon, Sangju
	Gyeonggi	Ansan, Anseong, Dongducheon, Gapyeong, Gimpo, Goyang, Gwanju, Hanam, Hwaseong, Icheon, Namyangju, Paju, Pocheon, Pyeongtaek, Seongnam, Siheung, Suwon, Uijeongbu, Yangju, Yangpyeong, Yeoju, Yeoncheon, Yongin
	Incheon	Incheon
	Sejong	Sejong
	Seoul	Seoul
South East	Busan	Busan
	Daegu	Daegu
	Gyeongbuk	Cheongdo, Chilgok, Goryeong, Gumi, Gunwi, Gyeongju, Gyeongsan, Seongju, Uiseong, Yeongcheon
	Gyeongnam	Changnyeong, Changwon, Geoje, Gimhae, Goseong, Hadong, Haman, Hamyang, Hapcheon, Jinju, Miryang, Namhae, Sacheon, Sancheong, Tongyeong, Yangsan
	Jeonbuk	Jangsu
	Jeonnam	Gwangyang, Suncheon, Yeosu
	Ulsan	Ulsan
Seouth West	Chungnam	Seocheon
	Gwangju	Gwangju
	Gyeongnam	Hamyang
	Jeonbuk	Buan, Gimje, Gochang, Gunsan, Iksan, Imsil, Jeongeup, Jeonju, Jinan, Muju, Namwon, Sunchang, Wanju
	Jeonnam	Boseong, Damyang, Gangjin, Goheung, Gokseong, Gurye, Gwangyang, Haenam, Hampyeong, Hwasun, Jangheung, Jangseong, Jindo, Mokpo, Muan, Naju, Sinan, Suncheon, Wando, Yeongam, Yeonggwang
Jeju	Jeju	Jeju, Seogwipo

RENEWABLE PORTFOLIO STANDARDS, THE LEARNING CURVE, AND RE100: ANALYZING THE IMPACT OF THE FIRM LOCATION DECISION

1. Introduction

RE100 is a global initiative led by influential companies that are committed to obtaining all of their electricity from renewable energy sources; wind, solar, geothermal, sustainably obtained biomass (including biogas), and sustainable hydropower.[1] The primary objective of RE100 is to accelerate the transition to renewable energy and reduce greenhouse gas emissions. It consists of companies from various industries that have publicly pledged to operate exclusively on renewable electricity.

Table 1 Status of participation companies in RE100 companies

Headquarter location	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Africa	0	0	0	0	0	0	0	0	0	0
Asia	0	2	2	4	14	20	26	38	40	12
Europe	10	18	9	18	13	18	20	15	6	4
North America	2	13	13	10	11	17	14	11	11	1
South America	0	0	0	0	0	0	0	0	0	0
Oceania	0	0	0	0	2	8	5	2	1	0
Cumulative Total	12	45	69	101	141	204	269	335	393	410

Source: Authors own calculations using data from RE100 website (https://www.there100.org/re100-members)

[1] According to RE100 Joining Criteria (2022), a company's annual electricity demand needs to at least 0.1 TWh. If its consumption is smaller than that level, joining is determined by considering the following criteria: *1) Key player in a RE100 priority region, 2) Key player in their industry/RE100 target sector, 3) Willing to be involved in policy advocacy in RE100 priority regions, 4) Globally or nationally recognized and trusted brand and/or major multi-national company (Fortune 1000 or equivalent), and 5) Other consideration of clear international or regional influence that is of benefit to RE100's aims*

The RE100 initiative started with the participation of 12 companies in 2014, and 410 companies are participating as of May 2023 (Table 1). Based on the location of their headquarters, initial membership comprised of companies based in Europe and North America (the United States), but over participation of companies based in Asia and Oceania (Australia) has increased significantly. Although there is no member company with its headquarters based in Africa or South America, there are RE100 companies that procured renewable electricity in Africa and South America (Figure 1).

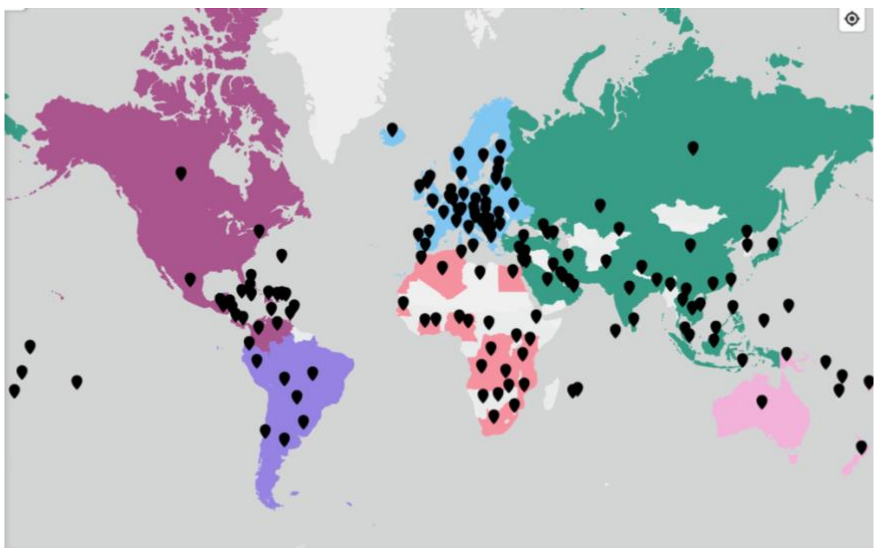

Figure 1 RE100 members' electricity and renewable electricity consumption by market around world

Source: RE100 website (https://www.there100.org/about-us)

Figure 2 shows that the industrial composition of 410 RE100 participating companies. The service industry, which is expected to consume relatively little electricity, accounts for the largest portion at 36%. But the manufacturing industry, whose companies generally consume relatively more electricity, accounts for the second largest portion at 23%. This highlights that the RE100 is a campaign promoted across industries, and not targeted at a specific industry.

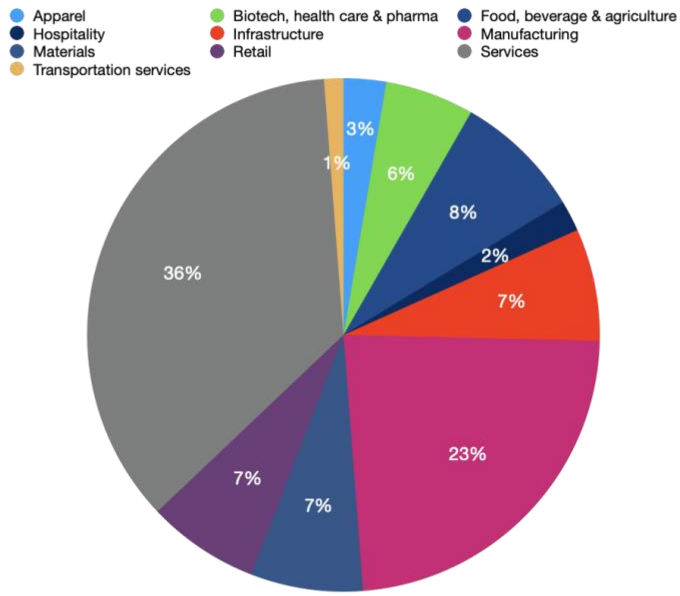

Figure 2 Industrial composition of RE100 companies

Source: Authors own calculations using data from RE100 website (https://www.there100.org/re100-members)

The electricity consumption of RE100 companies exceeds 420 TWh per year, which is equivalent to the energy consumption of medium-sized countries.[2] These companies have reported a gradual increase in their consumption of renewable electricity, reaching 49% in 2021 compared to 45% in 2020 and 41% in 2019.[3] As RE100 companies intensify their efforts to expand the use of renewable energy, manufacturers face a crucial decision. They must decide whether to continue producing their goods using expensive renewable power in their current country or to relocate to a foreign country that offers more favorable conditions for renewable energy production. This decision becomes

[2] See the RE100 homepage.
[3] See the RE100 homepage.

particularly significant considering initiatives like RE100, which strongly encourage companies to transition to 100% renewable energy.

If a company that meets the RE100 entry criteria, it must submit an implementation plan within a year, and must achieve at least 60% energy from renewable sources by 2030, 90% by 2040, and 100% by 2050. In addition, there are five possible ways to meet these requirements: 1) Self-generation, 2) Direct procurement, 3) Contracts with electricity suppliers, 4) Unbundled procurement of energy attribute certificate (EACs), and 5) Passive procurement (Climate group and CDP, 2022).

The important principle is that companies participating in RE100 must achieve renewable energy at all workplaces. For instance, suppose an international company A has workplaces in country B with low renewable electricity prices and country C with high renewable electricity prices. It cannot be admitted as implementation by purchasing more electricity (EACs) in country B to replace renewable electricity in country C. If a RE100 company is procuring parts and intermediate goods to produce final products, the parts and intermediate goods must also be produced using renewable electricity to be recognized as 100% renewably produced.

Renewable portfolio standards (RPS) are governmental policies implemented to promote the utilization of renewable energy sources in electricity generation. These policies mandate or incentivize electricity providers to ensure that a specified minimum portion of the electricity they supply to customers comes from eligible renewable resources. The aim of RPS is to foster the adoption and integration of renewable energy into the overall energy mix, thereby reducing reliance on fossil fuels and mitigating environmental impacts (EIA, 2023). RPS policy has emerged as a significant driver for the global adoption of renewable energy sources in power generation. This policy sets a minimum requirement for the supply of renewable energy and encourages the supply to go beyond that minimum level, aiming to improve the economic feasibility of renewable energy production.

Additionally, it is essential to consider the learning effect as renewable energy supply expands. The learning effect refers to the gradual decrease in costs that occurs as renewable energy technologies mature and gain wider acceptance. It is based on the premise that efficiency improvements, economies of scale, and technological advancements lead to cost reductions in renewable energy production over time.

The objective of this study is to examine how the RPS policy influences the decision-making process of manufacturers regarding the choice between staying in their current country or relocating to a foreign country in response to initiatives such as RE100. RE100 has influenced the location decision s of its members, for example Volvo has cancelled contracts with suppliers that cannot supply parts produced using renewable energy by 2025, and BMW is requiring parts be produced with renewable energy within 2-3 years (Lee, 2023). By analyzing the intricate relationship between renewable energy costs, government policies, and manufacturing strategies, this study aims to provide valuable insights into the factors that shape manufacturers' decisions regarding renewable energy adoption and location selection.

This chapter is organized as follows. Section 2 provides a summary of prior studies related to renewable portfolio standards (RPS), the RE100 initiative, and the learning curve. In Section 3, a game model is introduced for analysis. Sections 4 to 6 examine each subgame using backward induction. Section 7 explores the subgame perfect equilibrium, with discussion of the results in Section 8. Finally, we draw conclusions about this research method in Section 9.

2. Literature review

Several studies have examined the impact of renewable portfolio standards (RPS) on power generation and facility capacity using econometric models. Yin and Powers (2010), Upton and Snyder (2017), and Joshi (2021) are among the researchers who have explored this topic. Joshi’s study reveals that the adoption of RPS leads to a more than one-third increase in overall renewable electricity capacity. However, Upton and Snyder's findings do not provide evidence that states with RPS have experienced significant increases in renewable energy generation compared to other policy approaches such as mandatory targets.

Zhou and Solomon (2020) examined the role of RPS in influencing renewable electricity capacity deployment in the U.S. Specifically, it investigated whether RPS policies act as a floor or a cap on capacity additions beyond compliance. They discovered that stricter RPS policies are linked to a decrease in non-RPS related renewable electricity capacity additions, particularly when limited by renewable electricity potential capacity. However, this negative effect is attenuated in states with abundant renewable energy resources, as a stringent RPS policy can incentivize additional investments in renewable electricity capacity beyond the mandated targets.

Ma and Xu (2023) conducted a theoretical investigation into solar investment issues using a game model. Their findings suggest that higher RPS requirements can benefit regulators, particularly when there is less resistance to regulation and a high penalty rate. The study also indicates that the development of solar technology leads to an increase in the optimal price of photovoltaic (PV) panels and encourages investment in solar energy. Additionally, the study suggests that increasing solar investment is preferable for achieving higher renewable output when there is a high requirement for renewable energy. Furthermore, the research highlights that developers benefit from higher RPS requirements as it promotes PV adoption and increases panel prices.

Nasiri and Zaccour (2010) conducted a game-theoretic analysis on RPS because the peculiar attribute of an RPS system resembles a coupled constraint game. They provided a generic game-theoretic model for an RPS system and explored a 3-player case study. In that model, they provided some insight on equilibrium levels of electricity generation and certificate trading.

Zhao et al. (2021) analyzed the effectiveness of RPS by simulating power producers' behavior based on a subjective game model. They found three main results: 1) After RPS is implemented, the uncertainty of power producers' behavior steadily decreases, and the game equilibrium is created, destroyed, and then re-established. 2) When a given method yields a larger reward, power producers are more likely to use that technique in subsequent games. 3) When the fine is two times the price of a Tradable Green Certificate (TGC), electricity producers agree to trade TGCs, and the RPS becomes operational.

The concept of the learning curve was introduced by Wright (1936) and originated from observations of workers in aircraft factories gradually improving their performance as they repeatedly engaged in specific tasks. It represents the relationship between the cumulative experience or production volume and the improvement in productivity or efficiency over time. The learning curve concept has since been widely applied in various fields to understand and analyze the effects of experience, repetition, and learning on performance and cost.

The learning curve effect has been widely observed and studied in various industries and domains, including manufacturing (Argote and Epple, 1990), industry (Petrakis et al., 1997), semiconductor manufacturing (Irwin and Klenow 1994), technology (Plaza et al, 2010), firm competition (Spence, 1981) and renewable energy (van der Zwaan & Rabl, 2003; Nemet, 2006). The underlying principle is that as individuals, organizations, or industries gain experience and knowledge, they become better at what they do, leading to increased efficiency, economies of scale, and technological advancements. This, in turn, leads to cost reductions and improved performance. Over the course of its long history, the concept of the learning curve has been extensively studied, leading to the development of various models. These models, including the Plateau model, S-curve model, Dejong model, and Stanford-D model, have been proposed and discussed in numerous studies (Yelle and Lowell, 1979; Anzanello and Forliatto, 2011).

Van der Zwaan & Rabl (2003) studied the learning curve analysis of solar photovoltaics (PV) and they predicted that the cost of solar power would decrease rapidly in the subsequent years. Also, they predicted that considerable amount of PV electricity will appear in world electricity generation after 2020. In reality, the learning rate of renewable electricity, especially PV, has been much higher than their expectation. Nemet (2006) found that while learning from experience does have an impact, it only weakly explains the changes observed in the most critical factors, namely plant size, module efficiency and the cost of silicon. The paper emphasizes that other factors beyond learning from experience must be considered to fully understand and explain the variations in these key cost factors in the PV industry. Reichenbach and Requate (2012) conducted a study on the impact of learning by doing, learning spillovers, and imperfect competition in the energy sector. They found that implementing a tax in the fossil-fuel sector and an output subsidy for renewable energy equipment producers is the optimal policy approach to address pollution and promote the growth of renewable energy sources.

Lee et al. (2022) discovered that the cost of renewable energy generation decreases over time. They determined that deviating from traditional utility environments and opting for corporate power purchase agreements for implementing RE100 is a cost-effective strategy. The study emphasizes the importance of policymakers creating an environment that allows companies to freely choose from a range of power purchase options and certification methods to enhance their competitive advantage.

3. The Model

Consider a game in which three player groups participate: the government, RPS obligors, and firms supplying RE100 companies. This model comprises three stages, each involving different decisions by the player groups. In this model, we assume that the government maximizes the social net benefit from renewable energy supply, and it consider the change of employment by firms' location selection. The obligors of RPS are utilities, and they seek to maximize their profits.[4] Also, the firms supply their products to RE100 companies as parts or intermediate goods, and they are profit maximizing companies.

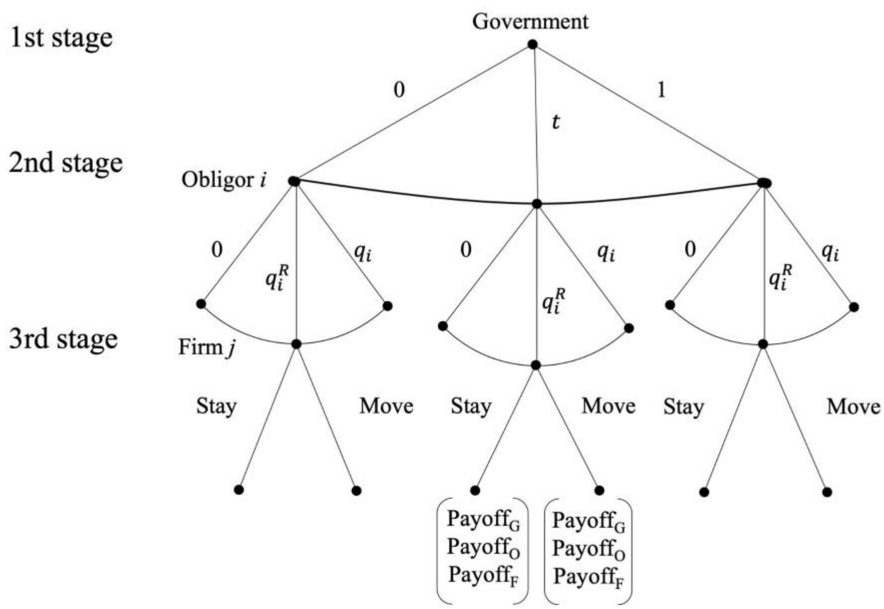

Figure 3 Game tree of RPS under RE100 initiative

In the first stage, the government sets the RPS target $t \in [0, 1]$ representing the percentage of renewable energy generation required in the country's electricity mix. The government's choice of the RPS target influences the overall framework for renewable energy adoption and serves as a crucial policy signal. Moving to the second stage, the RPS obligor *i* makes decisions regarding the amount of renewable electricity they will provide (q_i^R). The RPS obligors play a vital role in implementing renewable energy

[4] We assume the exclusion of purchasing renewable electricity from contracts with electricity suppliers, and passive procurement because self-generation does not use a market mechanism, and direct procurement does not change the behaviors of obligors. The purchase of unbundled EACs is another important topic to investigate for the RPS system because the firms and obligors may compete to secure EACs.

projects and determining the actual supply of renewable electricity to meet the RPS target. Finally, in the third stage, firm *j*s, which are responsible for supplying products to RE100 companies, face a critical decision. They must assess whether to remain in their current country or relocate to another country offering cheaper renewable electricity. This decision hinges on the cost of renewable electricity and its competitiveness compared to non-renewable energy sources. By making a strategic choice, the firms aim to maximize their payoffs while fulfilling the requirements of RE100 companies.

In this game, the players seek to maximize their expected payoffs while considering the decisions and actions of the other player groups. The interplay between the government's RPS target, the RPS obligors' renewable energy provision, and the firms' location decisions create a dynamic and complex strategic environment. By analyzing this game, we can gain insights into the interactions and outcomes that arise from the decisions made by these three player groups.

Table 2 Summary of game players

Participant	Description	Objective	Participant can change
Government	Represents the institution that sets the RPS. Could be national or local government	Meeting the RPS target, maximizing employment and social net benefit	RPS target
RPS obligors	The institution responsible for meeting the RPS. Would usually be a utility.	Meeting the RPS commitment and maximizing their profits	Amount of renewable electricity they will provide
Firms	Firms that are affected by RE100 initiative	Maximizing their profits by supplying their products to RE100 companies	Where they locate to produce their products

Now we will check the players' payoffs with general functions. The government payoff consists of some benefits and costs from renewable electricity and employment (labor) like below:

$$P_G = \sum_i^I \left[b^R q_i^R + b^{NR}(q_i - q_i^R) - c^R(q_i^R) - c^{NR}(q_i - q_i^R)\right] + \sum_j^J (b^L - c^L) l_j \quad (1)$$

where b^R is the marginal benefit of renewable electricity b^{NR} is the marginal benefit of non-renewable electricity. $c^R(\cdot)$ and $c^{NR}(\cdot)$ are cost functions of renewable electricity and non-renewable electricity, respectively. b^L and c^L are the marginal benefit and cost of labor, respectively. q and q^R are total and renewable electricity cumulative supplies, respectively. *I* is the total number of obligors for the RPS, and *J* is the total number of manufacturers to supply their products to RE100 companies.

Once, the government decides the level of obligation (*t*), then the RPS obligors have to decide how much renewable electricity to provide. In this game, we examine the scenario where the RPS is enforced as a mandatory obligation. This means that if an obligor fails to fulfill their obligation, they incur penalties at least equal to the renewable energy price of other obligors for the amount of unfulfillment. Then, the payoff of obligor *i* is defined below:

$$\begin{aligned}\pi_i = p_d^R(q_i^R) + p_d^{NR}(q_i - q_i^R) - c^R(q_i^R) - c^{NR}(q_i - q_i^R) \\ -(1+\gamma)\bar{c}_R \max[0, tq_i - q_i^R]\end{aligned} \quad (2)$$

where p_d^R is a price for electricity. q_i and q_i^R are total and renewable electricity supplies of obligor *i*. γ is the additive penalty when the RPS obligor *i* cannot achieve its obligation, and it is greater than or equal to 0. $\bar{c}_R$ is the average marginal cost of other obligors' renewable electricity.

Given output price and input prices, the payoff of firm *j* is defined below:

$$\pi_j = \begin{cases} pf(q_j, l_j) - p_d^R q_j - p_d^L l_j & \text{if Stay} \\ pf(q_j, l_j) - p_f^R q_j - p_f^L l_j - C_f & \text{if Move out} \end{cases} \tag{3}$$

where p is the product price received from RE100 companies. p_d^R and p_f^R are renewable electricity prices in domestic and foreign countries, respectively, which must contain the price of the renewable energy certificate. p_d^L and p_f^L are labor costs of domestic and foreign countries, respectively. C_f represents a fixed cost that arises when firms decide to relocate from their current country to a foreign country.

We observe that the cost function of renewable energy exhibits characteristics of a long-term average cost function due to the learning effect. As a technology that is still maturing and evolving compared to traditional power sources, historical data confirms that the marginal cost of renewable energy, particularly solar and wind power, decreases annually.

4. Subgame starting at the third stage

In this analysis, we assume the firm *j*s belong to the open small economy and they are identical. It means that the firm's supply cannot change the price of its product and the price is given. Also, there is no reason why RE100 companies discriminate against the quantity of their demand depending on the location, we assume that if firm *j* can supply its product produced by renewable electricity, then the quantities of its supply are the same in domestic and foreign countries.

Assumption 1. The firm *j*'s production function follows the Cobb-Douglas production function.

The payoff of firm *j* can be described below:

$$\pi_j = \begin{cases} pq_j^{\alpha} l_j^{\beta} - p_d^R q_j - p_d^L l_j & \text{if Stay} \\ pq_j^{\alpha} l_j^{\beta} - p_f^R q_j - p_f^L l_j - C_f & \text{if Move} \end{cases} \tag{4}$$

Given prices, we can find the maximized profits of firm *j* are described below:

$$\pi_j^* = \begin{cases} py - \left(y {p_d^L}^{\beta} {p_d^R}^{\alpha} \right)^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta} \right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} \right] & \text{if Stay} \\ py - \left(y {p_f^L}^{\beta} {p_f^R}^{\alpha} \right)^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta} \right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} \right] - C_f & \text{if Move} \end{cases} \tag{5}$$

Assumption 2. Assumes that labor costs are equal to 1 in both domestic and foreign countries to isolate the specific impact of renewable electricity.

Then, firm *j*'s strategy in the third stage is defined below:

$$S_j(p_d^R) = \begin{cases} \text{Stay} & \text{if } p_d^R \leq \left[\frac{C_f}{y^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta} \right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} \right]} + {p_f^R}^{\frac{\alpha}{\alpha+\beta}} \right]^{\frac{\alpha+\beta}{\alpha}} \\ \text{Move} & \text{otherwise} \end{cases} \tag{6}$$

Based on our analysis, we can ascertain that there exists a range where domestic production is influenced by both the price levels of previous domestic renewable energy and foreign renewable energy, even if the price of domestic renewable energy is higher than that of foreign renewable energy. Furthermore, it can be observed that in the event of an increase in foreign fixed costs and electricity prices, domestic production of renewable energy persists even if it is supplied at a comparatively higher price domestically.

Lemma 1. In optimal production, a larger quantity of renewable electricity is used when a firm produces its products in a foreign country compared to when it produces them in domestically.

5. Subgame starting at the second stage

Now, we are going to study the identical obligor *i*'s profit maximization problem under the RPS. The implementation of the policy means that the economic feasibility of renewable electricity is not secured when compared to non-renewable electricity. Since we assume that players are rational, we will ignore the situation of the excess supply of renewable electricity.

Assumption 3. There is a learning effect associated with renewable energy electricity, while non-renewable energy does not exhibit this learning effect because it is a mature technology.

For the cost function of renewable electricity, we will consider that there is a learning effect and adopt Wright's model. Meanwhile, for the non-renewable electricity cost function, we will assume the constant marginal cost because it is a mature technology. Using backward induction, the RPS obligor *i*'s maximization problem when the firm *j*s staying:

$$\max_{q_i^R} \pi_i = p_d^R q_i^R + p_d^{NR}(q_i - q_i^R) - c_1 q_i^{R^{-a}} q_i^R - \left[c_m^{NR}(q_i - q_i^R) + c_f^{NR}\right] - (1+\gamma)\bar{c}_R(tq_i - q_i^R)$$

s.t. $q_i^R \geq 0$ and $tq_i \geq q_i^R$ or

$$\max_{q_i^R} \pi_i = p_d^R q_i^R + p_d^{NR}(q_i - q_i^R) - c_1 {q_i^R}^{-a} q_i^R - \left[c_m^{NR}(q_i - q_i^R) + c_f^{NR}\right]$$

$$\text{s.t. } q_i^R \geq t q_i$$

where c_1 is the marginal cost of the 1st unit of renewable electricity, a is the learning rate where ($0 < a < 1$). When the learning rate is close to 1, it is high learning rate. c_m^{NR} is the marginal cost of non-renewable electricity, and c_f^{NR} is the fixed cost of non-renewable electricity. Then, we can derive the RPS obligor *i*'s best response correspondence with respect to the target share when the firms select to stay.

$$q_i^{R*}(t) = \begin{cases} \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} & \text{if } t \geq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ t q_i & \text{if } \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \leq t \leq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} & \text{if } 0 < t \leq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \\ 0 & \text{if } t = 0 \end{cases} \quad (7)$$

Let s_i be the share of obligor *i*'s market share ($\sum_{i=1}^{I} s_i = 1$) and assume that the demand decrease is affected by the amount of its share.

$$q_J^R = \sum_{j=1}^{J} q_j^{R*}, \; \bar{q}_i = s_i q_J^R = s_i \sum_{j=1}^{J} q_j^{R*}$$

where q_J^R is the total renewable electricity used from the firm *j*s. $\bar{q}_i$ is the amount of renewable electricity provided from obligor *i* to firm *j*s. The RPS obligor *i*'s maximization problem when firm *j*s moving is described below:

$$\max_{q_i^R} \pi_i = p_d^R q_i^R + p_d^{NR}(q_i - \bar{q}_i - q_i^R) - c_1 {q_i^R}^{-a} q_i^R - \left[c_m^{NR}(q_i - \bar{q}_i - q_i^R) + c_f^{NR}\right]$$
$$+ (1+\gamma)\bar{c}_R(t(q_i - \bar{q}_i) - q_i^R)$$

$$\text{s.t. } q_i^R \geq 0 \text{ and } t(q_i - \bar{q}_i) \geq q_i^R \text{ or}$$

$$\max_{q_i^R} \pi_i = p_d^R q_i^R + p_d^{NR}(q_i - \bar{q}_i - q_i^R) - c_1 {q_i^R}^{-a} q_i^R - \left[c_m^{NR}(q_i - \bar{q}_i - q_i^R) + c_f^{NR}\right]$$

$$\text{s.t. } q_i^R \geq t(q_i - \bar{q}_i)$$

Then, we can get the RPS obligor i's best response correspondence with respect to the target share when the firms decide to relocate to other countries.

$$q_i^{R*}(t) = \begin{cases} \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} & \text{if } t \geq \frac{1}{q_i - \bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ t(q_i - \bar{q}_i) & \text{if } \frac{1}{q_i - \bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \leq t \leq \frac{1}{q_i - \bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} & \text{if } 0 < t \leq \frac{1}{q_i - \bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \\ 0 & \text{if } t = 0 \end{cases} \tag{8}$$

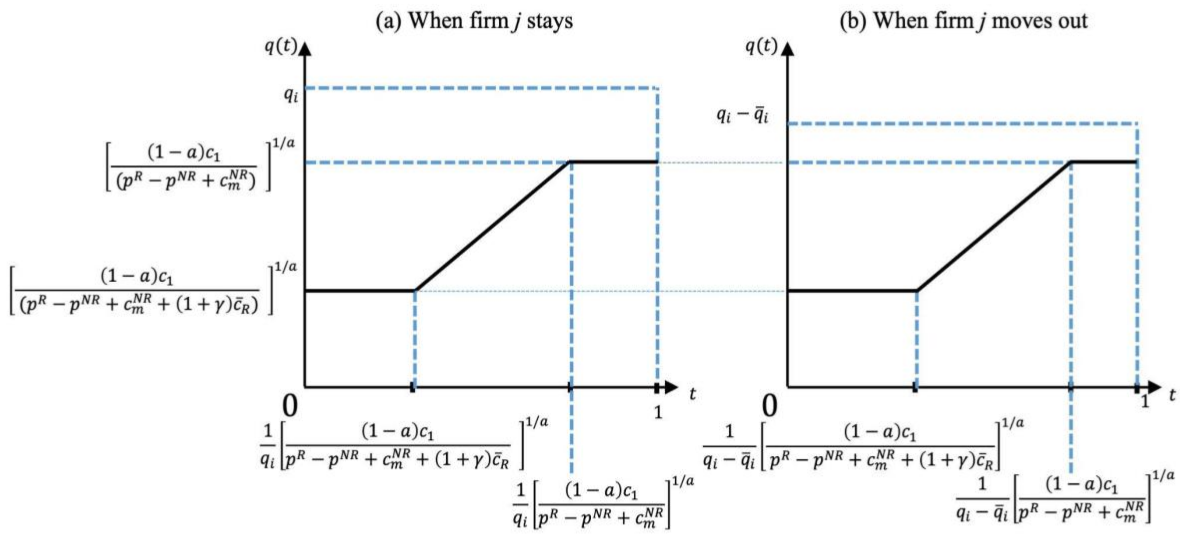

Figure 4 Obligor i's response correspondences

In Figure 4, we can observe that there is a range in which the RPS target share is binding, and it is evident that a higher target share must be chosen to supply the same level of renewable energy power. As the overall electricity demand decreases, it becomes apparent that the share must increase to meet the same quantity. However, it is important to note that the supply volume, which is bound by the RPS target share under the given price and cost conditions, remains the same in both cases.

Table 3 The minimum and maximum binding target shares

Subgame	Minimum Target Share	Maximum Target Share
Firm *j* staying	$\frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R-p_d^{NR}+c^{NR}+(1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}}$	$\frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R-p_d^{NR}+c^{NR}}\right]^{\frac{1}{a}}$
Firm *j* moving	$\frac{1}{q_i-\bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R-p_d^{NR}+c^{NR}+(1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}}$	$\frac{1}{q_i-\bar{q}_i}\left[\frac{c_1(1-a)}{p_d^R-p_d^{NR}+c^{NR}}\right]^{\frac{1}{a}}$

6. Subgame starting at the first stage

The government, utilizing backward induction, possesses knowledge of how other players respond in the game. It is aware that renewable energy, specifically renewable electricity, is still in its nascent stage, and its cost has been decreasing as a result of the learning curve effect. We simply assume that the marginal benefits from renewable electricity and non-renewable electricity are constant. Then, the government's payoff consists of benefits from using renewable electricity, benefits from using non-renewable electricity, benefits from avoiding unemployment, costs from renewable electricity, and costs from non-renewable electricity.

Assumption 4. RPS obligors supply an equal level of power and have an equivalent level of responsibility. i.e., they are identical in terms of their obligations and contributions.

The government knows the strategies employed by other players within the subgame and recognizes the specific range where the RPS policy is effective and binding. Consequently, the government's payoff maximization problem can be formulated as follows:

$$\max_t P_G = I\left[b^R t q_i + b^{NR}(q_i - tq_i) - c_1(tq_i)^{1-a} - \{c_m^{NR}(q_i - tq_i) + c_f^{NR}\}\right] + \sum_j^J (b^L - c^L) l_J \tag{9}$$

$$\max_t P_G = I\left[b^R t(q_i - \bar{q}_i) + b^{NR}(q_i - \bar{q}_i - t(q_i - \bar{q}_i)) - c_1(t(q_i - \bar{q}_i))^{1-a} - \{c_m^{NR}(q_i - \bar{q}_i - t(q_i - \bar{q}_i)) + c_f^{NR}\}\right] \tag{10}$$

The optimal target share for the government for both cases are derived as follows:

$t_S^* = \frac{1}{q_i}\left(\frac{(1-a)c_1}{b^R - b^{NR} + c_m^{NR}}\right)^{\frac{1}{a}}$, $t_M^* = \frac{1}{q_i - \bar{q}_i}\left(\frac{(1-a)c_1}{b^R - b^{NR} + c_m^{NR}}\right)^{\frac{1}{a}}$

And we can find the numerator is the same, and the difference in both cases is total electricity supply of obligor *i* in the denominator.

7. Subgame perfect equilibrium

In this section, we examine the payoffs of each player in the subgame perfect equilibrium. We initiate the analysis from the first stage by substituting the government's optimal target ratios, t_S^* and t_M^*, obtained in the previous section, into equations (9) and (10) respectively. This calculation allows us to determine the government's payoff in the subgame perfect equilibrium.

$$P_G^{S*} = I\left[b^R A + b^{NR}(q - A) - c_1 A^{1-a} - \{c_m^{NR}(q - A) + c_f^{NR}\}\right] + \sum_j^J (b^L - c^L) l_j \tag{11}$$

$$P_G^{M*} = I\left[b^R A + b^{NR}(q - \bar{q} - A) - c_1 A^{1-a} - \{c_m^{NR}(q - \bar{q} - A) + c_f^{NR}\}\right] \tag{12}$$

where $A \equiv \left(\frac{(1-a)c_1}{b^R - b^{NR} + c_m^{NR}}\right)^{\frac{1}{a}}$

Proposition 1. *If the social benefits of employment outweigh the costs and the marginal benefit of non-renewable electricity is equal to the marginal cost, then it is socially more beneficial to maintain employment*.

Proof) From equations (11) and (12), we can compare the optimal payoffs of government, and it is greater than or at least equal to 0. Therefore, the government decides the target share as t_S^*

$$P_G^{S*} - P_G^{M*} = \sum_j^J \underbrace{(b^L - c^L)}_{\geq 0} \underbrace{l_j}_{\geq 0} + I \underbrace{(b^{NR} - c_m^{NR})}_{\geq 0} \underbrace{\bar{q}}_{\geq 0} \geq 0$$

In the initial stage, the government determines the RPS obligation target, t_S^*, in order to incentivize the firms to remain in the market and maintain the current level of employment. In the subsequent stage, each obligor determines its optimal provision of renewable electricity by employing the best response correspondence, and the subgame perfect payoff is below:

$$\pi_i^* = (p_d^{NR} - c_m^{NR})(q_i - A) - c_f^{NR} + A\left(p_d^R - \frac{b^R - b^{NR} + c_m^{NR}}{(1-a)}\right)$$

Since the rational obligor will not select the electricity price which brings a negative profit, the minimum renewable electricity price that the RPS obligor can provide is below:

$$p_d^{Rmin} = \frac{c_f^{NR} - (p_d^{NR} - c_m^{NR})(q_i - A)}{A} + \frac{b^R - b^{NR} + c_m^{NR}}{(1-a)} \tag{13}$$

Proposition 2. *In cases where the electricity price information of the RPS obligors is not transparent during RE100 verification, it is possible to provide renewable electricity at lower prices by increasing the prices of non-renewable energy electricity.*

Proof) From equation (13), take a partial derivative with respect to p_d^{NR}, then

$$\frac{\partial p_d^{Rmin}}{\partial p_d^{NR}} = -\frac{q_i - A}{A} < 0$$

This implies that obligors can provide renewable electricity at a lower price, even if it results in a negative profit for renewable electricity. This is possible because they can offset the negative profit with the higher profit earned from the higher price of non-renewable electricity, ensuring a non-negative overall profit. However, the RE100 initiative prohibits the use of renewable electricity in the form of subsidies, which means that renewable electricity must be paid for.[5]

Assumption 5. The home country has the capability to offer renewable electricity at a price that is equal to or lower than the price that would induce the same payoff as if the firm were to relocate.

The price of renewable electricity in the current country will be decided between this range and the maximized profit will be below:

$$\frac{b^R - b^{NR} + c^{NR}}{(1-a)} \leq p_d^{R*} \leq \left[C_f y^{-\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} \right]^{-1} + p_f^{R\,\frac{\alpha}{\alpha+\beta}} \right]^{\frac{\alpha+\beta}{\alpha}}$$

If there are no restrictions on obligors' selection of renewable electricity prices, the price that maximizes their payoff will be determined at the highest possible level.

$$p_d^{R*} = \left[C_f y^{-\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} \right]^{-1} + p_f^{R\,\frac{\alpha}{\alpha+\beta}} \right]^{\frac{\alpha+\beta}{\alpha}}$$

[5] RE100 requires participating companies to use renewable electricity, and the principle is to pay the cost necessary to supply renewable electricity. Therefore, it is against the principle of lower the price of renewable electricity by increasing the price of non-renewable electricity.

Considering the domestic renewable electricity price, firm *j* maximizes its profit, and the subgame perfect equilibrium payoff is equivalent to the payoff obtained by selecting to relocate to the foreign country.

$$\pi_{jd}^{*} = py - \left(yp_f^{R\alpha}\right)^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}\right] - C_f$$

If the government could influence the pricing of renewable electricity or if there are other factors that result in the supply of renewable electricity at the lowest possible level, the payoff for firm j will be determined at the following level:

$$\pi_{jd}^{*} = py - \left(y\left(\frac{b^R - b^{NR} + c^{NR}}{(1-a)}\right)^{\alpha}\right)^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}\right]$$

Proposition 3. *Even in the presence of renewable energy expansion driven by RPS, if companies are unable to obtain renewable electricity at a certain price level, they may choose to relocate to foreign countries as an alternative option.*

Proof) This implies that assumption 5 does not hold. The lowest level of renewable electricity price is determined by all exogenous variables. It means that we cannot exclude the possibility that

$$\left[\frac{C_f}{y^{\frac{1}{\alpha+\beta}}\left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}\right]} + p_f^{R\frac{\alpha}{\alpha+\beta}}\right]^{\frac{\alpha+\beta}{\alpha}} \leq \frac{b^R - b^{NR} + c^{NR}}{(1-a)} \leq p_d^{R*}$$

In this case, the subgame perfect equilibrium outcome will be changed from staying in domestic country to moving foreign country.

8. Discussion

In the course of analyzing the game, several findings have emerged. Firstly, assuming equal prices for domestic and international labor, it was observed that more electricity was consumed when produced overseas due to the lower price of renewable electricity. This aligns with basic production-related properties.

Secondly, interesting results were obtained regarding the learning rate. Assuming an exogenous learning rate based on the learning curve, it was observed that higher input levels lead to lower average production costs. When comparing the learning rate, minimum price, and target weight, it was found that a higher learning rate corresponds to a lower minimum price and lower target weight. Consequently, as the total power supply increases, the target share decreases, which is contrary to initial expectations. This phenomenon is attributed to the fact that the effect of the learning curve does not incorporate the passage of time in production.

Therefore, taking the learning curve into consideration, it can be concluded that expanding the supply of renewable energy by increasing the proportion of renewable energy electricity through RPS is feasible.

9. Conclusions

This study examined the impact of Renewable Portfolio Standards (RPS) and the RE100 initiative on firm location decisions regarding renewable energy adoption. By analyzing the interplay between government policies, renewable energy costs, and manufacturing strategies, valuable insights were gained into the factors that shape manufacturers' decisions in the context of renewable energy adoption and location selection.

In the game model analysis, three player groups were considered: the government, RPS obligors, and firms supplying RE100 companies. The government's decision to set the RPS target influenced the overall framework for renewable energy adoption, while RPS obligors played a vital role in implementing renewable energy projects. Firms supplying RE100 companies faced the critical decision of whether to remain in their current country or relocate to another country with more favorable renewable energy conditions. The analysis revealed that domestic production of renewable energy persisted even when the price was higher domestically, depending on foreign fixed costs and electricity prices.

The findings indicate that a rational government will choose a target share that maintains employment as long as it brings a non-negative net benefit. Moreover, there exists a range where between domestic and foreign renewable energy prices to determine domestic production, even when domestic prices are higher. By increasing the price of non-renewable electricity, it is possible to subsidize renewable electricity depending on cost transparency. Unfortunately, some countries are unable to maintain the target share for domestic employment due to exogenous variables. Furthermore, it was observed that firms tend to utilize a larger quantity of renewable electricity when manufacturing their products in a foreign country compared to domestic production.

However, it is important to acknowledge certain limitations in our study. Firstly, we did not account for the time effect, despite this being the initial attempt to examine the RPS and RE100 initiative. Considering the passage of time may yield comparative statics in line with the expected direction. Secondly, our analysis was simplified and primarily focused on the supplying firm to the RE100 companies. However, there are other competing electricity technologies and firms that provide goods domestically. In such cases, it becomes necessary to construct a more comprehensive model to assess the overall effects on the entire economy.

Nevertheless, our primary objective was to investigate the RPS effect concerning the RE100 initiative while considering the learning curve. In this regard, our research provides valuable insights and answers to these questions.

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Appendix A. Subgame at the third stage

Firm *j* decides to stay.

$$\max_{q_j, l_j} \pi_j = p q_j^{\alpha} l_j^{\beta} - p_d^R q_j - p_d^L l_j$$

FOC with respect to q_j and l_j

$$\frac{\partial \pi_j}{\partial q_j} = p\alpha q_j^{\alpha-1} l_j^{\beta} - p_d^R = 0 \Leftrightarrow p\alpha \frac{l_j^{\beta}}{q_j^{1-\alpha}} = p_d^R \tag{A1}$$

$$\frac{\partial \pi_j}{\partial l_j} = p\beta q_j^{\alpha} l_j^{\beta-1} - p_d^L = 0 \Leftrightarrow p\beta \frac{q_j^{\alpha}}{l_j^{1-\beta}} = p_d^L \tag{A2}$$

From equation (A1) and (A2)

$$\frac{p_d^R}{p_d^L} = \frac{p\alpha \frac{l_j^{\beta}}{q_j^{1-\alpha}}}{p\beta \frac{q_j^{\alpha}}{l_j^{1-\beta}}} = \frac{\alpha l}{\beta q} \Rightarrow l_j = \frac{p_d^R q_j}{p_d^L} \frac{\beta}{\alpha} \tag{A3}$$

Plug (A3) into the production function, then

$$y = q_j^{\alpha} \left(\frac{p_d^R q_j}{p_d^L} \frac{\beta}{\alpha} \right)^{\beta} \Leftrightarrow y = \frac{q_j^{\alpha} {p_d^R}^{\beta} q_j^{\beta} \beta^{\alpha}}{{p_d^L}^{\beta} \alpha^{\beta}} = q^{\alpha+\beta} \left(\frac{p_d^R \beta}{p_d^L \alpha} \right)^{\beta}$$

$$\Leftrightarrow q_j^* = q_{dj}^{R*} = \left[y \left(\frac{p_d^L \alpha}{p_d^R \beta} \right)^{\beta} \right]^{\frac{1}{\alpha+\beta}} \tag{A4}$$

Plug (A4) into equation (A3)

$$l_j^* = l_{dj}^* = \frac{\beta\, p_d^R}{\alpha\, p_d^L} \left[y \left(\frac{p_d^L \alpha}{p_d^R \beta} \right)^{\beta} \right]^{\frac{1}{\alpha+\beta}} = y^{\frac{1}{\alpha+\beta}} \left(\frac{p_d^R \alpha}{p_d^L \beta} \right)^{\frac{1}{\alpha+\beta}} \frac{\beta\, p_d^R}{\alpha\, p_d^L} = \left[y \left(\frac{\beta\, p_d^R}{\alpha\, p_d^L} \right)^{\alpha} \right]^{\frac{1}{\alpha+\beta}} \tag{A5}$$

Then, the maximized firm *j*'s profit (payoff) is defined below:

$$\Leftrightarrow \pi_{dj}^* = py - \left(y {p_d^L}^{\beta} {p_d^R}^{\alpha} \right)^{\frac{1}{\alpha+\beta}} \left[\left(\frac{\alpha}{\beta} \right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} \right] \tag{A6}$$

Lemma 1.

We assume that firm *j* moves out to another country that can provide renewable electricity cheaper than the currently located country ($p_d^R > p_f^R$). When we compare the optimal electricity in both cases,

$$q_{fj}^{R*} - q_{dj}^{R*} = \left(\frac{y\alpha^{\beta}}{\beta^{\beta}}\right)^{\frac{1}{\alpha+\beta}} \left[\frac{1}{p_f^{R\frac{\beta}{\alpha+\beta}}} - \frac{1}{p_d^{R\frac{\beta}{\alpha+\beta}}}\right] > 0 \quad \because p_d^R > p_f^R$$

Appendix B. Subgame at the second stage

Firm *j* decides to stay in the third stage.

$$\mathcal{L}(q_i^R, \lambda, \mu) = p_d^R q_i^R + p_d^{NR}(q_i - q_i^R) - c_1 q_i^{R-a} q_i^R - \left[c_m^{NR}(q_i - q_i^R) + c_f^{NR}\right]$$
$$+(1+\gamma)\bar{c}_R(tq_i - q_i^R) + \lambda q_i^R + \mu(tq_i - q_i^R)$$

FOCs

$$\frac{\partial \mathcal{L}(q_i^R, \lambda, \mu)}{\partial q_i^R} = p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R + \lambda - \mu = 0$$

$$\frac{\partial \mathcal{L}(q_i^R, \lambda, \mu)}{\partial \lambda} = q_i^R, \quad \lambda q_i^R = 0$$

$$\frac{\partial \mathcal{L}(q_i^R, \lambda, \mu)}{\partial \mu} = tq_i - q_i^R, \quad \mu(tq_i - q_i^R) = 0$$

i) $\lambda > 0,\ \mu > 0$

$\lambda > 0 \quad \Rightarrow q_i^R = 0$

$\mu > 0 \quad \Rightarrow q_i^R = tq_i \neq 0$

Therefore, it is a contradiction.

ii) $\lambda > 0,\ \mu = 0$

$\lambda > 0 \quad \Rightarrow q_i^R = 0$

$\mu = 0 \quad \Rightarrow q_i^R \leq tq_i$

$q_i^R = 0 \leq tq_i$

$\therefore q_i^R = 0$

$p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R + \lambda = 0$

$\Leftrightarrow p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R < 0$

$$\Leftrightarrow 0 = q_i^R < \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \quad \text{(B1)}$$

iii) $\lambda = 0,\ \mu > 0$

$\lambda = 0 \quad \Rightarrow q_i^R \geq 0$

$\mu > 0 \quad \Rightarrow q_i^R = tq_i$

$\therefore q_i^R = tq_i$

$$p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R - \mu = 0$$

$$\Leftrightarrow p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R > 0$$

$$\Leftrightarrow tq_i = q_i^R > \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}}$$

$$\Leftrightarrow t > \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \tag{B2}$$

iv) $\lambda = 0,\ \mu = 0$

$\lambda = 0 \quad \Rightarrow q_i^R \geq 0$

$\mu = 0 \quad \Rightarrow q_i^R \leq tq_i$

$\therefore 0 \leq q_i^R \leq tq_i$

$$p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R - \mu = 0$$

$$\Leftrightarrow q_i^R = \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \tag{B3}$$

$$\mathcal{L}(q_i^R, \lambda, \mu) = p_d^R q_i^R + p_d^{NR}(q_i - q_i^R) - c_1 q_i^{R-a} q_i^R - \left[c_m^{NR}(q_i - q_i^R) + c_f^{NR}\right]$$
$$+\lambda(q_i^R - tq_i)$$

FOCs

$$\frac{\partial \mathcal{L}(q_i^R, \lambda)}{\partial q_i^R} = p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R + \lambda = 0$$

$$\frac{\partial \mathcal{L}(q_i^R, \lambda, \mu)}{\partial \lambda} = q_i^R - tq_i, \quad \lambda(q_i^R - tq_i) = 0$$

v) $\lambda > 0$

$$\lambda > 0 \quad \Rightarrow q_i^R = tq_i$$

$$p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + \lambda = 0$$

$$\Leftrightarrow p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} < 0$$

$$\Leftrightarrow tq_i = q_i^R < \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \tag{B4}$$

vi) $\lambda > 0$

$$\lambda = 0 \quad \Rightarrow q_i^R \geq tq_i$$

$$p_d^R - p_d^{NR} - c_1(1-a)q_i^{R-a} + c_m^{NR} + (1+\gamma)\bar{c}_R - \mu = 0$$

$$\Leftrightarrow q_i^R = \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \tag{B5}$$

From the (B1) to (B5), we can derive the best response correspondence of obligor *i*.

$$\therefore q_i^{R*}(t) = \begin{cases} \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} & \text{if } t \geq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ tq_i & \text{if } \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \leq t \leq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR}}\right]^{\frac{1}{a}} \\ \left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} & \text{if } 0 < t \leq \frac{1}{q_i}\left[\frac{c_1(1-a)}{p_d^R - p_d^{NR} + c_m^{NR} + (1+\gamma)\bar{c}_R}\right]^{\frac{1}{a}} \\ 0 & \text{if } t = 0 \end{cases}$$

THE IMPACT OF RPS POLICY ON THE PRIMARY CROPS PLANTED AREA IN THE UNITED STATES

1. Introduction

In the last 20 years, renewable energy has emerged as a promising solution to respond to climate change and reduce reliance on traditional fossil fuels. It has brought many advantages, including reducing greenhouse gas emissions and promoting sustainable energy systems, and jobs in related industries are also increasing. However, some renewable energy generation facilities require land. As a result, there is a growing interest in how renewable energy expansion has a potential impact land available for agricultural use.

One of the primary features of renewable energy is the relatively low energy density of its raw materials compared to fossil fuels. This often necessitates significant land area for the installation of renewable energy facilities, particularly in power generation (val Zalk and Behrens, 2018). While the increased supply of renewable energy is generally viewed as positive in addressing climate change, it is crucial to consider the potential adverse effects on agricultural land and crop acreage resulting from these installations.

There are a great many studies of acreage estimation, focusing on various factors influencing crop area, such as climate change, agricultural policies, and bioenergy. However, studies specifically examining the impact of renewable electricity, a relatively recent form of installed capacity that can affect crop cultivation and land use, are scarce.

In this context, understanding the implications of renewable energy policies, particularly Renewable Portfolio Standards (RPS), on crop acreage becomes crucial. RPS policies requires utilities or power suppliers to obtain a certain percentage of their electricity from renewable sources, aiming to promote renewable energy development, stimulate clean energy investments, and reduce greenhouse gas emissions.

From the 2000s to the early 2010s, there was a record surge in the enactment and enforcement of RPS related laws in the United States (Figure 1). In 2014, 34 states implemented RPS policies, the peak in terms of the number of enforcing states. Since then the number of RPS states has fallen due to two reasons: impossibility of implementation and achievement of implementation. In 2015 West Virginia repealed the RPS for the first reason, but four states, Montana, North Dakota, Oklahoma, and South Dakota, successfully met their RPS. As of 2021, out of all the states and Washington D.C., 29 have implemented RPS, which accounts for more than half of the total.[1]

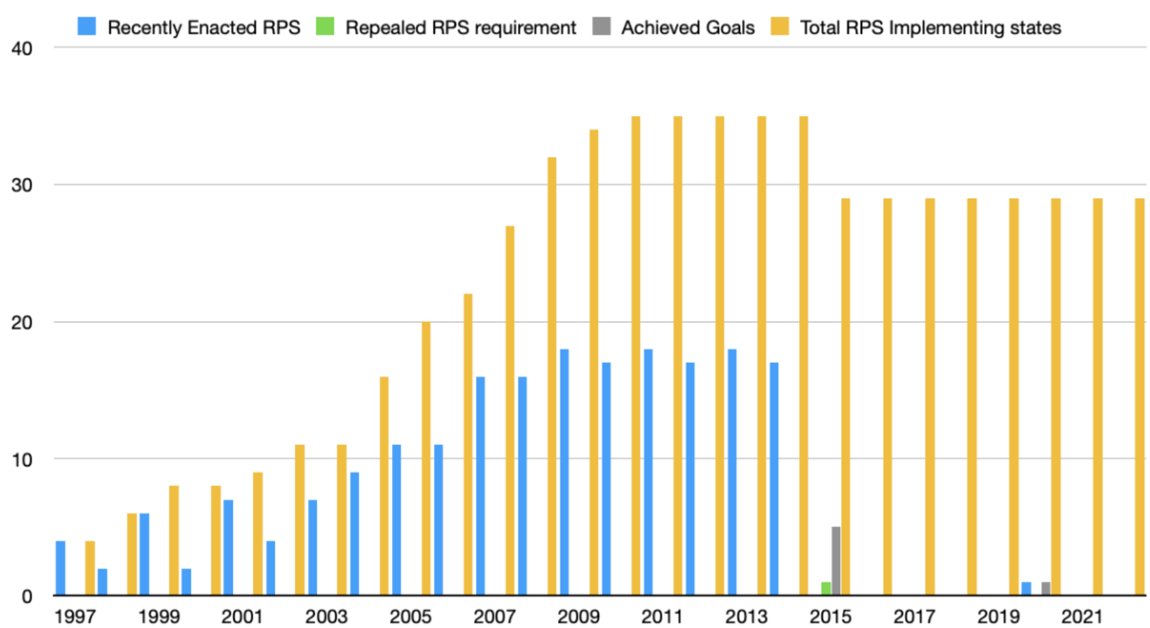

Figure 1 Historical evolution of RPS policies in the U.S. states (1997-2022)

Source: Authors own calculations using data from NCSL and DSIRE

[1] In 2020, Kansas achieved its RPS goals and changed its policy to voluntary target (enacted in 2015), while Virginia started implementation of RPS in 2020.

Notably, California, Colorado, Hawaii, Maine, Nevada, New Mexico, Virginia, Washington, and Washington D.C. have set ambitious targets of achieving 100% renewable (or clean) energy through their RPS policies.[2] These states are actively working towards a complete transition to renewable energy sources in their electricity generation. Across the U.S. there has been widespread adoption and varying goals of RPS policies across different states, with a significant focus on achieving high levels of renewable energy generation.

However, the expansion of renewable energy installations driven by RPS policies may compete with agricultural land, potentially leading to changes in total primary crops planted acreage (TPCA) and posing a threat to food security. In 2019 state of Ohio, farmers were offered $800-$1,200 per acre per year once a facility is constructed and operating (Donalson, 2019). In 2022 Callaway County in Missouri, there was an opposition to solar farm projects meanwhile a partner of solar farm leased about 400 acres of land for $800 per acre annually over 40 years (Brenner, 2022). A similar situation is observed in 2023 Minnesota where the state has a goal of 100 percent carbon-free energy by 2040. In this article, solar PV developers are offering landowners $800-$1,500 per acre per year, young farmers are hard to access land because the bidding of PV developers are outbidding compared to the farmers' bidding, $300 per acre per year (Marshall-Chalmers, 2023). Therefore, the issue of renewable energy expansion and arable land is an important topic to be investigated at the present time as similar problems are occurring throughout the United States.

[2] See Brief for the State Renewable Portfolio Standards and Goal of NCSL

For this topic, some research questions follow: do the target levels of renewable electricity make a significant impact on the total primary crops planted area in 48 adjacent states of the United States from 1997 to 2022? How much does it impact? Does Conservation Reserve Program (CRP) enrolled area have a significant effect that is expected to have similar effects to target levels of renewable electricity? This study aims to investigate the impact of RPS policies on total primary crop acreage in the United States. It seeks to assess the significant influence of RPS policies on crop acreage, providing insights into potential conflicts and trade-offs between renewable energy expansion and agricultural land use for the 48 states from 1997 to 2022. To achieve this objective, the study will conduct a comprehensive analysis of renewable energy policies, crop acreage data, and other relevant factors such as land availability, economic considerations, and agricultural practices.

The subsequent sections of this paper comprises a literature review in Section 2, research methodology is presented in Section 3, and data sources are discussed in Section 4. In Section 5, the results are analyzed, and conclusions are presented in Section 6. Through a rigorous examination of RPS policies and their effects on total primary crop acreage, this study aims to contribute to the ongoing discussions on the sustainable deployment of renewable energy and its implications for agricultural land use.

2. Literature review

Regarding the competition between agriculture and solar power, research suggests that the displacement of agricultural land due to solar power installations is relatively small (Mauro and Lughi, 2017). Even with less than 1% of agricultural land dedicated to solar power, global energy demands can be met (Adeh et al., 2019). Britz and Delzeit (2013) examined the impacts of Germany's biogas production on agricultural markets, land use, and the environment. They found that the significant increase in biogas output, driven by the Renewable-Energy-Act (EEG), had sizeable effects on global agricultural markets, causing significant land use changes outside of Germany.

According to Sacchelli et al. (2016), there is a trade-off between traditional food/feed cultivation and solar installation in unirrigated arable land in Italy. They found that regions with high crop yields and availability of non-irrigated arable land experienced a relevant decrease in crop production because of solar installation.

Several studies have explored the relationship between climate variables, technology, crop prices, and crop yield variations in the United States. For the total acreage, Barr et al. (2011) examined agricultural land elasticities and found that the implied acreage elasticity with respect to the expected price are from 0.007 to 0.029 depending on the time. Huang and Khanna (2010) conducted an extensive analysis using historical data from 1977 to 2007 at the county-level, examining the impacts on corn, soybeans, and wheat. Their findings shed light on how changes in output prices, climate conditions, and technological advancements affect crop yields over time. Miao et al. (2015) investigated the influence of crop pricing and climatic factors on rainfed corn and soybean yields and acreage, revealing price elasticities and potential climate change scenarios.

Uludere Aragon (2019) focused on examining the role of land quality in the response of corn acreage to price and policy changes from 1986 to 2015 in the western corn belt region. The author employed a multivariate panel model at the county-level and considered various factors such as fertilizer price index, CRP rental payment, and average precipitation in April. In addition to corn prices, she also analyzed the impact of soybean, wheat/oats, and hay prices, as well as the biofuel dummy variable based on the FAIR Act and the 2006 Added variable. The analysis divided the data into groups based on total acreage and land quality. The study found that the price elasticity of corn acreage ranged from 0.176 to 0.519, and these elasticities were statistically significant. Corn acreage responded positively to soybean prices but negatively to fertilizer prices, wheat/oats prices, and CRP payments. Furthermore, a statistically significant positive response was observed in the time trend for the entire dataset and quartiles I-III.

Salassi (1995) examined the response of rice acreage to the support price under government policy in a study on the U.S. rice acreage. The author found a price elasticity ranging from 0.18 to 0.43, based on average prices and divided into short-term and long-term periods.

DeLay (2019) confirmed that the Conservation Reserve Program (CRP) registered area responded positively to CRP rent. However, positive, and negative responses alternated depending on the inclusion of year fixed effects when considering expected prices using futures price.

Table 1 presents a collection of studies focused on acreage estimation, which examine the utilization of different price variables. In this context, researchers commonly consider two types of prices: the futures price and the received price, which play a significant role in determining farmer behavior. Additionally, the inclusion or exclusion of a lagged acreage term varies across different models employed in these studies.

Table 1 Estimates of Acreage Elasticities in Different Studies

Study	Price Used	Crop Type	Own-price Elasticity
Barr et al. (2011)	Futures	Total acreage	0.007-0.029
Chavas and Holt (1990)	Received	Corn	0.15
		Soybeans	0.45
Chembezi and Womack (1992)	Received	Corn	0.10
Lee and Helmberger (1985)	Received	Corn	0.05
		Soybeans	0.25
Lin and Dismukes (2007)	Futures	Corn	0.17-0.35
		Soybeans	0.30
Miller and Plantinga (1999)	Received	Corn	0.95
		Soybeans	0.95
Orazem and Miranowski (1994)	Futures	Corn	0.10
		Soybeans	0.33
Uludere Aragon (2019)	Received	Corn	0.291 (0.176-0.519)
Salassi	Supported	Rice	0.18-0.61
Tegene, Huffman, and Miranowski (1998)	Received	Corn	0.20
Huang and Khanna (2010)	Received	Total acreage	0.257
		Corn	0.510
		Soybeans	0.487
		Wheat	0.067
Miao et al. (2015)	Received	Corn	0.45
		Soybeans	0.63
This study	Received	Total acreage	0.297-0.314

Note: Adapted from Miao et al. (2015), p.3. Additional information added by the authors

3. Methodology

We model the state-specific acreage of total primary crops for state *i* and year *t* as

$$A_{it} = \beta_0 + \beta_1\Lambda_{it} + \beta_2\Psi_{it} + \beta_3\Gamma_{it} + \beta_4 P_{it} + \beta_5\Sigma_{it} + \beta_6\Omega_{it} + u_i + \epsilon_{it} \qquad (1)$$

where β_0 is a constant and β_1 to β_6 are vectors of parameters to be estimated; Λ, Ψ, Γ, P, Σ and Ω are vectors of prices, climate variables, time trends, population density, conservation reserve program, and RPS vectors, respectively; u_i is a state-level fixed effect, and ϵ_{it} is an error term.

The vector Λ encompasses the input and output prices, specifically represented by the fertilizer price index for input costs and the Laspeyres price index for the total output prices (Huang and Khanna, 2010). In contrast to previous studies that relied on a one-year lagged expected price, this model employs a two-year average lagged price. If there are no other factors at play and the decision is solely between cultivation and fallow, the one-year lagged price can effectively represent and clarify the situation. However, incorporating a two-year lagged price is necessary due to the complexities involved in the farmer's perspective when considering renewable energy factors. It is not merely a matter of choosing to cultivate a different crop or fallow for one year. The two-year lagged price accounts for the possibility of farmers opting to seek alternative employment opportunities outside of farming for an extended period, or even considering farming in a different location. Thus, using a two-year lagged price makes more sense in this context, as it allows for a broader consideration of the potential outcomes and decisions related to renewable energy transition.[3]

The climate variable vector (Ψ) incorporates seasonal precipitations, which are recognized as a crucial factor in determining crop acreage. Moreover, the time trend vector (Γ) is included to account for technological advancements and changes in agricultural practices over time. Both linear and quadratic time trends are considered to capture any non-linear patterns that may emerge. CRP vector (Σ) includes the area enrolled in conservation program. In addition to the analysis, notable additions include the inclusion of the RPS policy vector (Ω), which represents the targeted electricity supply in states implementing RPS policies. Furthermore, several electricity-related variables such as electricity interstate net flow, electricity consumption, and electricity net supply have been incorporated.

[3] Krause et al. (1995) utilized expected market prices based on a weighted average of the average price received by farmers over the previous three years.

The common endogeneity concern associated with price estimation in acreage analysis is that a high (or low) price of a crop tends to increase (or decrease) the acreage of that crop meanwhile large (or small) acreage of a crop might induce low (or high) price of that crop. To solve the endogeneity problem associated with crop price, we employ a panel data instrumental variable (IV) estimator with state-fixed effects. This approach enables us to account for the national level of TPCA while effectively mitigating endogeneity issues. To serve as a suitable instrumental variable, certain criteria must be met: 1) it should have an impact on prices, 2) it should not influence TPCA, and 3) it should be applicable across all 48 states to utilize all data. In this study, we utilize hay stocks as of December 1 of the previous year as an instrumental variable. Given that hay is cultivated in all states under examination and serves as a substitute for other crops, it meets the requirements for an appropriate instrumental variable.

4. Data

Our research aims to assess the impact of Renewable Portfolio Standard (RPS) policies on the land area dedicated to primary crops. As RPS policies are implemented at the state level, we require state-level data to analyze their effects. Specifically, we need data on individual crop types, climate variables, RPS policy implementation, electricity market dynamics, and agricultural policies. To fulfill this objective, we conduct an analysis of 48 states, excluding Alaska, Hawaii, and Washington, DC. These states are chosen based on the availability of adequate and reliable acreage-related data during the analysis period spanning from 1997 to 2022.

To obtain data on individual crops, we rely on the US Department of Agriculture's National Agricultural Statistics Service (USDA NASS). The USDA NASS provides information on various primary crops, including corn, sorghum, oats, barley, wheat (winter wheat, spring wheat, and durum wheat), rye, rice, soybeans, peanuts, sunflower, cotton, dry edible beans, potatoes, sugarbeets, canola, proso millet, all hay, tobacco, and sugarcane. We aggregate the planted and harvested areas of these crops from 1997 to 2022 to derive the total primary crop area for each state.[4]

However, estimating the total primary crop planted area poses challenges when utilizing individual crop prices. To address this issue, we employ the Laspeyres price index based on the production volume of individual crops in 2015. This index serves as a price variable corresponding to output. We gather state-level production data for each crop from 1997 to 2022, received price data from 1996 to 2022, and stock data as of December 1st from USDA NASS. In certain states, namely those belonging to the New England region and Utah, there is a lack of price data for corn and wheat, despite our ability to determine which states cultivated these crops. In such instances, we resort to using the prices from the nearest states.[5] Also, all price variables are adjusted to real prices using the GDP deflator in 2015 dollars.

To conduct a panel analysis, it is good to have fertilizer prices categorized by state and year. However, obtaining such data from the USDA or other sources is challenging. This might lead previous researchers to utilize the fertilizer price index provided by the Economic Research Services of USDA as a substitute for actual fertilizer

[4] We exclude dry edible beans and consider the entire primary crop planted area. This is because it is challenging to select specific dry edible beans, and there is no significant difference between the total area and the area excluding dry edible beans.

[5] To fill in the missing prices for the New England region, we utilize the corn prices of New York. Similarly, for the missing prices of Utah, we use the wheat prices of California as a substitute.

prices. (Huang and Khanna, 2010; Miao et al. 2015; Uludere Aragon, 2019) In line with these previous research practices, we will also utilize the fertilizer price index which covers the period from 1997 to 2022 as a representative measure of output prices for our analysis.

To assess the effectiveness of RPS policies, we obtain annual target shares of states implementing RPS from the Berkeley Lab. Additionally, we acquire variables related to the electricity market and new and renewable energy facilities from the US Energy Information Administration (EIA). These variables include solar nameplate capacity, electricity consumption (supply), and electricity interstate net flow by state from 1996 to 2020.[6] By multiplying the electricity consumption data from the EIA with the RPS target shares obtained from the Berkeley Lab, we generate the target level of renewable electricity variable.

To account for environmental factors, we collect monthly precipitation data from NOAA's National Centers for Environmental Information spanning from 1997 to January 2023. This data allows us to capture seasonal variations in precipitation, and we define the seasons as spring (March to May), summer (June to August), fall (September to November), and winter (December to February). As a convention, we categorize the precipitation of the first two months of the current year as belonging to the previous year to align with the seasonal classification.

Population data for each state is sourced from the US Department of Commerce Bureau of Economic Analysis, while inland area information is derived from US census data. We calculate an economic factor by dividing the population by the inland area. We

[6] In the electricity market, consumption is equal to supply. If there is any imbalance between consumption and supply, it can result in disruptions such as blackouts.

consider variables related to agricultural policies, specifically the Conservation Reserve Program (CRP). We utilize the enrolled acreage figures associated with the CRP from the Farm Service Agency, USDA.

Table 2 Descriptive Statistics

Parameter	Unit	Obs.	Mean	SD	Min	Max
Total Primary Crop acreage	acres	1,248	6,629,372	7,413,637	7,000	25,020,000
Target Level of Renewable Electricity (RE)	billion kWh	1,151	2.778	8.028	0	82.56
Electricity Consumption	billion kWh	1,152	74.35	67.76	5.239	429.3
Electricity Interstate Net Flow	billion kWh	1,152	-0.249	22.76	-77.81	89.52
Electricity Net Supply	billion kWh	1,152	74.60	64.56	3.535	419.3
CRP Enrolled Area	million acres	1,248	0.610	0.848	0	4.074
Composite Price Index		1,247	103.4	24.01	44.43	195.6
Fertilizer Price Index		1,248	68.55	28.05	31.90	131.4
Population Density	thousand residents/mi^2	1,248	0.198	0.264	0.00503	1.261
Precipitation in Spring	cm	1,248	24.98	11.27	1.041	64.21
Precipitation in Summer	cm	1,248	26.99	13.50	0.356	73.13
Precipitation Fall	cm	1,248	23.04	11.48	1.321	62.15
Precipitation in Winter	cm	1,248	21.53	12.55	0.584	70.18
Hay Stock on Farm on Dec. 1st	Tons	1,248	2,009,365	1,946,008	4,000	13,400,000

5. Results

This section presents the findings derived from the TPCA regression analysis employing four distinct model specifications. The models aim to examine the relationship between various factors and TPCA (Total Planted Crop Acreage). In Model I, certain variables such as the RPS (Renewable Portfolio Standard) electricity supply target, CRP (Conservation Reserve Program) enrolled area, electricity consumption, interstate electricity net flow, and electricity net supply are excluded. Model II incorporates these essential variables along with the RPS electricity supply target and CRP registration area. To account for state-specific characteristics of the electricity market, Models III and IV further include electricity consumption and interstate electricity net flow, and electricity net supply, respectively. Table 3 provides the results of estimations of all models.

Table 3 The estimated results of the fixed effects models

Variables	Model I	Model II	Model III	Model IV
Target Level of RE		-0.004***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)
E. Interstate Net Flow$_{-1}$			-0.000	
			(0.001)	
E. Consumption$_{-1}$			0.001**	
			(0.001)	
Net E. Supply$_{-1}$				0.001*
				(0.000)
CRP Enrolled Acres		-0.069***	-0.059***	-0.065***
		(0.013)	(0.012)	(0.012)
Composite Price$_{-1-2}$	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Fertilizer Price Index$_{-1}$	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Time Trend$_{-1}$	-0.000	0.001	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.003)
Time Trend Squared$_{-1}$	-0.000*	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Population Density	0.046	0.510	0.342	0.422
	(0.708)	(0.695)	(0.647)	(0.673)
Precipitation Spring$_{-1}$	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation Summer$_{-1}$	0.001**	0.001	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation Fall$_{-1}$	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation Winter$_{-1}$	0.000	0.001*	0.000*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,248	1,151	1,151	1,151
R-squared	0.208	0.263	0.297	0.282
Number of States	48	48	48	48
Kleibergen-Paap *rk* LM statistic	16.545	16.007	16.147	15.977
Kleibergen-Paap *rk* Wald F statistic	16.008	13.416	16.709	15.204
p-value of Hansen J statistic	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses.
*** 1% level, ** 5% level, * 10% level

The target level of renewable electricity, which captures the impact of RPS policy, demonstrates statistical significance and a negative relationship at the 1% level in all models. A 1 billion kWh (= 1 million MWh = 1,000 GWh = 1 TWh) increase in the target level of renewable electricity results in a reduction of 1.0% of TPCA in Model II, and reduction of 1.1% of TPCS in Model III and IV, respectively.[7] To calculate the acres change by 1 billion kWh change, a reduction of 24,335.76 acres in Model II. Model III, accounting for electricity consumption and interstate net flow to reflect state-specific power conditions, indicates a decrease of 26,832.38 acres while the coefficient associated with net flow (negative in the case of power exports) is negative but lacks statistical significance. Model IV, incorporating net electricity supply (electricity consumption - interstate net flow) to address this issue, reveals a decrease of 25,761.74 acres for every 1 billion kWh increase in the target level of renewable electricity, with net electricity supply displaying positive significance at the 10% level. In interpretation, this suggests that an abundance of surplus electricity within a state contributes to an increase in TPCA. Consequently, inadequate surplus electricity within a state, leading to an influx of electricity from other states, results in a reduction in acreage. This observation may correspond to scenarios where electricity-dependent facilities are established within the TPCA.

Integrating the CRP enrolled area into the analysis yields statistically significant negative coefficients across all models, which are increasing by 1 million acres in CRP enrollment reduces TPCA by 5.9%-6.9%. Additionally, the consistent magnitude of coefficients for input and output prices reflects a decline in acreage. Enrolling an area of

[7] 1 billion kWh is equivalent to 94,000 residential utility customers' annual electricity consumption based on the average annual electricity consumption for a U.S. residential utility customer in 2021 (EIA, 2022).

1 acre in CRP is associated with a reduction ranging from 0.39 to 0.46 acre.[8] Given that CRP targets objectives beyond TPCA exclusively, a reduction of less than 1 acre can be considered a reasonable outcome.

The outcomes displayed bottom of Table 3 show the test results of the instrument variable. Kleibergen-Paap *rk* LM statistic, Kleibergen-Paap *rk* Wald F statistic, and Hansen J statistic show the results of under-identification test, weak identification test, and over-identification test, respectively. The results indicate that using the farm hay stock on December 1st is an instrumental variable suitable for mitigating the endogeneity of the composite price index.

The outcomes displayed in Table 3 reveal a statistically significant positive response of TPCA to an increase in its output price across all four models, with significance observed at the 1% level. In Model I, the estimated acreage elasticity with respect to the composite price index is calculated as 0.329 (Table 4). However, upon controlling for the RPS electricity supply target and CRP enrolled acres, this acreage elasticity diminishes to 0.314. Moreover, incorporating the state-specific characteristics of the electricity market further reduces the elasticity to 0.297 and 0.304 in Models III and IV, respectively. Compared to other research, our elasticity falls between that of Barr et al., which is lower, and that of Huang and Khanna, which is higher. While it is challenging to directly compare elasticities across different crops, our findings do not lie at the extreme ends of the spectrum.

The coefficients associated with the fertilizer price index are found to be positive and statistically significant at the 1% level in all models. This indicates that higher

[8] Divide acres of CRP Enrolled Area in Table 4 by 1 million.

fertilizer prices contribute to a decline in planting intensity and a contraction of extensive margins (Black, 1929). The positive response to the output price and negative response to the input price imply the effective operation of the production function when acreage serves as a representative indicator of production levels.

The coefficients associated with the time trend fail to demonstrate statistical significance for linear terms, while quadratic terms display negative coefficients. Models excluding control variables for the electricity market yield statistical significance for the time trend at the 10% level. The negative coefficients for quadratic terms indicate a regression in technology and agricultural practices. Further investigation is required to ascertain whether this regression reflects the actual situation or if incorporating power market controls would offer a more satisfactory explanation.

The analysis indicates that fall precipitation has a negative impact on acreage across all models. On the other hand, positive summer precipitation shows statistical significance at the 5% level in Model I and at the 10% level in Model III. In Models II-IV, positive coefficients are observed at the 10% level. Given that we focus on primary crops, we may not directly identify the specific growing season. However, it is well-known that crops like corn, soybeans, and rice are typically harvested in the fall. Considering that corn and soybeans constitute a significant portion of U.S. agriculture, it is reasonable to assume that precipitation during the harvest season might not be conducive to production. Thus, a negative impact on previous year's production could lead to adverse effects on acreage.

Contrary to previous studies, the coefficients of population density exhibit positive values but lack statistical significance across all four models. This finding suggests that changes in population density do not exert a statistically significant influence on TPCA at the state level, as opposed to the county level, where the conversion of cropland to residential areas is more sensitive to population density variations.

Table 4 Summary of unit (acre) change and elasticities of key determinants at the means

Variables	change	Model I	Model II	Model III	Model IV
Target Level of RE	acres		-24335.76	-26832.38	-25761.74
	elasticity		-0.010	-0.011	-0.011
CRP Enrolled Acres	acres		-456887.04	-393396.88	-428541.17
	elasticity		-0.042	-0.036	-0.039
E, Interstate Net Flow$_{-1}$	acres			-1167.10	
	elasticity			0.000	
E. Consumption$_{-1}$	acres			8975.51	
	elasticity			0.101	
Net E. Supply$_{-1}$	acres				5562.04
	elasticity				0.063
Composite Price$_{-1-2}$	acres	21259.73	20253.39	19172.81	19658.74
	elasticity	0.329	0.314	0.297	0.304
Fertilizer Price Index$_{-1}$	acres	-13466.91	-13412.55	-12290.19	-12790.05
	elasticity	-0.209	-0.208	-0.190	-0.198
Precipitation Fall$_{-1}$	acres	-6732.79	-7794.82	-7520.36	-7739.79
	elasticity	-0.023	-0.027	-0.026	-0.027

Table 5 shows the land requirements (Capacity weighted average land use) for the solar PV, CSP and wind power from National Renewable Energy Laboratory (NREL) of U.S. Department of Energy (DOE) and STRATA group.[9] We can easily find that there are huge differences between them. We apply 24.7% and 36% capacity factors for average PV and wind power in the U.S. from NREL's data, respectively. From the calculation, we can find that PV requires 2.82 – 20.1 acres and wind power requires 9.51

[9] STRATA group did not specify the land requirements by size, and CSP data is from NREL 2013 report.

– 22.4 acres to generate 1,000 MWh per year. Crop acreage changes by target level of renewable electricity is similar to STRATA's data, however it can be seen as overestimated based on NREL's data.

Table 5 Land requirement by technology and size

	NREL		STRATA	
Technology	Capacity weighted average land use (acres / MW)	Generation weighted average land use (acres/1 GWh/yr)	Capacity weighted average land use (acres / MW)	Generation weighted average land use (acres/1 GWh/yr)
Solar PV (1-10MW)	6.1	2.82	43.5	20.1
Solar CSP	10	3.5		
Wind (<1 MW)	30	9.51	70.64	22.4
Wind (1 – 10 MW)	44.7	14.17		

Source: NREL (2013), NREL (n.d.), STRATA (2017) and authors' calculation

6. Conclusions

This research employs an econometric analysis to find the answer of the research questions: does the target levels of renewable electricity and CRP enrolled area have significant impacts on the total primary crop planted area across 48 states, excluding Alaska, Hawaii, and Washington, DC? How much do they impact? The answers are "They are not only statistically significant and negative but also important in economic point of view."

Utilizing state-level data spanning from 1997 to 2022, we examine the relationship between acreage and various factors. Drawing upon previous studies, our empirical framework is based on the premise that acreage is influenced by climatic factors, farmers' crop management practices, and land allocation decisions, while considering input and expected production prices. Additionally, we extend the framework to incorporate the influence of renewable electricity policy (RPS) and other agricultural policy (CRP). To address potential endogeneity concerns, we employ an instrumental variable (IV) panel data approach, ensuring a robust analysis across the 48 states.

The most important finding in this analysis is that the coefficient estimates for target level of renewable energy are statistically significant and negative. When this is calculated as elasticity, it is about -0.011, which does not have a large impact, but it can be confirmed that it clearly has a significant impact economically. In the states where the policy is in place, the RPS target level of renewable electricity is found to significantly reduce acreage, although the actual magnitude of reduction is relatively modest, estimated at around 24 to 26 acres per 1000 MWh. Considering that the supply of renewable energy will be further expanded in the future, this has an important meaning in that the effect of the current relatively small size is likely to be further expanded.

The findings indicate that both output price and input price are statistically significant at the 1% level. The coefficients of the composite price index are positively related to acreage, while the coefficients of the fertilizer price index exhibit a negative relationship. The estimated output price elasticities range from 0.297 to 0.329, and the elasticities from the models considering electricity market characteristics show similar magnitudes, approximately 0.30. The analysis reveals a negative impact of fall precipitation on acreage.

It is important to acknowledge certain limitations in our analysis of crop acreage. There are a complicated range of factors that influence agricultural land use decision. State-level analysis may not fully capture the influence of factors that a more granular county-level examination might. Secondly, the study focuses exclusively on the electricity sector within the realm of renewable energies, thus excluding the potential impact of policies such as Renewable Fuel Standards (RFS) on primary crop acreage and any interaction between policy.

Overall, the regression analysis provides valuable insights into the factors influencing TPCA, including the composite price index, fertilizer price index, population density, time trend, seasonal precipitation, CRP enrolled area, and the target level of renewable electricity. These findings contribute to a better understanding of the dynamics shaping TPCA at the state level and highlight the significance of considering various factors within the electricity market context.

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