Capacity Investment in Renewable and Conventional Energy Sources

by

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Business Administration

Duke University

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Robert Swinney

Dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Business Administration

in the Graduate School of Duke University

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Abstract

This dissertation studies capacity investments in energy sources, with a focus on renewable technologies, such as solar and wind energy. We develop analytical models to provide insights for policymakers and use real data from the state of Texas to corroborate our findings.

We first take a strategic perspective and focus on electricity pricing policies. Specifically, we investigate the capacity investments of a utility firm in renewable and conventional energy sources under flat and peak pricing policies. We consider generation patterns and intermittency of solar and wind energy in relation to the electricity demand throughout a day. We find that flat pricing leads to a higher investment level for solar energy and it can still lead to more investments in wind energy if considerable amount of wind energy is generated throughout the day.

In the second essay, we complement the first one by focusing on the problem of matching supply with demand in every operating period (e.g., every five minutes) from the perspective of a utility firm. We study the interaction between renewable and conventional sources with different levels of operational flexibility, i.e., the pos-

sibility of quickly ramping energy output up or down. We show that operational flexibility determines these interactions: renewable and inflexible sources (e.g., nuclear energy) are substitutes, whereas renewable and flexible sources (e.g., natural gas) are complements.

In the final essay, rather than the capacity investments of the utility firms, we focus on the capacity investments of households in rooftop solar panels. We investigate whether or not these investments may cause a utility death spiral effect, which is a vicious circle of increased solar adoption and higher electricity prices. We observe that the current rate-of-return regulation may lead to a death spiral for utility firms. We show that one way to reverse the spiral effect is to allow the utility firms to maximize their profits by determining electricity prices.

To Ezgi

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List of Abbreviations and Symbols

Symbols

Notation for Chapter 2

a_i	Market size in period i.
C_1, C_2, C_3, C_4	Cost paramaters in $g(\cdot)$.
CS^j	Consumer surplus under pricing policy j.
$D_i(p_i, p_{-i})$	Demand of electricity in period i.
e	Emission intensity of the new conventional source.
ECE^j	Expected carbon emissions under pricing policy j.
$g(\cdot)$	Generation cost function.
$i \in \{n, d\}$	Subscript for period.
$j \in \{\text{flat}, \text{peak}\}$	Superscript for pricing policy.
k_c, k_r	Capacity investment level in the conventional and renewable source, respectively.
p_i	Price of electricity in period i.
q_i	The probability that $\tilde{q}_i = 1$ when $\tilde{q}_i$ follows a two-point distribution.

$\tilde{q}_i$	Intermittency factor in period i.
v	Variable cost of the new conventional source.
$\alpha_r(\cdot), \alpha_c(\cdot)$	Investment cost function of renewable and conventional source, respectively.
β_r, β_c	Unit investment cost of renewable and conventional source, respectively.
δ	Cross-price sensitivity of demand.
γ	Own-price sensitivity of demand.
$\xi_i(\cdot, \cdot)$	Inverse demand function in period i.

Notation for Chapter 3

c_I, c_F	Variable generation cost of the inflexible and flexible source.
$i \in \{I, R, F\}$	Subscript for energy source.
$\boldsymbol{k} = (k_I, k_R, k_F)$	The vector of investment levels.
n	Subscript for period.
N	Total number of periods.
q_i	Dispatch level of source i.
q_S	Quantity of electricity sold in the spot market.
r	Penalty cost rate.
α_i	Investment cost of source i.
ϵ_n	Demand random variable in period n.
ξ	Realization of demand uncertainty.

Θ_n	Intermittency random variable in period n.
θ	Realization of intermittency uncertainty.
Γ_n	Spot market random variable in period n.
γ	Realization of spot market uncertainty.
λ_i	Dual variable associated with capacity constraint of source i.
∇	Gradient operator.

Notation for Chapter 4

a, b	Parameters of the diffusion process.
C, F	Parameters of the cost function $c(\cdot)$.
M	Number of customers.
N_t	Number of solar panel adopters at time t.
p_t	Price of electricity in period t.
$p_{\max}$	The maximum price that the utility firm can charge.
t	Index of time period.
T	Number of periods in the problem horizon.
α	Profit level under rate-of-return regulation.
γ	Discount factor.

Abbreviations

CSI	California Solar Initiative.

DG	Distributed Generator.
DR	Demand Response.
EE	Energy Efficiency.
EIA	Energy Information Administration.
ERCOT	Electric Reliability Council of Texas.
LOLP	Loss-of-Load Probability.
MAPE	Mean Absolute Percentage Error.
MW	Megawatt.
MWh	Megawatt-hour.
NERC	North American Electric Reliability Corporation.
NREL	National Renewable Energy Laboratory.
OM	Operations Management.
PG&E	Pacific Gas and Electric.
PJM	Pennsylvania-Jersey-Maryland.
SAM	System Advisory Modeling.
SEIA	Solar Energy Industries Association.
SPP	Southwest Power Pool.
TCDB	Transparent Cost Database.
UCDM	Unit Commitment and Dispatch Model.
UCF	Union of Concerned Scientists.

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1

Introduction

Amid growing concerns of the global warming, more than 190 countries have reached an agreement in the 2015 United Nations Climate Change Conference to limit greenhouse gas emissions (Dalton and Steinhauser 2015). The biggest contributor to the global emissions is the electricity generation sector (EPA 2016). To curb these emissions by encouraging investment in green energy sources, such as solar and wind power, policymakers have designed various policies. Thanks to these policies, in the U.S., renewable energy supply has grown 83% in the decade preceding to 2014 (NREL 2016). Despite ambitious policies, renewable sources supply only about 13% of the U.S. electricity; hence, more investment in green sources is needed.

In this dissertation, we study the capacity investments in energy sources, particularly focusing on renewables. We use real data from the state of Texas to corroborate our analytical findings. By accounting for the unique characteristics of the electricity markets and renewable energy sources, we study three major research questions. In the first essay, we take a strategic perspective and study the impact of electricity pricing policies (i.e., flat versus peak pricing) on the investments of utility firms in renewable and conventional sources. We complement this study by taking an operational perspective in the second essay. In particular, we focus on the problem of matching supply with demand in every operating period (e.g., every five minutes) for a utility firm. We investigate how operational flexibility, i.e., the ability to quickly ramp up or down the output of an energy source, affects the relationship between conventional and renewable sources. In the final essay, rather than the capacity investments of the utility firms, we focus on the capacity investment of households in the rooftop solar panels. Specifically, we investigate how these investments affect the traditional utility firms. Below, we provide an overview of each essay.

In the first essay, "Impact of Electricity Pricing Policies on Renewable and Conventional Energy Investments," we investigate the impact of pricing policies (i.e., flat pricing versus peak pricing) on the investment levels of a utility firm in two competing energy sources (renewable and conventional), with a focus on the renewable investment level. We consider generation patterns and intermittency of solar and wind energy in relation to the electricity demand throughout a day. Industry experts generally promote peak pricing policy as it smoothens the demand and reduces inefficiencies in the supply system. We find that the same pricing policy may lead to distinct outcomes for different renewable energy sources due to their generation patterns. Specifically, flat pricing leads to a higher investment level for solar energy and it can still lead to more investments in wind energy if considerable amount of wind energy is generated throughout the day. We validate these results by using electricity generation and demand data of Texas. We also show that flat pricing can lead to substantially lower carbon emissions and a higher consumer surplus. Finally, we explore the effect of direct (e.g., tax credit) and indirect (e.g., carbon tax) subsidies on the investment levels and carbon emissions. We show that both types of subsidies generally lead to a lower emission level but indirect subsidies may result in lower renewable energy investments. This essay suggests that reducing carbon emissions through increasing renewable energy investments requires a carefully designed pricing policy based on the market characteristics of each region.

In the second essay, "Investments in Renewable and Conventional Energy: The Role of Operational Flexibility," we study the capacity investment decision of a utility firm in renewable and conventional sources with different levels of operational flexibility, i.e., the ability to quickly ramp up or down the output of a source. Specifically, we consider a utility firm that aims to minimize its generation and investment costs. Following the practice, we model this problem as a two-stage stochastic program: In the first stage, the utility firm invests in inflexible (e.g., nuclear energy), renewable (e.g., wind energy), and flexible (e.g., natural gas) sources. In the second stage, for each period, the firm determines the dispatch (production) level from the renewable and flexible sources, whereas the inflexible dispatch level is constant across periods. We characterize the optimal capacity portfolio and identify the interaction between renewable and conventional sources. We find that operational flexibility determines these interactions: renewable and inflexible sources are substitutes, whereas renewable and flexible sources are complements. That is, a subsidy for the nuclear energy leads to a lower investment level in renewables, whereas a subsidy for natural gas leads to a higher investment in renewables. We validate this insight using real electricity generation and demand data from the state of Texas, similar to the first essay. We observe that a unit increase in the capacity of the natural gas-fired power plants approximately leads to 0.2 units increase in the renewable investment. Finally, we study the impact of carbon tax and show that the tax leads to a lower renewable investment if the inflexible source is carbon-free nuclear energy.

In the final essay, "Utility Death Spiral," rather than the capacity investments of the utility firms studied in the first two essays, we consider the capacity investments of households in rooftop solar panels. We investigate the concerns of the industry experts and policymakers that these investments may lead to very high electricity prices and undermine the traditional utility firms under current regulations. Specifically, under the net metering policy, a utility firm is required to purchase the electricity produced by the solar panels at the retail price of electricity. That is, by using net metering, electricity customers can reduce their demand by installing solar panels. Due to the decrease in the total demand, the utility firm increases the price of electricity to cover its fixed costs. As a result of higher electricity prices, more customers adopt solar panels, in a vicious circle, i.e., the so-called utility death spiral. We show that the current rate-of-return regulation is susceptible to the death spiral effect. We find that one way to reverse the spiral effect is to allow the utility firm determine the price of electricity so as to maximize its profit. Finally, we show that the greater speed of the diffusion of awareness about the solar panels may lead to a lower final adoption level in the end of the problem horizon.

2

Impact of Electricity Pricing Policies on Renewable Energy Investments and Carbon Emissions

2.1 Introduction

There is an unprecedented interest in growing renewable energy supply, particularly solar and wind energy, which provides electricity without generating carbon dioxide emissions. In an attempt to reduce carbon emissions and increase renewable energy supply, governments have launched various policies such as peak pricing for residential customers and net metering. Peak pricing (and other forms of time-of-use pricing) aims to smoothen the electricity demand throughout a day by charging higher prices at peak-usage times (i.e., daytime), therefore increasing the efficiency of electricity supply (Borenstein 2013). Net metering allows distributed generators (DGs, residential customers with rooftop solar panels) to sell their excess electricity back to the grid at retail prices (Forbes 2013). Coupled with higher daytime prices of the peak pricing policy, net metering can increase residential solar energy investments. In fact, The Wall Street Journal (WSJ 2013) recently defined net metering as “a backdoor subsidy for solar energy” and several experts confirmed this intuition (Mills et al. 2008, Ong et al. 2010, Darghouth et al. 2011). These claims are only based on the impact of peak pricing on residential solar investments and do not consider two important drivers of renewable energy investments. First, wind energy accounted for nine times more electricity output than solar energy in 2014 in the U.S. (EIA 2015a), and has a very different electricity generation pattern than solar. Second, rather than DGs, utility firms dominate the investment in energy supply chains. In fact, as of 2012, more than 98% of the U.S. renewable energy is generated in utility-scale facilities (SEIA 2013, EIA 2014b). In addition to the above net metering and peak pricing policies, governments also provide various direct subsidies (e.g., investment tax credits, cash grants) and indirect subsidies (e.g., carbon tax) to increase renewable energy investments. However, there seems to be no clear understanding of the interaction between pricing policies and these subsidies, and their joint effects on the investments of utility firms.

Utility firms need to determine investment levels for both conventional and renewable energy sources. Investments in conventional sources remain significant because these sources have low investment cost and can provide more reliable electricity supply than renewables, despite their higher marginal generation costs and emissions.

Moreover, recent technological breakthroughs, such as advanced coal power plants, have significantly reduced the generation costs and carbon emissions of conventional sources (Duke Energy 2015b). Our objective is to investigate the impact of electricity pricing policies on the investment levels of renewable and conventional energy sources from the perspective of utility firms. We consider both solar and wind energy sources because they account for the majority of the renewable energy output. We explore the following questions. Which pricing policy, i.e., either flat pricing or peak pricing, does lead to a higher renewable energy investment, lower carbon emissions, and a higher consumer surplus when these two competing sources are present? What are the key characteristics of energy sources that a government should consider when designing a pricing policy if its long-term goal is to increase the share of renewable energy in the total energy output? What are the effects of direct and indirect subsidies? Answering these questions is not straightforward because the amount of carbon emissions depends on not only the portfolio of energy investments, but also the electricity consumption shaped by the pricing policy.

There are several unique features of the renewable energy sources and electricity markets. First, the generation patterns of solar and wind energy are different throughout a day. They are non-dispatchable, meaning that utility firms cannot generate electricity from these sources on-demand. While the output of solar energy is generated mostly in the daytime, the output of wind energy heavily depends on geographical regions. In north California, for example, the majority of wind energy is generated during the nighttime (NERC 2009, pp. 15–16), whereas in Texas, the wind energy is generated relatively evenly throughout the day. Second, these renewable energy sources are intermittent. That is, the exact output of a solar panel or a wind turbine cannot be precisely predicted. Third, the demand of electricity depends on the price sensitivity of customers (c.f., Faruqui and Sergici 2010). Fourth, the marginal cost of generating electricity from the renewable energy sources is nearly zero. This fact has made the renewable sources the first choice for a utility firm to fulfill the demand (Economist 2013). Finally, different groups of renewable energy investors, i.e., utility firms and distributed generators (DGs), consider their own interests for investment. Thus, the same pricing policy may lead to different responses from these investors.

We build a stylized model that incorporates the above features to investigate the impact of pricing policy (either flat or peak pricing) on energy investments of a utility firm that has an existing fleet of conventional generators. Given a pricing policy mandated by the government, the utility firm determines the electricity price and *additional* renewable and conventional energy investments to its existing fleet so as to maximize its profit. In particular, to satisfy the electricity demand, the utility firm uses its *three* sources in the increasing order of their marginal generation costs: first, it uses the *renewable* source, followed by the *new conventional* source. Any unmet demand is satisfied by the *existing conventional* fleet. The utility firm has an incentive to make additional investments in renewable and conventional energy sources as these new energy sources generate electricity with lower costs than its existing fleet.

On the issue of renewable energy investments, we determine the conditions under which flat or peak pricing leads to a higher renewable energy investment. We find that flat pricing leads to a higher investment in solar energy than peak pricing. This is because under flat pricing, the electricity demand is higher during the daytime. Thus, the utility firm is motivated to invest more in solar energy to fulfill the increased demand as the solar energy is mainly generated in the daytime with negligible costs. While the industry experts and academics found that peak pricing can increase the investment level of solar energy for distributed generators (c.f., Mills et al. 2008), our result complements this finding and suggests that flat pricing leads to a higher solar energy investment for utility firms. Given that the capacity investment for electricity in the U.S. is heavily dominated by utility firms, our result reveals an important insight for the solar energy industry. For wind energy, the impact of pricing policy depends on the generation pattern. For the geographical regions in which most wind energy output occurs at night, peak pricing leads to a higher wind energy investment than flat pricing. The intuition is similar: peak pricing leads to a higher demand at night, which can be fulfilled by the nighttime wind energy. Interestingly, flat pricing can still lead to a higher wind energy investment than peak pricing if considerable amount of wind energy is generated during the daytime. We validate these insights through a case study by using real electricity generation and demand data obtained from the state of Texas. Our model also provides insights on the investment level of the new conventional energy source. For example, we find that under peak pricing, the utility firm will increase its investment in the conventional energy source if the firm invests in the solar energy. This is because the increased nighttime demand under peak pricing can be fulfilled by the new conventional source rather than the solar energy.

Regarding carbon emissions, we show that flat pricing, which leads to a higher investment in solar energy, results in lower carbon emissions than peak pricing if the emission intensity of the new conventional source is sufficiently high. This result suggests an interesting insight – if the new conventional source has a low emission intensity, a higher renewable investment (which reduces the conventional energy investment) does not necessarily lead to lower carbon emissions, as more emissions may be produced from the existing fleet. We demonstrate this interesting phenomenon through an example based on the Texas data in Section 2.4.2. Finally, we investigate consumer welfare under these two pricing policies. We find that the consumer surplus is higher under flat pricing.

Our model can be used to evaluate the effect of governmental subsidy policies on reducing carbon emissions. We show that a direct subsidy for renewable investments, such as a cash grant or a tax credit, leads to a higher investment in renewable energy but not necessarily leads to lower emissions. Interestingly, an indirect subsidy policy, such as a carbon tax, may not lead to a higher investment in renewable energy, although it leads to lower emissions. This is because a carbon tax increases the generation cost of the existing fleet and the utility firm may prefer to invest more in the new conventional source that has a low emission intensity and can provide more reliable energy supply than the renewable source.

The rest of the essay is organized as follows. Section 2.2 summarizes the related literature. Section 2.3 provides preliminaries for the energy markets and utility firms. Section 2.4 analyzes the impact of pricing policies on the investment level of different energy sources, the carbon emission level, and the consumer surplus. Section 2.5 reports the impact of subsidies on the investment and carbon emission levels. Section 2.6 validates our findings by presenting a case study based on the Texas data. Section 2.7 discusses the extensions and Section 2.8 concludes.

2.2 Literature Review

Our essay is related to three research streams: the peak pricing literature in economics, sustainability and capacity planing literatures in operations management (OM). Analytical models in the peak pricing literature are surveyed by Crew et al. (1995). According to Borenstein (2013), the economists are virtually unanimous in arguing that peak pricing improves the efficiency of electricity systems. Most papers in this stream consider a regulated monopoly firm that optimizes social welfare by determining the prices and the investment levels for energy sources. For example, Steiner (1957) characterizes the optimal investment and price levels in a deterministic setting. Crew and Kleindorfer (1976) study the investment levels for multiple generation technologies under demand uncertainty. Kleindorfer and Fernando (1993) determine the optimal prices and investment levels under supply uncertainty. Chao (2011) considers intermittent sources and characterizes the first order conditions with respect to the electricity price and the renewable energy investment in the ex-ante and ex-post pricing schemes (i.e., the electricity prices are determined before and after the realization of demand and supply uncertainties). In a simulation study, he finds that the optimal investment level in renewable sources is higher in ex-post pricing than that in ex-ante pricing. Compared to the peak pricing literature, we consider a profit maximizing utility firm instead of a social planner as utility firms are no longer owned by the government.

Several authors study the impact of peak pricing policy on investments and emissions. For example, Mills et al. (2008), Ong et al. (2010), and Darghouth et al. (2011) consider investments in residential solar energy and conclude that these investments increase in response to peak pricing. We complement these studies by mainly considering capacity investments of utility firms. Furthermore, Holland and

Mansur (2008) investigate the impact of real-time pricing (a more granular version of peak pricing) on carbon emissions in the short run, i.e., with exogenous investment levels and prices. They conclude that reducing the peak period demand leads to lower (higher, respectively) emissions if the peak period demand is fulfilled by carbon-intensive (carbon-free, respectively) generators. The difference of our essay is that by endogenizing pricing and capacity investment decisions, we find that flat pricing usually leads to lower emissions.

On the empirical side of the peak pricing literature, many papers quantify the impact of peak pricing on the electricity demand. See, for example, Aigner and Hausman (1980), Filippini (1995), and Matsukawa (2001). Faruqui and Sergici (2010) survey 15 of these papers to examine how customers respond to electricity prices. They find that customers respond to the time-varying electricity prices by shifting their demand from the peak period to the off-peak period. Our demand model is motivated by these empirical findings as it accounts for the shift of electricity consumption between the peak period and the off-peak period under different pricing policies.

The OM literature on sustainability has substantially been growing in recent years. See Kleindorfer et al. (2005) and Drake and Spinler (2013) for a review. This literature spans a broad range of topics including product designs (e.g., Plambeck and Wang 2009 and Raz et al. 2013), production technology choices (e.g., İşlegen and

Reichelstein 2011 and Krass et al. 2013), transportation systems (e.g., Kleindorfer et al. 2012 and Avci et al. 2015), supply chains (e.g., Cachon 2014 and Sunar and Plambeck 2015), and government regulations (e.g., Kim 2015 and Raz and Ovchinnikov 2015). Our essay is directly related to sustainability and operations of energy systems. In this domain, Lobel and Perakis (2011) study the feed-in-tariff policy for renewable energy sources in Germany and conclude that the subsidy levels are too low. In a similar vein, Alizamir et al. (2015) derive the optimal feed-in-tariff policy for renewable energy sources with a consideration of network externalities. Ritzenhofen et al. (2014) show that feed-in-tariff policy is more cost effective than other policies aiming to increase investments in renewable energy. Wu et al. (2012) propose a new heuristic for operations of seasonal storage facilities. Wu and Kapuscinski (2013) find that curtailing renewable energy output can be helpful in dealing with intermittency. Zhou et al. (2014a) study electricity storage with possibly negative electricity prices and derive the optimal disposal strategy. Zhou et al. (2014b) propose an easily implementable policy for operating wind farms in the presence of storage facilities. Hu et al. (2015) focus on energy investments of a distributed generator (DG) without considering utility firms and determine the optimal investment level for the DG.

We study a capacity allocation problem between a reliable (i.e., conventional) and an unreliable (i.e., renewable) source. For extensive reviews on supply reliability and capacity planning problems, see Yano and Lee (1995) and Van Mieghem (2003), respectively. As recent examples of this literature, Oh and Özer (2013) incorporate forecast evolution into capacity planning, and Wang et al. (2013) study capacity expansion and contraction in two competing technologies. In this stream of research, our essay is closely related to Aflaki and Netessine (2015) which study the competition between renewable and conventional energy sources. They analyze the impact of carbon tax in regulated and deregulated markets. They consider a single-period model with fixed prices and random demand, and assume a two-point intermittency distribution. They show that the intermittency plays a crucial role in determining the environmental impact of carbon tax. We also study a similar issue. Unlike their model, we assume that the daytime and nighttime electricity consumptions are affected by the prices set by the utility firm, and our goal is to investigate the impact of pricing policy on the investment levels of both energy sources.

2.3 Model Preliminaries

We investigate the impact of electricity pricing policy on the capacity investments in renewable and conventional energy sources of a utility firm. We consider a long-term investment horizon (e.g., 20 years), and model a representative day with two periods indexed by subscript i: the first period is the off-peak demand period or the nighttime ($i = n$) and the second period is the peak demand period or the daytime ($i = d$). In addition, we consider two pricing policies, flat pricing and peak pricing. We use superscript j for a variable whenever we need to differentiate these two pricing policies, where "j = flat" denotes flat pricing and "j = peak" denotes peak pricing.

Pricing. Governments usually specify an electricity pricing policy as either flat pricing or peak pricing and allow utility firms to determine the electricity price through a negotiation process (RAP 2011). We denote the consumer price of electricity as $p_i \geqslant 0$ in period $i \in \{n, d\}$. Under flat pricing, the utility firm has to determine the prices so that $p_n = p_d$. This constraint no longer applies if the government allows the use of peak pricing. Note that, in practice, the electricity prices are regulated. However, the peak pricing literature focuses on optimal prices (see Crew et al. 1995 for a review). This is because the optimal prices form the basis of regulated prices which are the outcome of the negotiation between the regulators and the utility firms. Following the peak pricing literature, we also optimize over prices. Nevertheless, all of our results can be extended to the case when prices are regulated (fixed) as long as the price under flat pricing falls in between the daytime and nighttime prices under peak pricing.

Demand. Electricity demand in the daytime period is $D_d(p_d, p_n) = a_d - \gamma p_d + \delta p_n$, and the nighttime demand is $D_n(p_n, p_d) = a_n - \gamma p_n + \delta p_d$, where $a_i > 0$ is the market size of period i; $\gamma > 0$ and $\delta > 0$ are the own and cross price sensitivities of the demand, respectively. We assume that the own price sensitivity is higher than the cross price sensitivity, i.e., $\gamma > \delta$, and that the market size is higher in the daytime period, i.e., $a_d > a_n$. In our model, the electricity demand refers to the amount of electrical energy demanded by consumers rather than the instantaneous consumption. Hence, the unit for demand is MWperiod per the representative day, where "period" refers to the 12 hours of the peak or the off-peak demand period. That is, a MWperiod is equal to 12 MWhours. Furthermore, we note that the sum of the daytime and nighttime demand under this demand model is given as $a_n + a_d - (\gamma - \delta)(p_n + p_d)$. Thus, the sum of price levels determines the total demand level as we discuss in detail following Lemma 1.

Intermittency. We use a random variable $\tilde{q}_i$ to represent the intermittency factor of a renewable energy source in period i. Specifically, let k_r be the amount of investment in renewable energy. By convention in the literature, k_r is measured in MW. Here MW represents electricity "power," measuring how much output can be instantaneously generated from an energy source. Thus, one can consider k_r as the instantaneous output rate. Running at the output rate of k_r MW for a period, the generated electricity "energy" is $k_r\tilde{q}_i$ MWperiod per day. We use a two-point distribution for $\tilde{q}_i$:

$$\tilde{q}_i = \begin{cases} 1 & \text{with probability } q_i, \\ 0 & \text{with probability } 1 - q_i. \end{cases} \tag{2.1}$$

This intermittency form allows us to represent the generation pattern of a renewable energy source. For instance, the generation of solar energy reaches its peak during the day and is close to zero at night. Thus, we can set q_d greater than q_n and q_n close to zero to represent the solar energy source. On the other hand, if the wind energy output occurs evenly throughout a day (at night, respectively), then q_d is equal to q_n (q_n is greater than q_d, respectively). In Section 2.7, we show that our main insights are valid for a generally distributed $\tilde{q}_i$ with a support of $[0, 1]$.

Supply. We assume that the utility firm maintains a fleet of conventional power plants and considers additional investments in new conventional and renewable sources. Since the renewable source does not consume any fuel to generate electricity, the generation cost is negligible. The generation cost of the newly invested conventional source, such as an advanced coal power plant, is higher than that of the renewable energy source but lower than that of the existing fleet (Duke Energy 2015b). According to the so-called Merit Order Dispatch rule, different types of power plants are brought online in the ascending order of their variable operating costs. Thus, in our model, the renewable energy source is dispatched into the grid first to satisfy the demand, followed by the newly invested conventional source, and then finally by the existing fleet.

Figure 2.1 plots the power plants in Texas in the increasing order of variable operating costs. Each circle in the graph corresponds to a specific plant with its variable operating cost on the vertical axis and the cumulative system capacity up to this plant on the horizontal axis. The size of a circle is proportional to the capacity of the plant that it represents. We pose two remarks about this graph. First, the

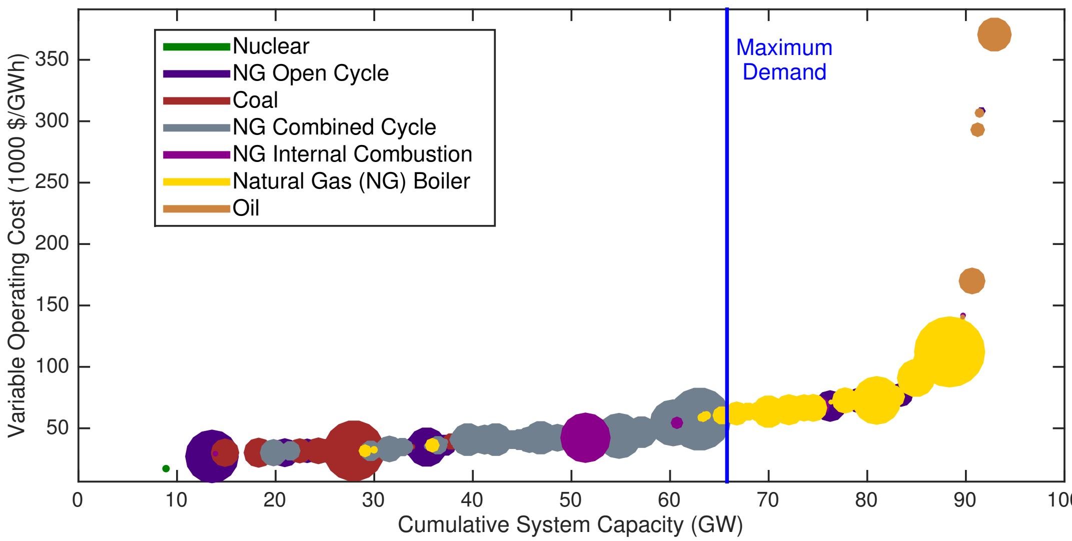


FIGURE 2.1: Variable operating costs of power plants in Texas electricity system

Notes. Each circle in this graph represents one conventional power plant, where the size of the circle is proportional to the capacity of the plant.

instantaneous demand rate never exceeded 68 GW in 2010; thus, there is considerable excess capacity in the system. Second, the cumulative capacity starts from 9 GW, which is the wind energy capacity that incurs zero variable operating costs.

Costs. We consider two types of costs: the electricity generation cost and the investment cost. In line with Figure 2.1 and the Merit Order Dispatch rule, the utility firm incurs a cost of $g(x)$ for generating x units of electricity from its existing conventional sources, where $g(x)$ is given as

$$g(x) = \frac{C_1}{3}x^3 + \frac{C_2}{2}x^2 + C_3 x + C_4. \tag{2.2}$$

We assume that the cost coefficients C_1, C_2, C_3, and C_4 are positive so that this function is convex and a generalization of the widely used linear and quadratic forms in the literature.[1]

For the new conventional source, let v denote the unit generation cost. Note that the generation cost from the existing conventional fleet is characterized by a polynomial function (i.e., $g(x)$), whereas the generation cost from the new conventional source is a linear function. This is because $g(x)$ is an approximation for the generation cost of different power plants, such as coal and nuclear plants (shown in Figure 2.1). Thus, the generation cost is convex and increasing in the total capacity. On the other hand, the new conventional source refers to a certain type of power plant, whose generation cost increases linearly. Finally, the renewable energy source incurs zero generation costs.

The investment cost of the renewable source is given as $\alpha_r(k_r) = \beta_r k_r$, where k_r is the renewable energy investment level measured in MW. Similarly, the investment cost of the new conventional source is $\alpha_c(k_c) = \beta_c k_c$, where k_c is the investment level in the new conventional source. We assume linear investment cost functions which are consistent with the peak pricing literature (e.g., Crew et al. 1995). Practitioners often use a linear cost rate to estimate the investment expense for each type of energy sources. Since the newly invested equipment has a fixed life expectancy, the investment cost function can be viewed as the average investment cost per representative day.

[1] We note that this functional form provides an adjusted R^2 value of 0.9958 when it is fitted to the generation cost curve, which can be obtained from Figure 2.1.

We present the estimates of the cost and intermittency parameters for various generation sources in Table 2.1. For the conventional sources, we normalize the intermittency factor to 1 for both periods. For the renewable energy sources, we compute the intermittency factor based on the electricity generation data of Texas given in the case study of Section 2.6. The estimation of the investment and generation cost rates are explained in Appendix A.3.

Carbon Emissions. We normalize the emission intensity of the existing conventional fleet to 1, that is, generating 1 unit of electricity from the existing fleet emits 1 unit of carbon dioxide. The emission intensity of the newly invested conventional source is denoted by e. We assume that $e \leqslant 1$, that is, the new conventional source is less polluting than the existing fleet. This assumption is consistent with the Environmental Protection Agency regulations which specify the emission limit for the newly invested conventional source to be almost half of the existing emission level (Plumer 2013). A similar assumption is also used in Aflaki and Netessine (2015). Finally, the renewable energy source does not consume any fossil fuels to generate electricity, so its emission intensity is assumed to be zero. In accordance with the merit order dispatch rule described above, we define the expected amount of carbon emissions due to electricity generation as

$$ECE = \sum_{i \in \{n,d\}} E_{\tilde{q}_i} \left[\left(D_i \left(p_i, p_{-i} \right) - k_c - k_r \tilde{q}_i \right)^+ + e \min \left(k_c, \left(D_i \left(p_i, p_{-i} \right) - k_r \tilde{q}_i \right)^+ \right) \right], \tag{2.3}$$

Table 2.1: Model parameters for different energy sources

Energy Source	Nighttime Intermittency Factor q_n	Daytime Intermittency Factor q_d	Unit Investment Cost β \$/MW/day	Unit Generation Cost v \$/MWperiod
Nuclear Energy	1.00	1.00	161.2	141.6
Natural Gas	1.00	1.00	61.2	589.2
Coal	1.00	1.00	91.2	363.6
Wind Energy	0.32	0.28	249.2	0.0
Solar Energy	0.07	0.23	138.9	0.0

Notes. See Appendix A.3 for the estimation procedure of β and v.

where $E[\cdot]$ denotes the expectation operator, $\tilde{q}_i$ is the intermittency factor in period i, and $(x)^+ = \max\{x, 0\}$. The first term in the brackets is the emission amount due to the existing fleet, and the second term is the expected emission amount from the new conventional source. In (2.3), we subtract capacity investments (e.g., k_c) given in MW from the demand level $D_i(p_i, p_{-i})$ given in MWperiod per the representative day. In this equation, one can view k_c and k_r as energy output with a unit of MWperiod per day. The usage of the energy units in this way is consistent with that of the literature (c.f., Crew and Kleindorfer 1976).

In the subsequent analysis, we use the terms "increasing," "convex," and "concave" in their respective weak senses. Also, for a function $h(\cdot)$, $h'(\cdot)$ refers to its derivative and $h^{-1}(\cdot)$ refers to its inverse function. All proofs are given in Appendix A.1.

2.4 Utility Firm Model

In this section, we analyze a vertically integrated utility firm that maximizes its profit by investing in conventional and renewable energy sources and setting the electricity prices for its customers. To satisfy the electricity demand, the utility firm first uses the renewable source followed by the new conventional source. Any unmet demand is fulfilled by the existing fleet. The profit maximization problem of the utility firm is given as:

$$\max_{k_r,k_c,p_n,p_d} \Pi\left(k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} E_{\tilde{q}_i}\left[p_i D_i\left(p_i,p_{-i}\right) - g\left(\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+\right)\right.$$
$$\left. - v\min\left(k_c,\left(D_i\left(p_i,p_{-i}\right)-k_r\tilde{q}_i\right)^+\right)\right] - \alpha_r\left(k_r\right) - \alpha_c\left(k_c\right). \tag{2.4}$$

The first term of the expectation above corresponds to the utility's revenue, the second term[2] is the electricity generation cost from the existing conventional fleet, the third term is the generation cost from the new conventional source, and the last two terms are the investment costs for the renewable and conventional sources. We next present the following assumption, imposed throughout the essay.

Assumption 1. *(i)* $\beta_r \geqslant (q_n + q_d)v + \max(q_n, q_d)g'(a_d - a_n)$. *(ii)* $a_d - a_n \geqslant (\gamma + \delta)(2v + \beta_c)$.

Assumption 1 part (i) states that the investment cost of the renewable source is sufficiently high so that the total investment level of both renewable and new

[2] See the discussion following (2.3) for an explanation of the units for the argument of $g(\cdot)$.

conventional energy sources is lower than the nighttime demand level under any pricing policy (see Proof of Lemma 1). This implies that, in addition to the new sources, the existing conventional fleet is also used to fulfill the demand in both periods. This assumption is plausible based on the real electricity generation data given in Section 2.6. Specifically, the term on the right hand side is 148.6 (88.2, respectively) for wind (solar, respectively) energy, whereas β_r is \$249.2/MW per day (138.9, respectively) as given in Table 1. This is also supported by the fact that the capacity of new investments in different energy sources is relatively small compared to that of the existing fleet. In particular, the former was approximately 1% of the latter in the U.S. in 2014 (FERC 2015a).

Assumption 1 part (ii) implies that the difference between the market sizes of the daytime and nighttime periods is large enough that the daytime demand level always exceeds the nighttime demand under any pricing policy (see Proof of Lemma 1). This part of the assumption is also consistent with the practice, as the left hand side is close to 9,000 MWperiod per day whereas the right hand side is approximately 7,000. Moreover, this assumption reflects the fact that the daytime demand is higher than the nighttime demand in practice (EIA 2011b). Furthermore, Assumption 1 part (ii) ensures that the optimal daytime price is higher than the optimal nighttime price under both pricing policies, i.e., $p_d^* \geqslant p_n^*$. This inequality is supported by the actual prices observed in practice (c.f., conEdison 2008 and Shao et al. 2010). For instance, Pacific Gas & Electric utility firm charges its customers ¢15.5/kWh as the nighttime price and ¢17.5/kWh as the daytime price under peak pricing, whereas the price is ¢16.4/kWh under flat pricing (PG&E 2014).

We next present a lemma on the optimal prices. Let p_n^{j*} and p_d^{j*} denote the optimal nighttime price and daytime price, respectively, under the pricing policy $j \in \{\text{peak}, \text{flat}\}$.

Lemma 1. *The maximization problem in (2.4) is jointly concave in* k_r, k_c, p_n, *and* p_d. *Furthermore, at optimality*

$$p_n^{j*} + p_d^{j*} = \frac{a_n + a_d + (\gamma - \delta)(2v + \beta_c)}{2(\gamma - \delta)}, \qquad j \in \{peak, flat\}. \tag{2.5}$$

Lemma 1 states that the sum of the optimal nighttime and daytime prices under peak pricing is equal to that under flat pricing. Intuitively, the sum of the prices represents the marginal revenue. To maximize the profit, the utility firm should keep its marginal revenue constant under both pricing policies because the marginal cost of investments is constant due to the linear investment costs. This result is consistent with the practice as the aforementioned PG&E policy (PG&E 2014) also shows that the sum of nighttime and daytime prices are approximately equal under both flat and peak pricing policies. Moreover, Lemma 1 implies that the optimal demand is constant under both pricing policies. This result suggests that, in response to peak pricing, consumers only change the time they consume electricity but not the amount. Empirical studies also suggest a very low reduction in the total demand under peak pricing compared to flat pricing (e.g., King and Delurey 2005).

2.4.1 Energy Investment Levels

We next consider the impact of pricing policy on the renewable energy investment. Let $f(\cdot)$ denote the inverse of the derivative of the generation cost function, i.e., $f(\cdot) = (g')^{-1}(\cdot)$.

Proposition 2. *(i) If*

$$\frac{q_n}{q_d} \leqslant 1, \tag{2.6}$$

then $k_r^{flat} \geqslant k_r^{peak}$. *(ii) On the other hand, if*

$$\frac{q_n}{q_d} \geqslant R_1 = \frac{C_1\left(f\left(\beta_r/q_n\right) + \left(a_d - a_n\right)\right) + C_2}{C_1\left(f\left(\beta_r/q_n\right) - \left(a_d - a_n\right)\right) + C_2}, \tag{2.7}$$

then $k_r^{flat} \leqslant k_r^{peak}$.

Proposition 2 compares the investment level of a renewable energy source between flat pricing and peak pricing. Proposition 2 (i) states that for a renewable source whose electricity output in the daytime is greater than that in the nighttime (i.e., $q_d \geqslant q_n$), flat pricing leads to a higher investment level than peak pricing. Clearly, solar energy satisfies this condition as the majority of the solar energy output occurs during the daytime. Proposition 2 (ii), on the other hand, provides a condition that complements part (i). It is straightforward to show that $R_1 \geqslant 1$. Thus, Proposition 2 (ii) states that for a renewable source whose electricity output in the nighttime is sufficiently greater than that in the daytime (i.e., $q_n/q_d \geqslant R_1 \geqslant 1$), peak pricing leads to a higher investment level than flat pricing. As we state in Section 2.1, the output of wind energy in a day depends on geographical regions. For the region where the output of wind energy is sufficiently high at night, peak pricing leads to a higher investment level. For the region where $1 < q_n/q_d < R_1$, we have numerically observed that there exists a threshold value such that if q_n/q_d is less than this value, flat pricing leads to a higher investment. According to the case study of Texas data in Section 2.6, R_1 is 1.17, and q_n/q_d is 1.14 for the wind energy source, which falls in the indeterminate region (i.e., $1 < q_n/q_d < R_1$) of Proposition 2. We shall see that flat pricing indeed increases wind energy investments in the Texas region.

Proposition 2 shows that flat pricing increases the investment level in a renewable source if this source generates most of its output during the peak demand period. This result can be explained by the relationship between the electricity demand pattern under a pricing policy and the electricity generation pattern of a renewable source. Consider the case of flat pricing and solar energy as an example. When flat pricing is used, the daytime demand increases and the nighttime demand decreases. This demand pattern better matches with the generation pattern of solar energy as more electricity from solar is generated during the daytime with zero costs. Thus, the utility firm invests more into solar energy under flat pricing. On the other hand, peak pricing, which increases the nighttime demand, motivates a higher investment in wind energy if it has sufficiently high output at night.

We next consider the investment level for the new conventional source. Notice that the main role of this conventional source is to satisfy the electricity demand that cannot be satisfied by the renewable source due to intermittency. Thus, we shall construct conditions based on $(1 - q_i)$, the probability that the renewable source is not available in period i, $i \in \{n, d\}$.

Proposition 3. *(i) If*

$$\frac{1 - q_n}{1 - q_d} \leqslant 1, \tag{2.8}$$

then $k_c^{flat} \geqslant k_c^{peak}$. (ii) On the other hand, if

$$\frac{1 - q_n}{1 - q_d} \geqslant R_2 = \frac{C_1 \left(f \left(\beta_r / q_d \right) + \left(a_d - a_n \right) \right) + C_2}{C_1 \left(f \left(\beta_r / q_d \right) - \left(a_d - a_n \right) \right) + C_2}, \tag{2.9}$$

then $k_c^{flat} \leqslant k_c^{peak}$.

Proposition 3 (i) suggests that flat pricing leads to a higher investment level for the new conventional source if the utility firm decides to invest in a renewable energy source whose $(1 - q_d)$ is greater than $(1 - q_n)$. This condition is satisfied by the wind energy if its output is mostly generated at night (i.e., $q_n > q_d$). This is because, due to higher daytime demand under flat pricing, the utility firm needs to invest more into the new conventional source as the renewable source has low output during the daytime. Proposition 3 (ii) presents a similar result if the utility firm decides to invest in solar energy with $q_d > q_n$. In this case, peak pricing, which increases the nighttime demand, leads to a higher investment level for the conventional source in order to satisfy the increased demand at night.

2.4.2 Carbon Emissions

In this section, we consider the impact of pricing policy on carbon emissions. Under Assumption 1, the expected amount of carbon emissions defined in (2.3) reduces to

$$ECE = \sum_{i \in \{n,d\}} \left[D_i \left(p_i, p_{-i} \right) - q_i k_r - (1-e) k_c \right], \tag{2.10}$$

where we normalize the emission intensity of the existing fleet to 1, and $e \leqslant 1$ denotes the emission intensity of the new (less-polluting) conventional source.

Everything else being equal, (2.10) shows that increasing the capacity of the renewable source k_r by one unit results in q_i units of reduction in carbon emissions in period i, whereas increasing the capacity of the new conventional source k_c by one unit results in $(1-e)$ units of reduction in emissions. Based on this observation, we define the threshold emission intensity level $\bar{e}$ as

$$\bar{e} = \frac{2 - q_n - q_d}{2}. \tag{2.11}$$

This threshold value suggests that for the new conventional source whose emission intensity is sufficiently high, i.e., $e \geqslant \bar{e}$, the total emission reduction by increasing one unit of renewable energy capacity is higher than that by increasing one unit of the new conventional energy capacity.

While the emission threshold $\bar{e}$ is derived for any fixed prices, it can be used as a condition to compare the emission levels under the optimal flat and peak pricing policies. Proposition 4 shows this comparison.

Proposition 4. *Suppose $e \geqslant \bar{e}$. (i) $ECE^{flat} \leqslant ECE^{peak}$ if $q_n/q_d \leqslant 1$. (ii) On the other hand, $ECE^{flat} \geqslant ECE^{peak}$ if $q_n/q_d \geqslant R_1$, where R_1 is defined in* (2.7)*. (iii) If $e < \bar{e}$, the statements in part (i) and (ii) might not hold.*

Proposition 4 (i) states that if the emission intensity of the new conventional source is sufficiently high and the utility firm invests in solar energy, flat pricing leads to lower emissions. This is a joint result of two contradicting effects. On one hand, flat pricing leads to a higher investment in solar energy, resulting in lower carbon emissions. On the other hand, a higher solar energy investment leads to a lower investment in the new conventional source. As a result, the electricity demand not satisfied by the solar energy has to be satisfied by the existing fleet. If the emission intensity of the new conventional source is relatively high and close to that of the existing fleet, the increased emission amount will be relatively small. Together, flat pricing still leads to a lower emission level. Proposition 4 (ii) shows a similar result for the wind energy source that generates considerably more electricity at night: peak pricing leads to a higher wind energy investment level and lower emissions if the emission intensity of the new conventional source is high.

Proposition 4 (iii) reveals an interesting insight: a pricing policy might lead to both higher renewable energy investment and higher emissions if $e < \bar{e}$, i.e, the emission intensity of the new conventional source is low. This is because a pricing policy that leads to a higher renewable energy investment may reduce the investment level of the new conventional energy source. This results in a higher fraction of demand to be satisfied by the existing fleet that has a higher emission intensity. We provide an illustrative example of this case in Figure 2.2 based on the parameters estimated from the Texas data in the case study of Section 2.6. Figure 2.2 plots the optimal investment levels and the resulting carbon emissions for the peak and flat pricing policies with $q_d = 0.28$, which is the daytime intermittency parameter of wind energy given in Table 2.1. Here, a lower value of q_n corresponds to a power generation pattern similar to solar energy, whereas a higher value of q_n represents wind energy. As q_n increases, the renewable energy source becomes more reliable. This increases the optimal investment level in renewable energy and decreases the conventional energy investment under both pricing policies, which, in turn, leads to a decrease in the emission level. As long as q_n is smaller than 0.35, flat pricing leads to a higher renewable energy investment and lower carbon emissions. When q_n is greater than 0.35, peak pricing leads to a higher renewable energy investment and higher carbon emissions due to a lower investment in the new conventional source.

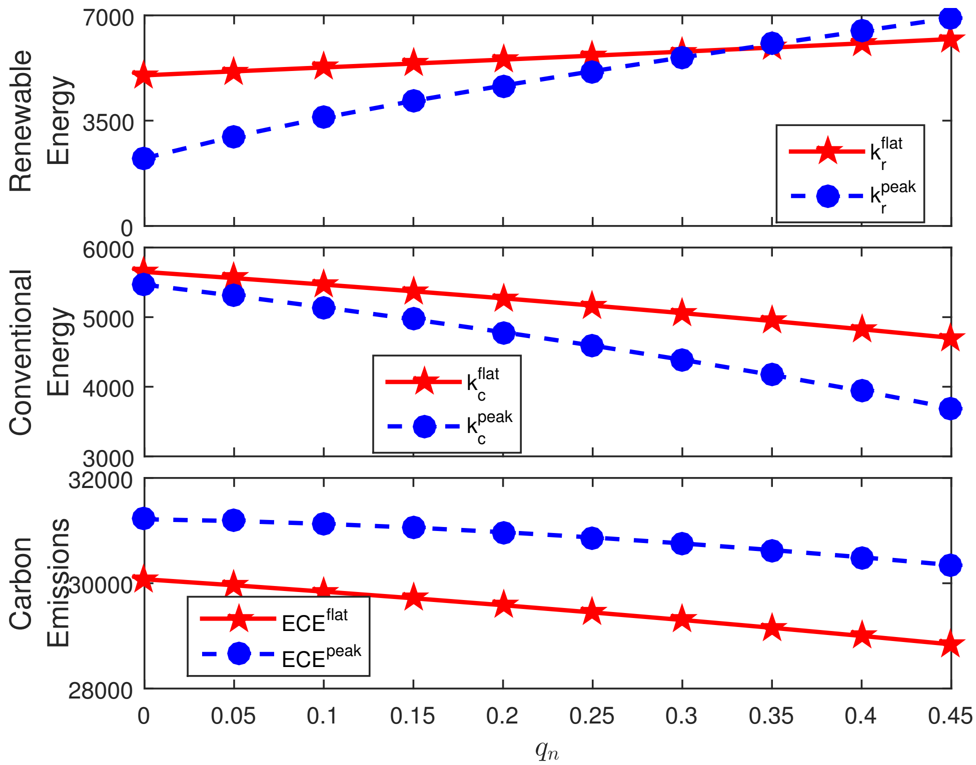
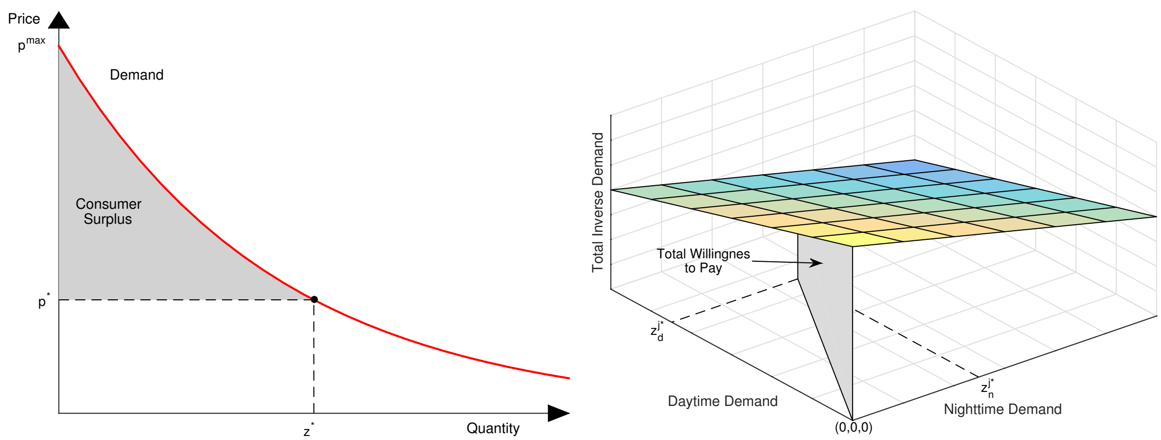


FIGURE 2.2: Investment levels and carbon emissions

Notes. We set $a_n = 30000$ and $a_d = 40000$ MWperiod per day. q_d is 0.28. $C_1 = 10^{-6}$ and $C_2 = 10^{-2}$. These are in line with the real data used in the case study of Section 2.6. Furthermore, we set $\gamma = 13$ and $\delta = 3$ because the optimal prices under these parameters are close to the observed prices in practice. We consider nuclear energy as the new conventional source so that $e = 0$, $\beta_c = \$161.1$/MW per day, and $v = \$141.6$/MWperiod. Finally, we consider wind energy as the renewable source and to ensure that the investment level is positive even under low q_n values, we impose a 75% subsidy for wind energy by setting $\beta_r = \$62.3$/MW per day.

2.4.3 Consumer Surplus

In this section, we study the impact of pricing policy on consumer surplus. We first define the consumer surplus in a single product setting before extending this definition to our setting of two products (peak and off-peak electricity) with interdependent demand. The consumer surplus for a single product is given as $\int_{p*}^{p^{\max}} D(p)dp$, where p^* is the optimal market price and $p^{\max}$ is the maximum price. An equivalent and more convenient definition for our purposes is $\int_0^{z^*} D^{-1}(p)dz - p^* z^*$, where z^* is the optimal quantity demanded at p^*, and $D^{-1}(p)$ is the inverse of the demand function. Intuitively, the inverse demand function corresponds to the price that consumers are willing to pay. Thus, the consumer surplus is the difference between what the consumers are willing to pay ($\int_0^{z^*} D^{-1}(p)dz$) and what they actually pay ($p^* z^*$). We illustrate this definition in Figure 2.3a.



(a) Single product (b) Two products

FIGURE 2.3: Consumer surplus

It is more complicated to define the consumer surplus for two products with interdependent demand. We refer the reader to Pressman (1970) for a detailed discussion. Here, we adopt the definition suggested by Pressman (1970) and Takayama (1993, p.625) which employs the concept of line integral. First, let $\xi_i(\cdot,\cdot) = D_i^{-1}(\cdot,\cdot)$, and define this inverse demand function in period i as

$$\xi_i(z_i, z_{-i}) = \frac{\gamma(a_i - z_i) + \delta(a_{-i} - z_{-i})}{\gamma^2 - \delta^2}, \qquad i \in \{n, d\}, \tag{2.12}$$

where z_i is the demand level in period $i \in \{n, d\}$. Then, for the pricing policy $j \in \{\text{flat}, \text{peak}\}$, the consumer surplus CS^j is given as

$$CS^j = \oint_{C=(0,0)}^{(z_n^{j*}, z_d^{j*})} \xi_n (z_n, z_d)\, dz_n + \xi_d (z_d, z_n)\, dz_d - p_n^{j*} z_n^{j*} - p_d^{j*} z_d^{j*}, \qquad (2.13)$$

where p_i^{j*} is the optimal price, z_i^{j*} is the corresponding demand level in period $i \in \{n, d\}$, and C represents some path on (z_n, z_d) plane that starts at (0,0) and ends at (z_n^{j*}, z_d^{j*}).[3]

We illustrate this definition in Figure 2.3b. The line integral on the right hand side of (2.13) represents the area under the sum of the inverse nighttime and daytime demand curves (i.e., willingness to pay) along the path in which the nighttime and daytime demand levels change from zero to their respective optimal levels. The comparison of the consumer surplus between flat and peak pricing is shown in the following proposition.

Proposition 5. $CS^{flat} \geqslant CS^{peak}$.

According to Proposition 5, the consumer surplus under flat pricing is higher than that under peak pricing. Intuitively, there are two contradicting effects of flat pricing on the consumer surplus. First, the electricity price is lower in the daytime under flat pricing, leading to an increase in the consumer surplus. Second, the electricity price is higher in the nighttime under flat pricing, leading to a decrease in the consumer

[3] See Appendix A.4 for a discussion on computing this line integral.

surplus. The former effect outweighs the latter because the market size is greater in the daytime period, i.e., $a_d > a_n$. Consequently, flat pricing leads to a higher consumer surplus than peak pricing.

We finally note that consumer surplus is an approximate measure of consumer welfare and the accuracy of this approximation is widely discussed in the literature (Takayama 1993, p.625). This is because the consumer surplus is calculated based on the demand function whereas the consumer welfare is calculated directly from the utility of the consumers. To address this issue, we present the underlying utility formulation behind our demand model in Appendix A.4. We prove that the utility of consumers under flat pricing is higher than that under peak pricing. This result is consistent with our conclusion that the consumer surplus is higher under flat pricing.

2.5 Impact of Subsidies on Investment and Emissions

2.5.1 Direct Subsidies

Policy instruments such as investment tax credits and cash grants are commonly used in shaping energy markets across the world. For example, the U.S. government provides tax credits for nuclear power plants and solar farms (EIA 2014c). These are effectively a form of direct subsidies as they reduce the cost of investment for conventional and renewable sources, which is equivalent to reducing β_c and β_r, respectively. Below we show the impact of direct subsidies on the investment levels as well as the corresponding carbon emission levels.

Proposition 6.

(i) A direct subsidy for the renewable energy source results in higher renewable and lower conventional energy investments. Furthermore, carbon emissions decrease in response to the renewable energy subsidy if $e \geqslant \bar{e} = (2 - q_n - q_d)/2$*; otherwise, carbon emissions might increase.*

(ii) A direct subsidy for the conventional energy source results in lower renewable and higher conventional energy investments. Furthermore, carbon emissions increase in response to the conventional energy subsidy if $e \geqslant \max\{\bar{e}, (\gamma + \delta)/2\gamma\}$*, where* γ *and* δ *are the price sensitivity parameters; otherwise, carbon emissions might decrease.*

Proposition 6 (i) indicates that a cash grant for the renewable source can be used to increase the renewable energy investment and reduce the corresponding carbon emissions as long as the emission intensity of the new conventional source is high. This is because the cash grant reduces the investment cost of the renewable source. Thus, the utility firm increases the investment of renewable energy, which, in turn, decreases the investment level of the conventional energy source. Consequently, a bigger fraction of the electricity demand has to be satisfied by the existing fleet. In this case, increasing the renewable investment due to direct subsidies might lead to a higher emission level if e is relatively small (i.e., $e < \bar{e}$). This effect is similar to that discussed at the end of Section 2.4.2. We present an illustrative example of this

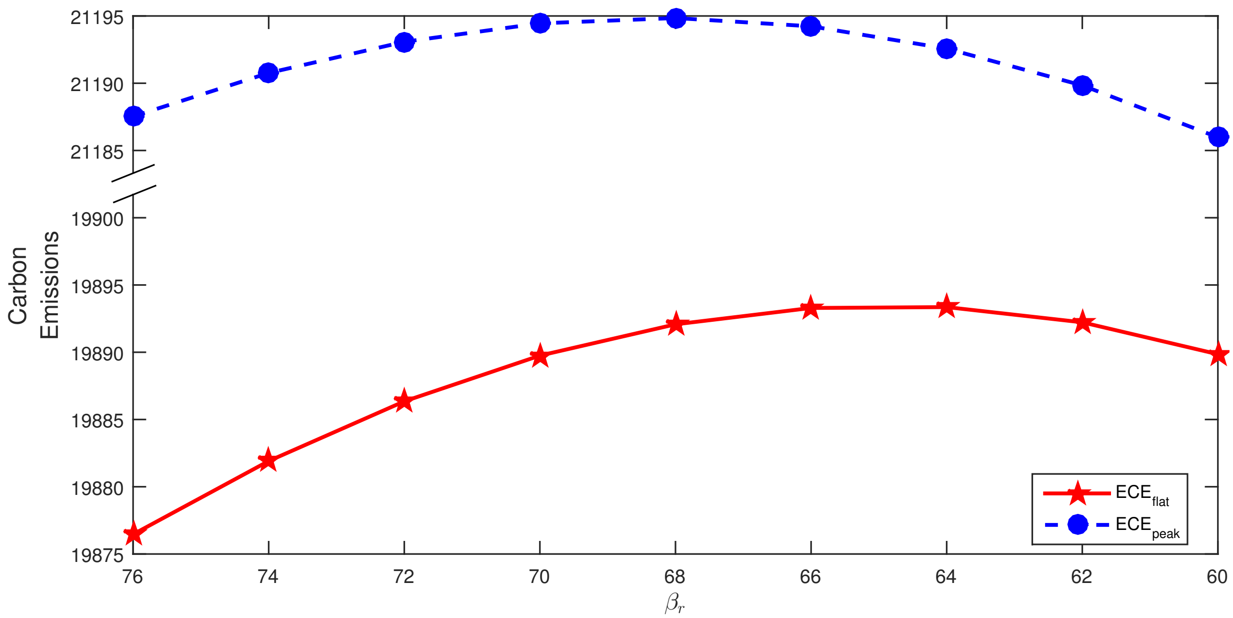


FIGURE 2.4: Effect of a direct subsidy on expected carbon emissions

Notes. We use the same values for $a_n, a_d, C_1, C_2, \gamma, \delta, \beta_c, v$, and e as in Figure 2.2. We consider solar energy as the renewable source and use its intermittency and cost parameters reported in Table 2.1.

case in Figure 2.4 by plotting the expected carbon emissions as a function of a cash grant for the renewable energy source. As seen in Figure 2.4, the amount of expected carbon emissions increases in the cash grant as long as the unit investment cost (β_r) is less than \$68/MW per day. Furthermore, flat pricing leads to lower emissions. This is because the renewable energy investment level is higher under flat pricing.

Proposition 6 (ii) shows that providing a cash grant for the new conventional source leads to a higher conventional energy investment, which, in turn, leads to a lower renewable energy investment. If the new conventional source is carbon-intensive, due to the reduction of the renewable energy investment, the amount of carbon emissions will increase.

2.5.2 *Indirect Subsidies*

In order to reduce the amount of carbon emissions or increase the adoption of renewable energy, carbon taxes have been implemented in almost 40 countries. Whether a carbon tax should be charged remains a topic of debate in the U.S. (World Bank 2014). A carbon tax is a form of an indirect subsidy for carbon-free energy sources as it increases the cost of generating electricity from conventional energy sources with high emission intensities. We denote the carbon tax level with t and modify the utility firm's objection function as

$$\begin{aligned}\max_{k_r,k_c,p_n,p_d} \Pi\left(k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} & E_{\tilde{q}_i}\Big[p_i D_i\left(p_i,p_{-i}\right) - g\left(\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+\right) \\ & -t\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+ \\ & -\left(v+te\right)\min\left(k_c,\left(D_i\left(p_i,p_{-i}\right)-k_r\tilde{q}_i\right)^+\right)\Big] - \alpha_r\left(k_r\right) - \alpha_c\left(k_c\right)\end{aligned} \tag{2.14}$$

Intuitively, the carbon tax should lead to a higher renewable energy investment, as the generation cost of the conventional source increases. However, the proposition below shows that it is not always the case.

Proposition 7. *An indirect subsidy results in (i) higher renewable and lower conventional energy investments if* $e \geqslant \max\{\bar{e},(\gamma+\delta)/2\gamma\}$*; otherwise, the indirect subsidy might lead to lower renewable energy investment. (ii) Furthermore, the indirect subsidy results in a lower amount of carbon emissions.*

Proposition 7 (i) suggests that the renewable energy investment might decrease in response to a carbon tax if the emission intensity of the new conventional source is sufficiently low, i.e., $e < \max\{\bar{e}, (\gamma + \delta)/2\gamma\}$. To see this, notice that the carbon tax increases the generation cost of the existing conventional source. To avoid the increased generation cost, the utility firm will invest more into the energy source with low emissions.[4] If the emission intensity of the new conventional source is low (e.g., nuclear), the utility firm will increase the investment level in the new conventional source rather than the renewable source. This is because the renewable source provides electricity intermittently, whereas the low emission conventional source can provide a steady electricity supply. For this case, we provide an illustrative numerical study in Figure 2.5. As seen in this figure, the renewable energy investment decreases with carbon tax when the new conventional source is carbon-free nuclear energy.

Proposition 7 (ii) implies that the carbon tax always reduces carbon emissions. This is because the carbon tax increases the generation cost of the existing fleet. Thus, the utility firm will increase its investment in less polluting sources (either new conventional or renewable), leading to a decrease in emissions.

[4] Also, due to the increased cost, the utility firm charges a higher price, which, in turn decreases the demand. Thus, the need for the renewable source decreases if the tax level is sufficiently high. Similar observations are made in the literature for spending in pollution abatement technologies by Farzin and Kort (2000) and Baker and Shittu (2006).

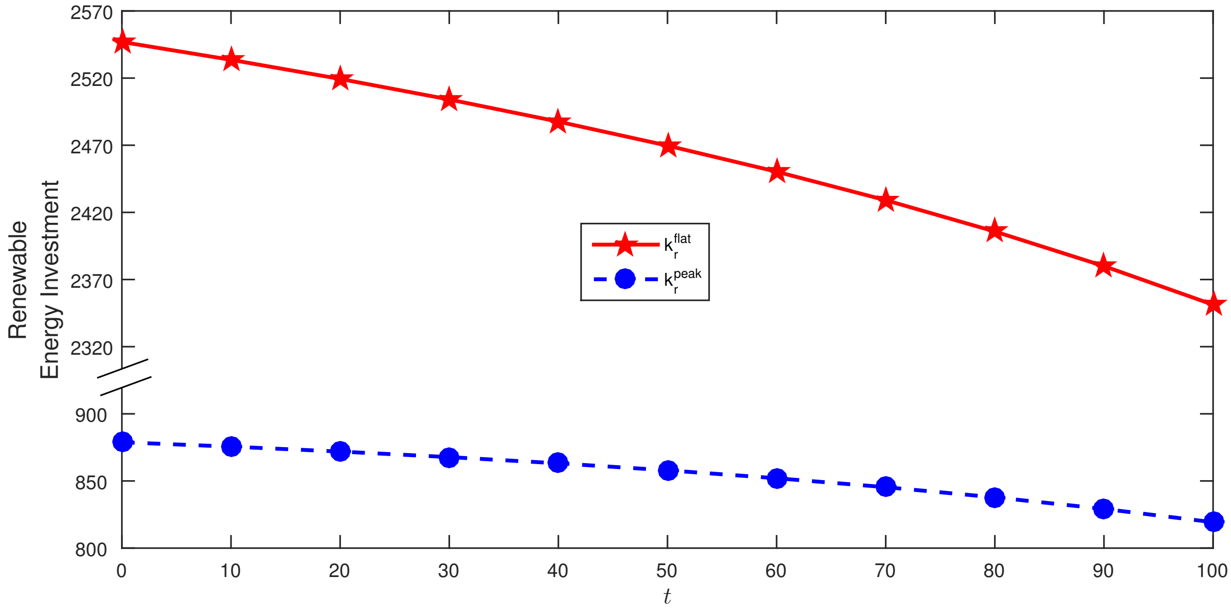


FIGURE 2.5: Effect of an indirect subsidy on renewable energy investment level

Notes. We use the same parameter values as in Figure 2.4.

2.6 Case Study: Texas Data

We use real electricity generation and demand data from the state of Texas in 2010 to validate Propositions 2 and 3.

Recall that our result is obtained by solving the problem in (2.4). In this optimization model, we assume a convex and increasing function $g(\cdot)$ to represent the electricity generation cost. However, in practice, the electricity generation cost is obtained from an optimization model called *unit commitment and dispatch model* (UCDM) solved by an independent system operator (ISO). A UCDM minimizes the electricity generation cost by choosing the set of generators (e.g., coal, natural gas power plants) as well as their output levels to satisfy the electricity demand in a time period. The UCDM considers a few electricity generation characteristics, such as capacity limitations and fixed generation costs, that we do not incorporate in the utility firm model described in Section 2.4. Using the detailed and realistic UCDM, this case study allows us to test the robustness of our insights obtained from the assumed $g(\cdot)$ function.

We use Cohen (2012)'s UCDM, which is a mixed integer program that mimics the dispatch procedure of the Electric Reliability Council of Texas (ERCOT, the ISO serving the state of Texas), to replace the $g(\cdot)$ function. With the real electricity demand and supply data as inputs, we run the UCDM for different levels of renewable and conventional energy investments. From the resulting generation costs, we aim to validate Propositions 2 and 3.

The most important components to validate this result are the inputs for the UCDM. These inputs are the electricity demand data under each pricing policy and the supply data of electricity generation of Texas in 2010. Below we provide a detailed explanation for each of these inputs.

Demand Data. We use the observed 15-minute demand data of Texas as a proxy for the electricity demand under flat pricing as the majority of the customers were charged according to flat pricing in 2010. To obtain the electricity demand under peak pricing, we use the observed demand data as a basis and allow a certain (parametric) percentage of the demand in the peak period to shift to the off-peak period. To determine the peak and the off-peak periods, we use the original demand data and label a twelve-hour peak demand period for each day such that the midpoint of the peak demand period temporally coincides with the occurrence of the maximum demand in that day. In other words, in each day, the peak demand period starts six hours before the occurrence of the highest demand level and lasts for twelve hours. The remaining twelve hours of the day is considered as the off-peak demand period. Note that in each day, the peak demand period changes slightly and it might include early evening hours depending on the season of the year. However, to ensure consistency with the rest of the essay, we still refer to the peak demand period as the daytime and to the off-peak demand period as the nighttime.

To determine the daytime and nighttime demand under the peak pricing policy, we use the result given in Lemma 1. That is, the sum of the optimal nighttime and daytime prices under peak pricing is equal to that under flat pricing. This result indicates that, when peak pricing is used, the decrease in the daytime demand is equal to the increase in the nighttime demand. To determine the exact amount of the reduction in the daytime demand, we develop an approach based on the empirical studies on customer demand responses to peak pricing (see Faruqui and Sergici 2010 for a summary). These studies suggest a broad range of estimates (2-32%) for the percentage reduction in the demand of the peak period with an average value of 13%. Based on these estimates, we consider three scenarios as low response (5%), medium response (10%), and high response (15%). That is, under the high response scenario, for example, we assume that 15% of the daytime demand is shifted to the nighttime. With this treatment, we generate the demand data under peak pricing.

Supply Data. We use two data sources for the electricity generation of Texas in 2010. The first is the electricity generation data set used in Cohen (2012). This rich data set provides variable generation costs and the other operational characteristics (e.g., capacity limitations, fixed generation costs, etc.) for all of the 144 conventional power plants in Texas. In addition to the conventional power plants, Cohen (2012)'s data set includes the wind energy output in Texas for 15-minute intervals. Unfortunately, the data set has no information on the solar energy output as the solar energy capacity in Texas was negligible in 2010.

To generate the solar energy supply data, we conduct a simulation study. The author worked for National Renewable Energy Laboratory (NREL) in Colorado, U.S. and used an NREL simulation package called System Advisory Modeling (SAM) to predict the solar energy generation based on the observed solar radiation data for 79 weather stations in Texas. We use the output of this simulation study as the solar energy generation data in Texas.

Optimal Investment Levels. We turn to our analysis and determine the optimal investment levels for both renewable and conventional energy sources under flat and peak pricing. With the $g(\cdot)$ function replaced by the UCDM, the utility firm optimizes its profit under each pricing policy $j \in \{\text{flat}, \text{peak}\}$ by choosing the renewable and conventional energy investment levels:

$$\max_{k_r,k_c} \Pi^j(k_r,k_c) = \mathit{Revenue}^j - G^j(k_r,k_c) - \alpha_r(k_r) - \alpha_c(k_c), \tag{2.15}$$

where $G^j(k_r,k_c)$ is the generation cost obtained from the UCDM for a renewable investment level k_r and a conventional investment level k_c under the pricing policy j. Here, as introduced in Section 2.3, $\alpha_r(k_r) = \beta_r k_r$ and $\alpha_c(k_c) = \beta_c k_c$ are the investment costs for the renewable and conventional sources, respectively, which are the same between the two pricing policies. Also, the revenue under each pricing policy ($\mathit{Revenue}^j$) is not affected by the energy investments as the prices are fixed under each scenario described above. Define the net benefit of investing k_r units of renewable energy and k_c units of conventional energy compared to zero investments under the pricing policy j as follows:

$$\begin{aligned}\pi^j(k_r,k_c) &= \Pi^j(k_r,k_c) - \Pi^j(0,0)\\ &= [G^j(0,0) - G^j(k_r,k_c)] + [\alpha_r(0) - \alpha_r(k_r)] + [\alpha_c(0) - \alpha_c(k_c)].\end{aligned}$$

Note that the first bracket $[G^j(0,0) - G^j(k_r,k_c)]$ is the cost reduction by installing k_r units of renewable energy and k_c units of conventional energy, which is positive. Intuitively, using the renewable source and the new conventional source to satisfy demand results in lower variable generation costs, so the generation cost obtained from the UCDM becomes smaller after the investments. On the other hand, the second and the third brackets, $[\alpha_r(0)-\alpha_r(k_r)]$ and $[\alpha_c(0)-\alpha_c(k_c)]$, are the investment costs, which are negative.

To find the optimal investment levels by maximizing $\pi^j(k_r, k_c)$, we estimate the cost reduction function, i.e., $[G^{\mathrm{j}}(0,0) - G^{\mathrm{j}}(k_r, k_c)]$ under each pricing policy j for both solar and wind energy. First, we evaluate the cost reduction function at k_r levels, where $k_r \in \{0, 5000, ..., 20000\}$ MW and k_c levels,[5] where $k_c \in \{0, 1000, 3000, 5000\}$ MW through the UCDM. Then, we fit a surface to these investment level pairs and the corresponding cost reduction values. In particular, we consider the following function:

$$[G^j(0,0) - G^j(k_r, k_c)] = l_r^j \times k_r + m_r^j \times \sqrt{k_r} + l_c^j \times k_c + m_c^j \times \sqrt{k_c}, \quad (2.16)$$

where we estimate the parameters l_r^j, m_r^j, l_c^j, and m_c^j from the fitted surface.[6] With this estimated cost reduction function, we can obtain the best investment levels k_r and k_c that maximize the net benefit, $\pi^j(k_r, k_c)$. These levels are presented in Tables 2.2 and 2.3 when solar and wind energy, respectively, is considered as the renewable source. Additional details of this procedure as well as the estimated parameters are given in Appendix A.2.

According to Table 2.2, flat pricing leads to a higher solar energy investment than peak pricing if the utility firm considers solar energy as its renewable source. In

[5] As the new conventional energy source, we consider advanced coal power plants, which have a lower generation cost than the existing fleet, as shown in Figure 2.1. This is consistent with the aforementioned investments in advanced coal units (Duke Energy 2015b).

[6] This functional form provides a very good fit for our data points as indicated by the high adjusted R^2 values given in Tables 2.2 and 2.3.

Table 2.2: Case study results for solar energy

	Response Level	Energy Investment Level (MW) Solar	Conventional	Adjusted R^2
Flat Pricing	N/A	3,391	607	0.9996
Peak Pricing	Low (5%)	2,024	949	0.9995
	Medium (10%)	1,469	1,174	0.9993
	High (15%)	1,316	1,460	0.9987

Table 2.3: Case study results for wind energy

	Response Level	Energy Investment Level (MW) Wind	Conventional	Adjusted R^2
Flat Pricing	N/A	3,615	5,916	0.9965
Peak Pricing	Low (5%)	3,316	3,006	0.9972
	Medium (10%)	2,596	4,241	0.9991
	High (15%)	1,839	5,382	0.9982

this case, the new conventional energy investment is lower under flat pricing. Table 2.3 shows that if the utility firm considers wind energy as the renewable source, flat pricing leads to a higher wind energy investment. In this case, the new conventional energy investment is also higher under flat pricing. In summary, this analysis, based on the real data sets and a practical dispatch process used in the Texas electricity market, shows two results. First, for the renewable source (either solar or wind), flat pricing leads to a higher investment. Second, for the conventional source, flat pricing leads to a higher (lower, respectively) investment if wind (solar, respectively) energy is considered as the renewable source. We shall verify that these results are consistent with what Propositions 2 and 3 predict.

Validation of Propositions 2 and 3. Proposition 2 suggests that flat pricing leads to a higher renewable energy investment for an energy source whose q_n/q_d is less than 1; peak pricing leads to a higher investment if q_n/q_d is greater than R_1.

We estimate the problem parameters as follows. To estimate the coefficients C_1, C_2, C_3, and C_4, we fit a cubic function to the generation cost curve, which can be obtained from the marginal generation cost curve given in Figure 2.1. We find that $C_1 = 8 \times 10^{-8}, C_2 = 4 \times 10^{-3}, C_3 = 158$, and $C_4 = 160$. We use the average demand in the daytime (nighttime, respectively) period as a proxy for the market size a_d (a_n, respectively) and find that $a_d = 40,834$ MWperiod per day ($a_n = 32,003$, respectively). Finally, we determine the intermittency parameters of the wind energy for each of the 15-minute intervals by dividing the wind output in that interval with the wind energy capacity. Then, we take an average of the intermittency parameters in the daytime and the nighttime. We find that $q_n = 0.32$ and $q_d = 0.28$ for the wind energy. Using the same method, we determine the intermittency parameters for the solar energy as $q_n = 0.07$ and $q_d = 0.23$. Based on these estimates, we find that R_1 is 1.17.

For the solar energy, q_n/q_d is 0.3, which is smaller than 1. Thus, Proposition 2 (i) predicts that the investment in solar energy is higher under flat pricing. This is consistent with our numerical finding in Table 2.2. For the wind energy, q_n/q_d is 1.14, which falls in the indeterminate region $(1, R_1)$. Nevertheless, our stylized model (with the $g(\cdot)$ function) still predicts that the investment in wind energy is higher under flat pricing as shown in Figure 2.2. This numerical observation is consistent with the finding in Table 2.3 which also suggests that the investment in wind energy is higher under the flat pricing policy. This completes the validation of Proposition 2.

For the new conventional source, Proposition 3 states that if the renewable source satisfies $(1 - q_n)/(1 - q_d) \leqslant 1$, flat pricing leads to a higher investment in the new conventional source compared to peak pricing. If this ratio is greater than or equal to R_2, flat pricing leads to a lower new conventional energy investment. With the estimated problem parameters above, we find that $R_2 = 1.19$. For the wind energy, $(1 - q_n)/(1 - q_d) = 0.94$ and for the solar energy, $(1 - q_n)/(1 - q_d) = 1.21$. Thus, the wind energy satisfies the first condition, whereas the solar energy satisfies the second. Our numerical findings in Tables 2.2 and 2.3 are consistent with what Proposition 3 predicts. This completes the validation of Proposition 3.

2.7 Extensions

Distributed Generator (DG) Model

In this section, we consider the same investment issue for distributed generators (DGs, e.g., households). These investments include, for example, residential rooftop solar panels or small scale wind turbines used in distant farms. Although the current share of DGs in the U.S. electricity generation capacity is very small, DGs are expected to play a vital role in the "smart grid" market in the near future (ZPRYME

2012). According to Sherwood (2013), more than 90% of the distributed solar installations are connected to the electricity grid under a net metering agreement: the electricity customer who owns the generator has a bi-directional electricity meter that spins backwards when the generator produces more electricity than the customer's usage. This excess generation is credited at the full retail electricity price (Sherwood 2013).

As reported in recent articles in The Wall Street Journal (Sweet 2013) and The New York Times (Cardwell 2013), net metering has fueled a heated debate between the utility firms and the DGs. According to the utility firms, under net metering, DGs are overcompensated for their excess generation. The utility firms claim that DGs only cancel out generation costs while they receive much higher retail prices as compensation. On the contrary, the DGs counterclaim that their actual value for the utilities is much higher than the avoided generation costs. They assert that by generating electricity at the consumption sites, they also avoid transmission losses and congestions in the transmission lines. So far, regulators have favored the claims of the DGs. For instance, California Public Utility Commission (PUC) expanded its net metering program in 2012 (Sweet 2012) and Arizona PUC decided to maintain its net metering policy in 2013 (WSJ 2013).

In line with the recent decisions of the regulators, we investigate the impact of electricity pricing policies on distributed renewable energy investments under net metering. Specifically, we consider a Stackelberg game, where the utility firm acts as the leader who maximizes its profit by setting the energy investment level and the electricity prices. Each DG acts as the follower and decides whether or not to invest in a distributed energy source by comparing its investment cost to the benefit of investments due to net metering (which is affected by the electricity price set by the utility firm).

We assume that each DG can invest in one unit of the renewable energy capacity by incurring a cost of $\theta \times \beta_{DG}$, where β_{DG} is the average unit investment cost for DGs, and $0 < \theta < 1$ represents the heterogeneity in the investment cost. This heterogeneity is mainly due to the differences in the state level subsidies and the roof work required for installing solar panels (Gillingham et al. 2014). The customers compare their investment costs to the expected benefits of investment under net metering. The expected benefit is $q_n p_n + q_d p_d$, as one unit of investment yields q_i amount of electricity in period $i \in \{n, d\}$, which is compensated at the electricity price of p_i due to net metering. Thus, a type θ customer invests if and only if

$$\theta \leqslant \bar{\theta} = \frac{q_n p_n + q_d p_d}{\beta_{\text{DG}}}. \tag{2.17}$$

That is, the customers whose type is less than the indifferent type $\bar{\theta}$, invest in renewable energy. Without loss of generality, we assume that the potential market size is 1 unit, so the total investment level is given as $F(\bar{\theta})$, where $F(\cdot)$ is the cumulative distribution of the type parameter θ. For tractability, we assume that θ is distributed uniformly between 0 and 1 and we define the total investment of DGs as $k_{DG} = F(\bar{\theta})$. Given the investment of k_{DG}, the utility firm determines its own renewable and conventional energy investment level as well as the electricity prices so as to maximize its profit given as:

$$\begin{aligned}\max_{k_r,k_c,p_n,p_d} \Pi\left(k_{DG},k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} & E_{\tilde{q}_i}\left[p_i\left(D_i\left(p_i,p_{-i}\right) - k_{DG}\tilde{q}_i\right)\right. \\ & -g\left(\left(D_i\left(p_i,p_{-i}\right) - k_c - \left(k_{DG}+k_r\right)\tilde{q}_i\right)^+\right) \\ & \left.-v\min\left(k_c,\left(D_i\left(p_i,p_{-i}\right) - \left(k_{DG}+k_r\right)\tilde{q}_i\right)^+\right)\right] \\ & -\alpha_r\left(k_r\right) - \alpha_c\left(k_c\right) \qquad (2.18)\end{aligned}$$

Proposition 8. *(i) The maximization problem in (2.18) is jointly concave in* k_r, k_c, p_n, *and* p_d. *(ii) If* $q_n \geqslant q_d$, *then* $k_{DG}^{flat} \geqslant k_{DG}^{peak}$; *otherwise,* $k_{DG}^{flat} \leqslant k_{DG}^{peak}$.

Proposition 8 states that flat pricing leads to a higher renewable energy investment for DGs if $q_n \geqslant q_d$, as in the case of wind energy. On the other hand, if $q_n < q_d$, as in the case of solar energy, peak pricing leads to a higher investment. These observations are in contrast with the conclusions derived from the utility firm model. This contrast is due to the net metering policy. Under peak pricing, the electricity price is higher during the daytime when the majority of the solar energy output is generated. Thus, due to net metering, DGs enjoy a higher return for their solar energy investments under peak pricing. Hence, peak pricing leads to a higher solar investment. On the other hand, under flat pricing, the electricity price is higher during the nighttime when the majority of the wind energy output is generated. Thus, DGs receive a higher reimbursement for their wind investments and increase their investments under flat pricing.

General Intermittency Distribution

In the original model, we assume that the intermittency factor $\tilde{q}_i$ is distributed according to a two-point distribution. We can relax this assumption by considering $\tilde{q}_i$ as a random variable with a support of $[0, 1]$ in period $i \in \{n, d\}$. The generation pattern for a renewable source can be represented by these two random variables. For example, solar energy can be represented with $\tilde{q}_d$ being stochastically larger than $\tilde{q}_n$. For this generalization, the following assumption is needed.

Assumption 2. *Suppose* $g(\cdot)$ *is quadratic, i.e.,* $C_1 = C_3 = C_4 = 0$ *in* (2.2)*, and*
$$\beta_r \geqslant (E[\tilde{q}_n] + E[\tilde{q}_d])\, v + (E[\tilde{q}_n] - E[\tilde{q}_n^2] - E[\tilde{q}_d^2])\, g'((3a_n - a_d)/4)$$
$$+E[\tilde{q}_d]\, g'((-a_n + 3a_d)/4).$$

Note that Assumption 2 implies Assumption 1 if $\tilde{q}_i$ is distributed with a two point distribution and $g(\cdot)$ is assumed to be quadratic. Under this assumption, the investment cost of the renewable source is sufficiently high so that the total investments in the renewable and new conventional sources do not exceed the nighttime demand level. We next extend Propositions 2, 3, and 4 in the following proposition.

Proposition 9. *Suppose that Assumption 2 holds. Consider the utility firm model in (2.4),*

(i) (solar) if $E[\tilde{q}_d] \geqslant E[\tilde{q}_n]$*, then* $k_r^{flat} \geqslant k_r^{peak}$*,* $k_c^{flat} \leqslant k_c^{peak}$ *and* $ECE^{flat} \leqslant ECE^{peak}$*;*

(ii) (wind) if $E[\tilde{q}_d] \leqslant E[\tilde{q}_n]$*, then* $k_r^{flat} \leqslant k_r^{peak}$*,* $k_c^{flat} \geqslant k_c^{peak}$ *and* $ECE^{flat} \geqslant ECE^{peak}$*.*

Proposition 9 shows that flat pricing leads to a higher renewable energy investment, a lower conventional energy investment, and lower carbon emissions if $E[\tilde{q}_d] \geqslant E[\tilde{q}_n]$, i.e., when solar energy investments are considered. On the other hand, if wind energy investments (i.e., $E[\tilde{q}_d] \leqslant E[\tilde{q}_n]$) are considered, peak pricing leads to higher renewable and lower conventional energy investments, and lower carbon emissions. These insights are consistent with those derived from the original model with the two-point intermittency distribution when $g(\cdot)$ is assumed to be quadratic.

Demand Uncertainty

We can incorporate demand uncertainty into the utility firm model if the intermittency parameter follows a two point distribution as in (2.1). Specifically, consider that the demand in period i is $D_i(p_i, p_{-i}) = a_i - \gamma p_i + \delta p_{-i} + \epsilon$, where ϵ is a random variable with zero mean and a support of $[-L, U]$. In this case, as long as $\beta_r \geqslant q_n(v + g^{'}(L)) + q_d v + \max(q_n, q_d) g^{'}(a_d - a_n + L)$ and the $g(\cdot)$ function is quadratic, the results in Proposition 9 can be established. The proof is available from the authors.

2.8 Concluding Remarks

This essay studies the impact of the flat and peak pricing policies on renewable energy investments and carbon emissions. We investigate this question from the perspective of utility firms, and incorporate several unique features of the energy sources, such as generation patterns and intermittencies, into our model. We find that flat pricing motivates the utility firm to invest more in the solar energy source and leads to lower carbon emissions. The same is true for wind energy if a reasonable fraction of wind energy is generated during the day. These findings and the relevant parameter ranges are verified through a case study based on the electricity data of Texas. We also investigate the effect of pricing policies on DGs and find an opposite result: peak pricing leads to a higher solar energy investment. This result is due to the net metering policy. We also use our model to study the effects of direct and indirect subsidies.

This essay has significant policy implications. Policy makers and academics have been arguing in favor of the peak pricing policy (or more granular policies such as real-time pricing) as a means to smooth out electricity demand throughout the day. Some experts have further argued that peak pricing may also lead to an increase in renewable energy investments under certain cases. This essay shows that the peak pricing policy may not produce the desired increase in renewable energy investments. In particular, we show that flat pricing leads to a higher renewable energy investment, lower emissions, and a higher consumer surplus[7] if the investors are traditional utility firms. This is particularly relevant in the U.S. where the energy investments are mainly undertaken by utility firms. The impact of pricing policies on renewable energy investments requires a careful consideration of three factors together: (*i*) the electricity generation pattern of the renewable sources, (*ii*) the demand pattern throughout the day, and (*iii*) the investor in energy sources (utility firms or DGs). In addition, policies such as carbon tax and cash grants for renewable investments may not produce the desired outcomes either: our results suggest that a high level of carbon tax may reduce renewable energy investments, and cash grants to renewable sources may increase carbon emissions.

Our model has limitations which merit further research. For example, we do not consider the capacity investment problem dynamically in a horizon in which the demand evolves with a trend or seasonality. In addition, we do not model renewable portfolio standards (RPS) that specify a percentage target for the renewable energy capacity in the overall electricity mix. Although our results hold if the RPS target is low, the impact of high RPS targets on investment levels remains an open question. Another limitation of our model is that we assume the utility firm invests only in

[7] We note that consumer surplus measures the difference between the consumer willingness to pay and market prices. Hence, it is not a measure of total welfare, which is affected by the producer surplus as well as the long-term implications of carbon emissions in our case.

a single renewable source instead of multiple renewables with different generation patterns. Finally, we do not consider the impact of pricing policies on the variance of demand uncertainty.

3

Investments in Renewable and Conventional Energy: The Role of Operational Flexibility

3.1 Introduction

Policymakers have introduced various subsidy policies to encourage investments in clean energy sources in order to reduce carbon emissions. For instance, the U.S. government provides a 30% subsidy for the investment costs in solar energy (SEIA 2016a) and the state of New York is planning to offer a multibillion-dollar subsidy to the nuclear power plants (Yee 2016). However, it remains unclear how an increased investment in one type of energy source (due to a subsidy) affects the investment in others. On one hand, Forbes claimed that carbon-free nuclear and renewable energy sources are "best friends" because nuclear can provide a steady back-up electricity supply for intermittent renewables (Kelly-Detwiler 2014). On the other hand, the former chairman of the Federal Energy Regulatory Commission argued that the nuclear source is inflexible (i.e., nuclear power cannot be ramped up or down quickly) to deal with intermittency (Straub and Behr 2009). Contradictory claims were also reported on the interaction between renewable and natural gas-fired power plants. The New York Times claimed that low natural gas prices are a "trap" for renewables because, in response to lower natural gas cost, a utility firm would invest more in natural gas-fired plants rather than renewables (Kotchen 2012). On the contrary, The Wall Street Journal called this claim a "myth" related to the renewables and argued that natural gas can complement renewables by alleviating the intermittency problem (Keith 2013). This essay investigates these interactions between energy sources, with a focus on the capacity investment decisions of utility firms, which constitute the majority of the total energy investment in the U.S.

In recent years, utility firms have significantly invested in renewable sources, such as solar and wind energy, because they provide electricity with negligible generation costs. To cope with the intermittency of the renewable energy sources, utility firms need to invest in conventional sources as well. Conventional sources are categorized into two groups as inflexible and flexible, based on operational flexibility, i.e., whether or not the output of a source can be ramped up or down quickly. A nuclear or coal-fired power plant, for instance, is inflexible because its output cannot be changed rapidly due to technical reasons. On the other hand, a natural gas-fired power plant is flexible (DOE 2011). From the perspective of cost structures, an inflexible source has higher investment but lower generation costs than a flexible one. With these characteristics, it becomes challenging for a utility firm to determine the right capacity investment portfolio which minimizes its investment and generation costs while maintaining a certain reliability level (i.e., the chance of no blackouts). For example, The Wall Street Journal has recently identified a "looming energy crisis" for the utility firms in California because they do not have "the right mix of power plants" and are vulnerable to reliability problems due to over-reliance on intermittent renewables (Smith 2013). Motivated by these policy discussions, we pose the following research questions. What is the optimal capacity portfolio for a utility firm that aims to minimize its investment and generation costs in the presence of inflexible, renewable, and flexible sources? What is the role of operational flexibility in the interaction between the conventional and renewable sources? How do other policies, such as a carbon tax, affect investments and the probability of blackouts (i.e., reliability) in an electricity system?

We model this problem following the decision process of a utility firm while making capacity investments. More specifically, a utility firm first takes a long-term, strategic capacity decision by investing in different energy sources. The invested capacity level of a source becomes the maximum output that the utility firm can dispatch from that source during each of the operating periods, i.e., five minutes. The decision of dispatching energy supply to match the demand is based on the five-minute-ahead forecasts of the electricity demand and the intermittency of renewable energy sources. After the uncertainties of demand and supply realize, a penalty cost is incurred if the electricity demand cannot be fully satisfied. This penalty cost represents consumer's inconvenience costs and the costs that the utility firm has to purchase excess energy from external sources. With this practice, we formulate this problem as a two-stage stochastic program with recourse. In the first stage, subject to demand and supply uncertainties, the firm makes a strategic decision by determining the capacity investment in the inflexible, renewable, and flexible sources. In the second stage, the firm determines the amount of electricity dispatched from these energy sources for each operating period based on the forecasts. The objective of the utility firm is to minimize the total expected cost, which is the sum of the initial investment costs, the electricity generation costs, and the penalty costs of supply shortage within finite operating periods.

We solve the utility firm's investment problem by using backward induction and characterize the optimal dispatch policy: all inflexible capacity is first used, followed by the renewable energy capacity as the latter's generation cost is negligible compared to the flexible source. Based on this optimal dispatch policy, we determine the optimal investment level for each source. We obtain a multi-dimensional newsvendor-type solution. That is, the utility firm balances the underage cost (e.g., the penalty cost due to supply shortage) with the overage cost (i.e., the investment cost) for each energy source in the demand and intermittency space. In the most practical case where the investment levels of all sources are positive, the critical fractile associated with the flexible source determines the probability of meeting the demand. This indicates that the reliability of the electricity system is determined by the cost parameters of the flexible source and the penalty cost rate. This finding reveals an important policy insight that the reliability is only affected by a subsidy provided for the flexible source but not the subsidies for renewable and inflexible sources.

To identify how a subsidy for one source affects the investment level of the other sources, we examine the interaction between energy sources. In particular, we define two sources as *substitutes* (*complements*, respectively) if a decrease in the investment cost of one source, which results in an increase of the investment level of that source, leads to a decrease (an increase, respectively) in the investment level of the other. We find that the inflexible and renewable sources are substitutes. Intuitively, the inflexible and renewable sources share similar characteristics in the capacity portfolio: both are costly to invest, inexpensive to operate, but uncontrollable (inflexible or intermittent). An implication of this result is that lowering the investment cost for nuclear or coal-fired plants leads to a lower investment in wind or solar energy. On the other hand, under certain conditions, we show that the renewable and flexible sources are complements as they have opposite characteristics: the flexible source is inexpensive to invest but costly to operate, and is controllable. Thus, in response to a price reduction of natural gas, a utility firm will increase its investment level in renewables. Lastly, the inflexible and flexible sources are substitutes. This is because the flexible source is complementary to the renewable source which is a substitute for the inflexible source. These results suggest that the relationships between the investment levels of renewable and conventional sources are determined by the operational flexibility and the cost structures. We validate these results by using real electricity generation and demand data from the state of Texas in Section 3.7. Our results indicate that a unit increase in the capacity of the flexible source approximately leads to 0.2 units increase in the optimal capacity of the renewable source.

Finally, we consider the impact of a carbon tax on the investment decision of the utility firm. Many experts claim that taxing carbon emissions motivates the investment in renewable sources (c.f., EIA 2013, Tyson 2013, and Walls 2015). Our analysis shows that this claim does not hold when the inflexible source is carbon-free nuclear energy. In this case, the carbon tax increases the generation cost of the flexible energy source, which results in a reduction of the investment of flexible source, which, in turn, reduces the investment of the renewable source due to the complementarity effect.

The rest of the essay is organized as follows. Section 3.2 reviews the related literature. Section 3.3 introduces our model. Section 3.4 derives the optimal capacity investment portfolio. Section 3.5 analyzes the relationships between energy sources under the optimal capacity portfolio. Section 3.6 studies the effects of carbon tax, generation subsidies, and penalty cost. Section 3.7 validates our main results by using real data through a case study. Section 3.8 considers several extensions of our model. Section 3.9 concludes.

3.2 Literature Review

3.2.1 Dual Sourcing

Dual sourcing literature dates back to Barankin (1961) who studied an inventory model with two suppliers: the first supplier features a long lead time but a low procurement cost, whereas the other has a short lead time but a high cost. Although we consider capacity investments, this classical trade-off between cost and responsiveness also exists in our model. In a different context, Allon and Van Mieghem (2010) analyzed a tailored base-surge policy that replenishes inventory from an offshore supplier to satisfy constant demand and from an onshore supplier to satisfy demand shocks. In addition to the cost and responsiveness trade-off, supplier reliability is studied extensively in the literature. See Yano and Lee (1995) and Minner (2003) for reviews. In this domain, Dada et al. (2007) investigated the procurement decision of a newsvendor who orders from multiple unreliable and capacitated suppliers. They showed that the newsvendor selects suppliers based on their cost and determines the order size based on the reliability of selected suppliers. Federgruen and Yang (2008) studied a similar setting with fixed costs of retaining suppliers and proposed heuristics to determine order sizes. Tomlin (2009) used Bayesian learning for the reliability parameter of suppliers and showed that an increase in the reliability forecast increases the attractiveness of a supplier. Wang et al. (2010) compared a dual sourcing strategy and a process improvement strategy in order to mitigate supplier risk. They showed that in a random yield model (similar to the intermittency in our case), process improvement can be favored over dual sourcing if the reliability heterogeneity is high among suppliers.

The paper closest to our setting is Sting and Huchzermeier (2012). The authors considered a manufacturer who invests capacity in a responsive, onshore facility and also replenishes from an offshore supplier who is unreliable but less expensive. After demand and supply uncertainties are realized, the manufacturer orders from its responsive capacity to satisfy the demand. They characterized the optimal production policy and showed that the service level is determined by the critical fractile of the responsive capacity. We extend these results in that we consider three sources: the two reliable sources, i.e., flexible and inflexible, can be viewed as an onshore and a (reliable) offshore supplier, respectively; the intermittent renewable source can be viewed as an (unreliable) onshore source. Our results suggest that not all sources are substitutes. Interestingly, any two source combination (e.g., flexible and renewable, or flexible and inflexible) of our model gives the same result as Sting and Huchzermeier (2012), indicating that our model is a generalization of theirs in this respect.

3.2.2 Supply Chain Flexibility

Our definition of operational flexibility is similar to volume flexibility, where the production quantity can be altered, perhaps at a cost, depending on the realized demand. In this domain, Van Mieghem and Dada (1999) considered postponing production decision in a single source setting. Tomlin (2006) found the importance of volume flexibility for a firm that can either source from an unreliable supplier or a reliable and flexible supplier. A similar notion of volume flexibility is quick response, where a firm can place additional orders after observing some initial information on demand (c.f., Fisher and Raman 1996, Fisher et al. 2001, and Bensoussan et al. 2011). Goyal and Netessine (2011) also analyzed volume flexibility by comparing the profit of a firm that invests in a volume flexible or a dedicated source. We consider three sources where each source is either flexible, inflexible, or unreliable to study the interaction between these sources. As noted by Goyal and Netessine (2011), the notion of flexibility in energy sources is different from the flexibility in production facilities because energy sources are either fully flexible or fully inflexible.

Another flexibility type is the product mix or process flexibility, studied first by Fine and Freund (1990). This type of flexibility refers to the ability to manufacture different products at the same facility. In this domain, Jordan and Graves (1995) introduced the concept of *long chain* and showed that limited flexibility, if configured in the right way, can perform almost as good as full flexibility (i.e., all products can be produced in all facilities). Van Mieghem (1998) studied optimal capacity investments in two inflexible (dedicated) and one flexible source to meet stochastic demand for two products. Bish and Wang (2004) extended the model of Van Mieghem (1998) by considering price flexibility and showed that similar insights hold. Bernstein et al. (2007) studied the impact of decentralization in an assemble-to-order system where two dedicated and one common component is used to produce two end-products. They showed that decentralization, i.e., component capacity levels being determined by independent suppliers, might reduce the value of operational hedging. In a similar setting, Bernstein et al. (2011) investigated how aggregating demand information affects the profit level and the allocation of the common component between the two end-products. Tomlin and Wang (2008) investigated flexibility in product-mix and pricing in a two-product, two customer class setting. While our model with volume flexibility is different from those of process flexibility, the main insights are related: the renewable and flexible sources are complements and the inflexible source is a substitute for both.

3.2.3 Sustainable Operations and Energy Economics

Our essay is directly related to the growing literature on sustainable operations (see Drake and Spinler 2013 for a review) and particularly sustainability of energy systems. Many papers including, Aflaki and Netessine (2015), Hu et al. (2015), and Kök et al. (2015) model capacity investments in renewable and conventional sources.

Their results indicate that conventional and renewable sources are substitutes. We refine this conclusion by modeling operational flexibility of conventional sources and show that a renewable and a conventional source are substitutes (complements, respectively) if the conventional source is inflexible (flexible, respectively). In an earlier study, Gardner and Rogers (1999) investigated the capacity investment problem under different lead times of construction for power plants. They did not consider renewable energy investments (hence supply uncertainty) and operational flexibility, which jointly constitute the main focus of our essay. Wu and Kapuscinski (2013) also considered operational flexibility to determine ways to cope with intermittency, but capacity investment is not endogenous in their model.

There is an extensive literature in economics dealing with energy investments. See Crew et al. (1995) for a review. More recently, through a simulation study, Chao (2011) observed that wind energy is substituted by combined cycle, natural gas turbines (i.e., inflexible sources) and complemented by regular gas turbines (i.e., flexible source). Lee et al. (2012) also pointed to potential reasons for complementarity between natural gas and wind investments. Baranes et al. (2015) analytically showed the conditions under which natural gas and wind are complements. Unlike our model, they only considered investments in a renewable source under deterministic demand without operational flexibility.

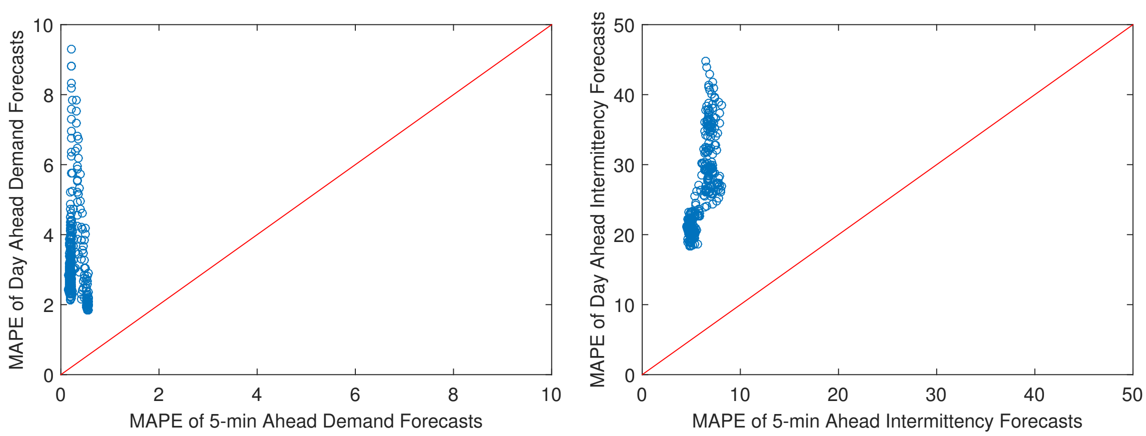
3.3 Model

To facilitate the formulation of our model, we first describe how a monopolist utility firm makes its capacity investment decision in practice. A typical process starts from forecasting the electricity demand and the intermittency of renewable energy supply in a targeted demographic region. Using these demand and supply forecasts as an input, the utility firm makes a one-time, strategic decision on its investment level in inflexible, renewable, and flexible energy sources. The invested capacity level of a source becomes a constraint for the energy output from that source. In the daily operations, the utility firm's objective is to match the random demand with electricity supply for each operating period, which is often set to be five minutes. The utility firm uses the five-minute ahead forecasts of demand and supply as inputs and decides how much electricity to generate from the renewable[1] and flexible sources in each operating period. The inflexible source, on the other hand, is dispatched at a constant level throughout the day. This is because a utility firm cannot frequently change the output of an inflexible source due to technical reasons (c.f., Shively and Ferrare 2008, p. 39, Denholm et al. 2010, and DOE 2011).

The utility firm uses the short-term forecasts as inputs in the dispatch decision because they are quite accurate. In Figure 3.1, we plot the Mean Absolute Percentage Error (MAPE) for demand and intermittency forecasts in 2014 for the Southwest

[1] In most cases, renewable energy is not curtailed. That is, the entire capacity of the renewable source is dispatched as its generation cost is negligible.

Power Pool (SPP), the network of utility firms in the southwest region of the U.S. Each circle represents one of the 288 operating periods (i.e., five-minute intervals) during a day. On the vertical axis, we plot the MAPE of day-ahead forecasts, and on the horizontal axis, we plot the MAPE of five-minute ahead forecasts. All circles remain well above the 45 degree line, indicating that the forecasts made a day ahead are much less accurate compared to the forecasts made five-minutes ahead. Thus, a typical utility firm has relatively reliable forecasts of demand and supply before deciding the dispatch quantities. See Wu and Kapuscinski (2013) for describing a similar practice.



(a) Demand forecasts (b) Intermittency forecasts

FIGURE 3.1: Forecast errors in Southwest Power Pool (SPP), 2014

The costs involved in the above process are one-time investment costs and the generation costs of electricity. The generation cost is different for each energy source. In general, the generation cost of the renewable source is negligible. The generation cost of inflexible sources, such as nuclear or coal-fired power plants, is usually smaller than that of flexible sources, such as natural gas. Furthermore, in some rare occasions, if the demand cannot be fulfilled by the dispatched supply, blackouts occur. Blackouts are costly because a utility firm usually has to purchase electricity from external sources to avoid fines imposed by governmental regulations. The objective of the utility firm is to minimize the total cost consisting of the investment costs, generation costs, and penalty costs due to potential blackouts. We refer to the latter two costs as the generation-related cost.

We now formulate our problem as a stochastic program with recourse based on the above practice. We consider a representative day with N operating periods. The problem consists of two stages, that is, the first stage is related to the initial capacity investment decision and the second stage is related to the dispatch decision to match demand with supply. Let the variable generation cost (in dollars per unit capacity for a period) of the inflexible and flexible sources be c_I and c_F, respectively. We normalize the variable generation cost of the renewable source to zero ($c_R = 0$). The five-minute ahead demand forecast is given as a bounded, nonnegative random variable ϵ_n. Available capacity of renewable energy is denoted as $\Theta_n k_R$, where Θ_n is a random variable with a support of [0,1], representing the intermittency forecast. The sequence of events is illustrated in Figure 3.2.

We formulate the problem backwards. Let q_I, q_R, and q_F represent the dispatch levels of the inflexible, renewable, and flexible sources, respectively. Any unmet

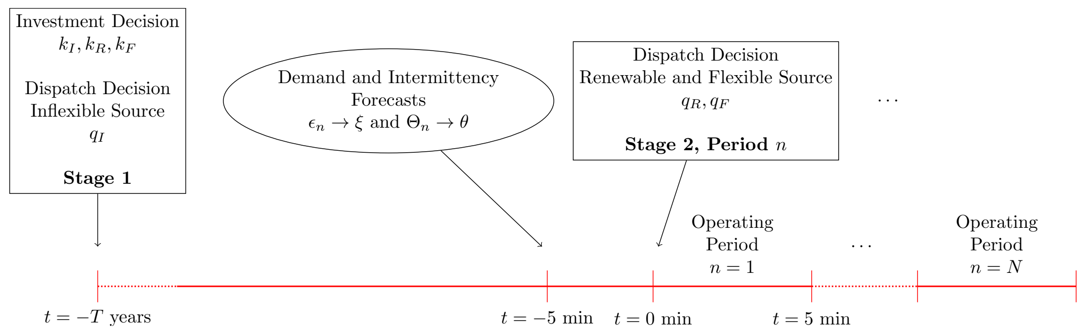


FIGURE 3.2: Sequence of events

demand results in a penalty cost, with rate r, proportional to the amount of electricity demand that cannot be satisfied by the dispatched electricity from the three sources. This linear penalty cost is consistent with the literature (c.f., Crew et al. 1995). The second stage problem of the utility firm is to minimize the sum of the generation-related cost for each period n after observing demand and intermittency forecasts ξ and θ:

$$C\left(q_I, k_R, k_F, \xi, \theta\right) = c_I q_I + \begin{cases} \min_{q_R, q_F \geqslant 0} & c_F q_F + r\left(\xi - q_I - q_R - q_F\right)^+ \\ \text{subject to} & q_R \leqslant \theta k_R \\ & q_F \leqslant k_F \end{cases}, \tag{3.1}$$

where $(x)^+ = \max\{x, 0\}$.

In the above formulation, the decision variables are the dispatch levels of the renewable and flexible sources, whereas the dispatch level of the inflexible source q_I is given as a state variable. This is to reflect the fact that the inflexible source is dispatched at a constant level and cannot be adjusted in each period. Thus, we shall view q_I as a long-term decision, which will be optimized in the subsequent stage

1 problem. This formulation implicitly assumes that the inflexible source will be dispatched earlier than the other two sources, which is consistent with the current practice.[2]

We now turn to the stage 1 problem. The utility firm determines its nonnegative capacity investment levels along with the dispatch decision of the inflexible source so as to minimize its expected total cost:

$$\min_{\boldsymbol{k}\in\mathbb{R}^3_+} \bar{\Pi}(\boldsymbol{k}) = \alpha_I k_I + \alpha_R k_R + \alpha_F k_F + \min_{0\leqslant q_I\leqslant k_I} E\left[\sum_{n=1}^{N} C\left(q_I, k_R, k_F, \epsilon_n, \Theta_n\right)\right], \quad (3.2)$$

where $E[\cdot]$ denotes the expectation operator, $\boldsymbol{k} = (k_I, k_R, k_F)$, and $C\left(q_I, k_R, k_F, \epsilon_n, \Theta_n\right)$ is the solution of the second stage problem given in (3.1). The expectation is with respect to non-stationary random variables ϵ_n and Θ_n, which jointly represent the demand and supply uncertainty in the planning stage for the utility firm. Here, in addition to the capacity investment levels, the utility firm determines the dispatch level of the inflexible source.

Notice that we consider a monopolist utility firm that does not have access to an electricity spot market in our base model. In this setting, the firm is responsible for matching supply and demand by using its own generation sources. This is not an uncommon setting because approximately half of the U.S. utility firms operate in

[2] In fact, it is also optimal to first dispatch the renewable source in this case. That is, it is also optimal to set $q_R = \theta k_R$ in all periods as $c_R = 0$ and there is no overproduction penalty. Nevertheless, we explicitly consider q_R to ensure consistency with the second stage problem of the spot market setting given in (3.16)–(3.19). In the presence of a spot market, it might not be optimal to dispatch all renewable capacity as we explain in Section 3.8.

such settings (FERC 2015b). In Section 3.8, we extend our model by incorporating an electricity spot market.

In the remainder of the essay, we use terms "increasing," "decreasing," and "convex" in their respective weak senses. We denote the gradient operator as ∇. For a random variable X, we let $f_X(\cdot)$ be the probability density function. Finally, "$X|\cdot$" denotes the conditional probability. All proofs are given in Appendix B.1.

3.4 Optimal Capacity Investments

In this section, we characterize the optimal capacity investments of a utility firm. We first simplify the problem given in (3.2) by showing that at optimality, the dispatch level of the inflexible source is always equal to its capacity investment level, i.e., $q_I = k_I$. The intuition is that the firm should always dispatch all of its inflexible capacity at every period because the firm can otherwise achieve a strictly lower cost by decreasing k_I.

Lemma 10. *Consider the investment problem given in* (3.2)*. It is optimal to set* $q_I = k_I$.

Lemma 10 is consistent with the practice as the utilization of nuclear power plants in the U.S. is close to 90% (EIA 2015c), indicating that these plants operate continuously during the day. By using Lemma 10, we substitute k_I for q_I in the second stage dispatch problem given in (3.1) and obtain:

$$C(\boldsymbol{k}, \xi, \theta) = \min_{q_R, q_F \geqslant 0} \quad c_F q_F + r(\xi - k_I - q_R - q_F)^+ \tag{3.3}$$

$$\text{subject to} \quad q_R \leqslant \theta k_R \tag{3.4}$$

$$q_F \leqslant k_F. \tag{3.5}$$

Similarly, under Lemma 10, the capacity investment problem in the first stage becomes:

$$\min_{\boldsymbol{k} \in \mathbb{R}^3_+} \bar{\Pi}(\boldsymbol{k}) = E\left[\sum_{n=1}^{N} C(\boldsymbol{k}, \epsilon_n, \Theta_n)\right] + (\alpha_I + c_I N) k_I + \alpha_F k_F + \alpha_R k_R, \tag{3.6}$$

where we charge the generation cost of the inflexible source to its entire capacity for each of the N periods. In the remainder of the essay, we focus on these simplified formulations of the first and second stage problems.

We next characterize the optimal capacity investments by backward induction, i.e., by first solving the second stage problem given in (3.3)–(3.5). Let $q_i^*(\boldsymbol{k}, \xi, \theta)$ be the optimal dispatch level of energy source $i \in \{R, F\}$ given an investment vector $\boldsymbol{k}$, demand forecast ξ, and intermittency forecast θ. The optimal dispatch policy for renewable and flexible sources is shown in the following lemma.

Lemma 11. *Consider the dispatch problem given in* (3.3)–(3.5). *The optimal dispatch policy is to set* $q_R^*(\boldsymbol{k}, \xi, \theta) = \min(\theta k_R, \xi - k_I)^+$ *and* $q_F^*(\boldsymbol{k}, \xi, \theta) = \min(k_F, \xi - k_I - \theta k_R)^+$.

Lemma 11 shows that the utility firm first dispatches its renewable source up to its available capacity θk_R if demand forecast ξ exceeds the inflexible source capacity k_I in a period. Then, the flexible source is dispatched for the remaining demand. This is due to the fact that the renewable source incurs a negligible generation cost compared to the flexible source. Lemmas 10 and 11 conclude the optimal dispatch policy: in every period, all of the inflexible capacity is dispatched, followed by the renewable source, and then by the flexible source.

We next use this optimal dispatch policy to characterize the optimal capacity portfolio. Our analysis involves constructing the dual of the dispatch problem in (3.3)–(3.5) such that $\lambda_i^*(\boldsymbol{k}, \xi, \theta)$ denotes the optimal dual variable associated with the capacity constraint related to source $i \in \{I, R, F\}$. We present this dual problem in the proof of Proposition 12, where each dual variable represents the shadow price of the associated capacity constraint.

Table 3.1: Shadow prices of capacity constraints

Partition for $(\xi, \theta) \in \mathbb{R}_+ \times [0, 1]$	$\lambda_I^*(\boldsymbol{k}, \xi, \theta)$	$\lambda_R^*(\boldsymbol{k}, \xi, \theta)$	$\lambda_F^*(\boldsymbol{k}, \xi, \theta)$
$\Omega_1(\boldsymbol{k}) = \{(\xi, \theta) \mid \xi \leqslant k_I + \theta k_R\}$	0	0	0
$\Omega_2(\boldsymbol{k}) = \{(\xi, \theta) \mid k_I + \theta k_R \leqslant \xi \leqslant k_I + \theta k_R + k_F\}$	c_F	θc_F	0
$\Omega_3(\boldsymbol{k}) = \{(\xi, \theta) \mid k_I + \theta k_R + k_F \leqslant \xi\}$	r	θr	$r - c_F$

Note that Lemma 11 is obtained by partitioning the demand and intermittency space into three regions as listed in Table 3.1. These regions are identical across all N periods but the probability that a pair of ξ and θ falls into a specific region in each period depends on the (non-identical) distributions of ϵ_n and Θ_n. Furthermore, within each region, the optimal dispatch levels as well as the dual variables have the same structure for different realizations of demand and supply forecasts. For example, for all ξ and θ in $\Omega_1(\boldsymbol{k})$, it is optimal to set q_R to $\xi - k_I$ and q_F to 0. In this case, no capacity constraint is binding so that $\boldsymbol{\lambda}^* = (0,0,0)$. In addition, since $\bar{\Pi}(\boldsymbol{k})$ is convex, the Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient for the investment problem given in (3.6). Moreover, we can show that $\nabla_{\boldsymbol{k}} E[C(\boldsymbol{k},\xi,\theta)] = -E[\boldsymbol{\lambda}(\boldsymbol{k},\xi,\theta)]$. That is, the derivative and expected value can be interchanged, where the expected value of the dual variables can be easily computed by using Table 3.1. With these observations, in Proposition 12, we present the KKT conditions of the investment problem given in (3.6), where $\boldsymbol{v}$ is the vector of Lagrange multipliers of the nonnegativity constraints and $P^n(\Omega)$ is the probability that ξ and θ is in Ω for ϵ_n and Θ_n.

Proposition 12. *Consider the problem given in* (3.3)–(3.6). *An investment vector* $\boldsymbol{k}^* \in \mathbb{R}^3_+$ *is optimal if and only if there exists a* $\boldsymbol{v} \in \mathbb{R}^3_+$ *such that*

$$\sum_{n=1}^{N}\left(E\left[\begin{array}{c|c} c_F & \\ \Theta_n c_F & \Omega_2(\boldsymbol{k}^*) \\ 0 & \end{array}\right] P^n\left(\Omega_2\left(\boldsymbol{k}^*\right)\right) + E\left[\begin{array}{c|c} r & \\ \Theta_n r & \Omega_3(\boldsymbol{k}^*) \\ r - c_F & \end{array}\right] P^n\left(\Omega_3\left(\boldsymbol{k}^*\right)\right)\right) = \begin{pmatrix} \alpha_I + N c_I - v_I \\ \alpha_R - v_R \\ \alpha_F - v_F \end{pmatrix}. \tag{3.7}$$

$$\forall i \in \{I,R,F\} : k_i v_i = 0. \tag{3.8}$$

Equation (3.7) is obtained by taking the partial derivative of the Lagrangian function with respect to k_I, k_R, and k_F, respectively. Based on the KKT conditions, there are a total of eight cases that we should consider in order to find the optimal investment levels. These eight cases form four investment strategies: (i) no investments (i.e., $\boldsymbol{k}^* = 0$), (ii) single sourcing (three cases, e.g., $k_I^* > 0$ and $k_R^* = k_F^* = 0$), (iii) dual sourcing (three cases, e.g., $k_I^*, k_R^* > 0$ and $k_F^* = 0$), (iv) triple sourcing (i.e., $\boldsymbol{k}^* > 0$). No investments strategy is optimal if $rN < \alpha_i + c_i N$ for $i \in \{I, F\}$, and $r \sum_{n=1}^{N} E[\Theta_n] < \alpha_R$, i.e., when the investment costs are higher than the penalty cost. Unfortunately, we are not able to analytically characterize the range of the cost parameters that ensures the optimality of the rest of the investment strategies due to the nonstationarity in demand and supply uncertainty. Nevertheless, based on the estimates of the cost parameters and the electricity demand data of Texas, we observe that the triple sourcing strategy is optimal. This is consistent with the practice that utility firms simultaneously invest in inflexible, renewable, and flexible sources (FERC 2015a). Motivated by these facts, in the subsequent discussion, we shall focus on the triple sourcing strategy as this is the most interesting and relevant case. We also investigate the other strategies in Section 3.8.

Proposition 12 provides a method to find the optimal investment levels for the triple sourcing investment strategy. The idea is to solve three newsvendor problems simultaneously with $\boldsymbol{v}^* = 0$, each corresponding to one energy source. More specifically, for the inflexible source, from Equation (3.7), the underage cost includes the expectation of the two events associated with the demand exceeding the capacity of this source. In the first case, the capacity of the flexible source is sufficient to meet the remaining demand. In the second, the total demand may exceed the entire capacity and a penalty cost r is incurred in addition to the generation cost of the flexible source. Hence, the underage cost for the inflexible source is the probability weighted sum of these two costs. The overage cost for the inflexible source, on the other hand, is the investment and the generation cost. Note that we include the generation cost of the inflexible source in the overage cost because the entire capacity of this source is dispatched at every period even if its capacity exceeds the demand.

For the renewable source, the underage cost is similar to the inflexible source. However, supply uncertainty Θ_n is also considered while computing the expectation. The overage cost only includes the investment cost but not the variable generation cost for two reasons. First, we assume that the variable cost is zero for the renewable source. Second, even in the absence of this assumption, the utility firm would not dispatch the renewable source when its capacity exceeds the demand, so the variable generation cost should not be included in the overage cost.

For the flexible source, the underage cost only involves the event of demand exceeding the total capacity. In this case, the penalty cost is incurred and the underage cost is given as $(r - \alpha_F - c_F)$. Note that we deduct the investment and generation cost from the penalty cost, i.e., as in the classical Newsvendor model, we consider the net underage cost. The overage cost for the flexible source is only the capacity cost, α_F.

In summary, the optimality condition suggests that there is a pair of underage cost and overage cost that determines the optimal investment level for each energy source. The utility firm balances underage and overage costs of inflexible, renewable, and flexible sources for demand and supply realizations as we illustrate in Figure 3.3. The thick line in the figure represents the maximum demand that the firm is able to serve. By adjusting its investments, the utility firm determines the probability of each region so that the underage cost is balanced with the overage cost for each energy source.

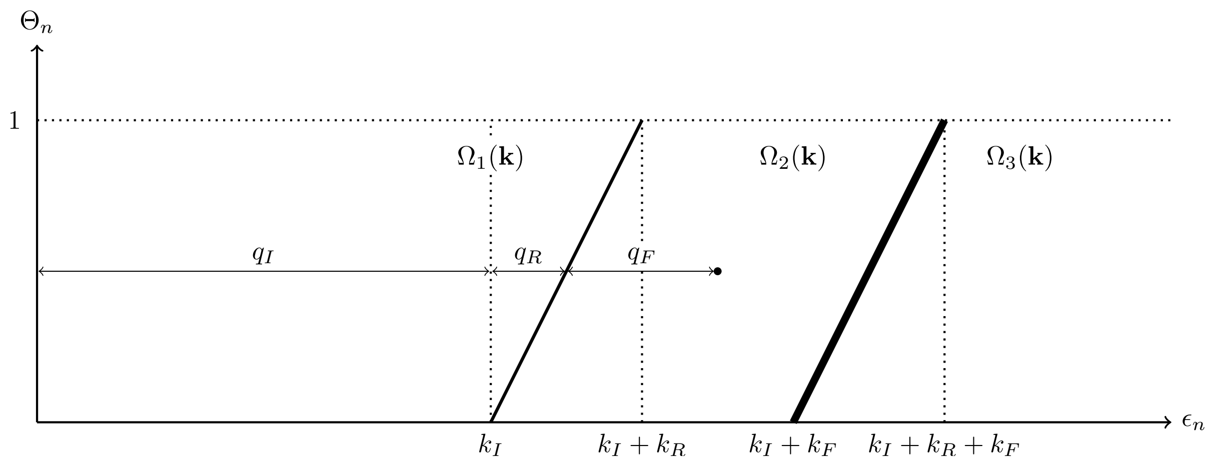


FIGURE 3.3: Partitions of demand and intermittency space

Notes. In Figure 3.3, for illustration purposes, we assume that $k_F > k_R$.

Next, we consider the relationship between the investments and the reliability of the electricity grid. In the energy economics literature, reliability is defined based on the so-called loss-of-load probability (LOLP), i.e., the probability that the demand exceeds the supply of electricity (Telson 1975). This definition is similar to the concept of service level in the supply chain management literature. Let ρ^* denote the LOLP corresponding to the optimal investment levels:

$$\rho^* = \sum_{n=1}^{N} P^n(\Omega_3(\boldsymbol{k}^*)),$$

where $\Omega_3(\boldsymbol{k}^*)$ is the demand and intermittency space region in which demand exceeds available supply.

Corollary 1. $\rho^* = \alpha_F/(r - c_F)$.

In the triple source strategy (i.e., $\boldsymbol{k}^* > 0$), this corollary immediately follows from the third dimension of the optimality condition (i.e., with respect to k_F) given in (3.7) in Proposition 12. It suggests that the reliability of the electricity grid is only affected by the penalty cost rate r and the cost parameters of the flexible source. That is, the newsvendor critical fractile of the flexible source determines the service level. Intuitively, the flexible source is the last option for the utility firm to satisfy the demand and the firm finds the optimal investment level in this source by comparing the penalty cost of not satisfying demand and the investment cost. This result is an extension of the similar observations made in the energy economics (c.f., Chao 1983) and the dual sourcing literature (c.f., Sting and Huchzermeier 2012) to our setting.

Corollary 1 suggests an important policy insight. Because subsidies for the renewable or the inflexible source do not affect r, c_F, or α_F, these subsidies do not change the reliability level of the grid. This result provides a different perspective than the claims that renewable energy subsidies undermine the reliability and nuclear subsidies enhance the reliability (c.f., Gronewold 2011, Garman and Thernstrom 2013, Karnitschnig 2014, Fisher 2015, and Smith 2015). This is because, our model optimizes investments in all energy sources simultaneously and can identify the impact of subsidies on the entire capacity portfolio rather than considering the impact on a single source.

3.5 Interaction Between Energy Sources

Two consumption goods are substitutes if a decrease in the price of one good leads to a lower level of consumption in the other (Singh and Vives 1984). From the utility firm's perspective, energy sources are consumption goods and their price is the investment cost. Hence, we define two energy sources as *substitutes* if a decrease in one's investment cost leads to a decrease in the other's investment level. That is, sources i and j are substitutes if a decrease in α_i leads to a decrease in k_j^* (i.e., $dk_j^*/d\alpha_i > 0$) and vice-versa (i.e., $dk_i^*/d\alpha_j > 0$). Analogously, we define two sources as *complements* if a decrease in one's investment cost leads to an increase in the other's investment level. We refer to the decrease in the investment cost as an investment subsidy. In practice, such a decrease is not necessarily limited to the subsidies provided by the government but can also represent a technological breakthrough that reduces the cost of investment. For example, a new technology has reduced investment cost for coal-fired power plants (Duke Energy 2015b), which can be considered as a decrease in α_I. We first present a preliminary result before identifying the interaction between energy sources (i.e., how a subsidy for one source affects investment in others).

Proposition 13. *For $i, j \in \{I, R, F\}$, (i) $\frac{dk_i^*}{d\alpha_i} \leqslant 0$, (ii) $\frac{dk_i^*}{d\alpha_j} = \frac{dk_j^*}{d\alpha_i}$.*

Proposition 13 part (i) shows that providing a subsidy for an energy source leads to a higher investment level in that source. Intuitively, the subsidy leads to a lower investment cost, in response, the utility firm increases its investment. Part (ii) shows that the cross effect of a subsidy is symmetric: the change in the investment level for source i in response to a change in the investment cost of source j is equivalent to that for source j in response to a change in the investment cost of source i. Next, we present our main result under the following assumption, which we impose in the remainder of the essay.

Assumption 3. *(i) In each period n, ϵ_n is independent of Θ_n. (ii) Demand distribution ϵ_n is strictly log-concave. (iii) Intermittency distribution Θ_n follows a Bernoulli distribution:*

$$\Theta_n = \begin{cases} 1 & \textit{with probability } q_n \\ 0 & \textit{with probability } 1 - q_n \end{cases} . \tag{3.9}$$

The first part of this assumption is consistent with the forecast errors presented in Figure 3.1. This is because the correlation coefficient of demand and intermittency forecast errors are -0.0219, indicating no linear dependence. The second part of the assumption requires $\log f_{\epsilon_n}(\cdot)$ to be a strictly concave function. Many well-known probability distributions including Normal, Logistic, Extreme Value, and Gamma (with the shape parameter greater than one), satisfy this condition (Bagnoli and Bergstrom 2005). Finally, since we consider N periods with each period corresponding to a five-minute interval, Assumption 3 part (iii) is not too restrictive. This assumption is also made in the literature for intermittency of renewables (c.f., Aflaki and Netessine 2015, Baranes et al. 2015, and Kök et al. 2015) as well as supply disruptions (c.f., Tomlin and Wang 2005, Tomlin 2006, and Yang et al. 2012). Moreover, this assumption can be relaxed, as we explain in Section 3.8, if the demand is assumed to be stationary. Below we present our main result.

Proposition 14. *(i) The inflexible and renewable sources are substitutes. (ii) The inflexible and flexible sources are substitutes. (iii) Suppose $q_n = q$ for all n and $g(\cdot) = \sum_{n=1}^{N} f_{\epsilon_n}(\cdot)$ is log-concave, then the renewable and flexible sources are complements.*

Proposition 14 (i) and (ii) indicate that a subsidy for the inflexible source leads to a lower investment level in the renewable and flexible sources. However, Proposition 14 (iii) shows that a subsidy for the flexible source leads to a higher investment in the renewable source under two sufficient conditions. First, the intermittency distribution needs to be stationary. Second, the sum of the density functions for demand over N periods is required to be log-concave. Notice that the sum of log-concave density functions is not necessarily log-concave. Although these two conditions are required for tractability, the case study presented in Section 3.7 reveals that our insights hold in the general case when real electricity demand and generation data is used.

The intuition behind Proposition 14 can be explained by considering a utility firm that forms a portfolio with its capacity investments. The inflexible source and the renewable source are almost *identical twins* in this portfolio, as both of these sources have low generation but high investment costs. Furthermore, these sources are uncontrollable because the renewable source is intermittent and the utility firm cannot increase the output of the inflexible source on demand. Hence, these two sources are substitutes. On the other hand, the renewable source and the flexible source possess opposite features: the flexible source has high generation and low investment cost, and its output can be ramped up or down quickly according to the demand. Thus, the flexible source complements the renewable source. Finally, the inflexible and the flexible sources are substitutes because the flexible source already complements the renewable source.

3.6 Effects of Other Policies

In this section, we first consider the effects of a decrease in the generation cost of inflexible and flexible sources. Such a decrease can be either due to a governmental subsidy policy or decreased input prices in commodity markets. For example, natural gas prices in the U.S. have fallen considerably in recent years due to the increase in the supply of shale gas (Puko 2015). This corresponds to a decrease in c_F in our model.

Proposition 15. *(i) A decrease in the generation cost of the inflexible source leads to a higher investment level in the inflexible source but a lower investment level in the renewable and flexible sources. (ii) A decrease in the generation cost of the flexible source leads to a lower investment level in the inflexible source but a higher investment level in the flexible source.*

Proposition 15 part (i) indicates that the effects of a generation subsidy and an investment subsidy for the inflexible energy source are equivalent. That is, in both cases, investment in the inflexible source increases, whereas investments in other sources decrease. Part (ii) shows that the effect of a generation subsidy for the flexible source on the inflexible source is also equivalent to that of an investment subsidy. Unfortunately, we are not able to analytically characterize the impact of a generation subsidy for the flexible source on the renewable energy investment. Nevertheless, we numerically observe that, similar to the investment subsidy for the flexible source, a generation subsidy for the flexible source also leads to a higher investment level in the renewable source. The intuition behind these findings remains to be the substitution and complementarity effects between these energy sources.

We next investigate the effects of the carbon tax policy, which, in various forms, has been adopted by many countries to reduce carbon emissions. Consider a carbon tax given as t, and let the emission intensity of a source be denoted as e_i for $i \in \{I, F\}$. The emission intensity of the renewable source is zero, i.e., $e_R = 0$ because it does not burn any fossil fuel to generate electricity. Under the carbon tax, the investment problem of the utility firm becomes:

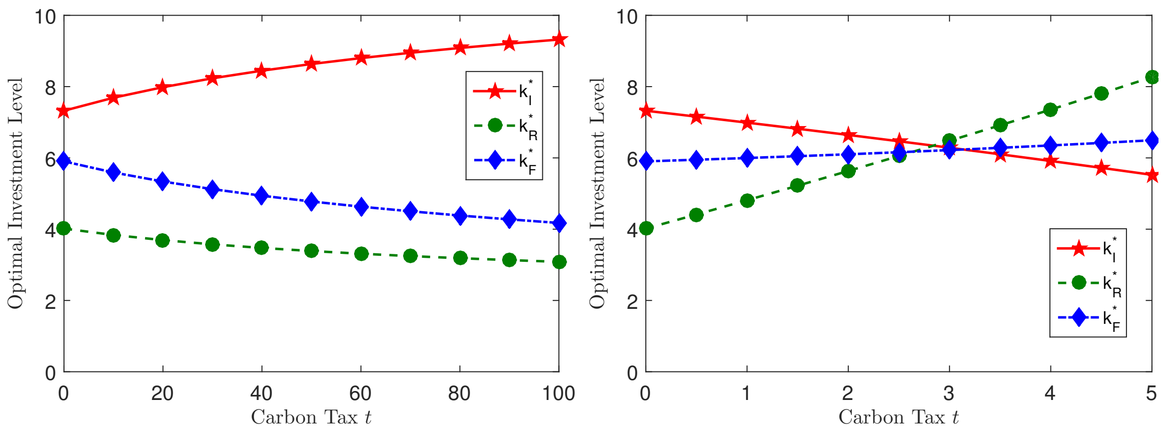
$$\min_{\boldsymbol{k} \in \mathbb{R}_+^3} \bar{\Pi}(\boldsymbol{k}) = (\alpha_I + (c_I + te_I)N)\, k_I + \alpha_F k_F + \alpha_R k_R + E\left[\sum_{n=1}^{N} C(\boldsymbol{k}, \epsilon_n, \Theta_n)\right], \tag{3.10}$$

where

$$C(\boldsymbol{k}, \xi, \theta) = \min_{0 \leqslant q_R \leqslant \theta k_R, 0 \leqslant q_F \leqslant k_F} (c_F + te_F)\, q_F + r\left(\xi - k_I - q_R - q_F\right)^+ . \tag{3.11}$$

Proposition 16. *Assume that $e_I = 0$, that is, the inflexible source is carbon-free such as nuclear energy. Then, a carbon tax leads to a higher investment level in the inflexible source and a lower investment level in the flexible source.*

Proposition 16 shows that in response to a carbon tax, a utility firm increases its investment in the inflexible source and decreases its investment in the flexible source, provided that the inflexible source is carbon-free (e.g., nuclear energy). This is because carbon tax increases the cost of generating electricity from the flexible source, whereas it does not affect the inflexible source. In this case, although we cannot analytically characterize the effect of the tax on the renewable investment, one can conjecture that the tax would lead to a lower investment in the renewable source due to the complementarity effect. We present a numerical study in Figure 3.4a that confirms this intuition by plotting optimal investment levels in response to the carbon tax when $e_I = 0$. In addition, we present another numerical study in Figure 3.4b assuming that the inflexible source is carbon-intensive such as coal power. In this case, both the inflexible and flexible source are taxed so the overall impact on the renewable source is not clear. As seen in Figure 3.4b, the carbon tax leads to a lower investment in the inflexible source, whereas investments in the flexible and renewable sources are higher.



(a) Nuclear energy ($e_F > e_I = 0$) (b) Coal power ($e_I > e_F$)

FIGURE 3.4: Effect of carbon tax on optimal investment levels

Notes. In Figure 3.4, we set $N = 1$, $e_F = 1.21$ and for coal $e_I = 2.07$ (EIA 2015b). Note that, compared to panel (a), we report a limited range of t levels in panel (b). This is because for high carbon tax levels, coal power becomes uneconomic and the utility firm does not invest in it.

We close this section by considering the effect of the penalty rate r, which corresponds to the cost when the utility firm is not able to satisfy the demand. One way to reduce such a cost is to introduce a real-time electricity spot market, such as the Energy Imbalance Market of SPP. Such markets enable utility firms to buy and sell electricity, effectively reducing the costs associated with demand and supply imbalance. We present the effect of r below. Recall that $g(\cdot) = \sum_{n=1}^{N} f_{\epsilon_n}(\cdot)$.

Proposition 17. *Suppose $q_n = q$ for all n and $g(\cdot)$ is log-concave. Then, a decrease in the penalty rate r, leads to (i) a decrease in the investment levels of the inflexible and the flexible sources, and (ii) an increase in the investment level of the renewable source.*

Proposition 17 shows that penalty rate r affects investment in the inflexible and flexible sources similarly: investment in both conventional sources decrease with a decrease in r. The effect is opposite for the renewable source: the utility firm increases its renewable investment if r decreases. This is because as r decreases demand and supply mismatch becomes less costly, enabling the utility firm to make more (risky) investment in the intermittent renewable source rather than the conventional sources. This result indicates that an electricity spot market can help a utility firm in dealing with intermittency. Motivated by this observation, we consider an extension of our model with an electricity spot market in Section 3.8.

3.7 Case Study: Texas Data

In this section, we validate our main insight by using real electricity generation and demand data from the state of Texas in 2010. In our analytical model, presented in (3.3)–(3.6), we implicitly assume that conventional sources are either fully flexible or inflexible. However, in practice, flexibility is defined in greater granularity through plant-level generation characteristics. For example, there are limits on how fast the output of a flexible source can be ramped up. In this case study, by considering these generation characteristics, we validate our conclusion that the renewable energy investment is higher if the capacity of flexible sources is also higher.

Table 3.2: Sample plant characteristics for Texas, 2010

Plant Name	Fuel Type	Startup Cost ($)	Minimum Output (MW)	Ramp Up Limit (%/min)	Minimum Down Time (hr)
South Texas Project	Nuclear	15,000	812	1	168
Morgan Creek	Natural Gas	1,203	122	10	0.5

Consider Table 3.2, where we report generation characteristics that determine operational flexibility for a representative nuclear and natural gas power plant in Texas (Cohen 2012). Here, startup cost, minimum output and minimum downtime are all greater for the nuclear power plant compared to the natural gas plant. Furthermore, a utility firm can increase the output of the natural gas plant by 10% of its capacity every minute, whereas nuclear can only be ramped at a rate of 1% of its capacity. In practice, a utility firm takes these salient features into account and determines the least costly way to satisfy electricity demand with its available set of generators. In doing so, the firm uses a so-called *unit commitment and dispatch model* (UCDM), a mixed integer program that minimizes the generation cost subject to electricity system constraints such as capacity limits, ramp up/down constraints and minimum up/down times. We use Cohen (2012)'s dispatch model that mimics the operations in Texas electricity system to quantify the value of renewable energy for a utility firm. Our objective is to determine whether or not the utility firm finds it optimal to make more renewable investment when its generation mix consists of more flexible generators.

Next, we describe the data required to run the UCDM. As an input, the UCDM uses the demand data and generation characteristics of available power plants. We use the observed 15-minute demand data from the state of Texas in 2010. For generation mix (available set of power plants), we combine the same three sources as in Kök et al. (2015). First, we use the rich dataset given in Cohen (2012) that reports various generation characteristics including those related to the operational flexibility of the 144 conventional power plants in Texas. We consider solar and wind energy as the two intermittent renewable sources. Wind energy output is also provided by Cohen (2012). For solar energy output, we rely on a simulation study, conducted by one of the authors while working at National Renewable Energy Laboratory using System Advisory Modeling tool based on solar radiation data of 79 weather stations in Texas. This is because solar capacity was actually negligible in Texas in 2010.

We now turn to our analysis. To determine the value of renewable energy in Texas, we consider two generation mixes. The first one is the *inflexible mix*, in which we double the capacity of nuclear power plants from its original level of approximately 5GW to 10GW, so that the total system capacity becomes approximately 92GW.

The second is the *flexible mix* in which we scale the nuclear capacity back to its original level and increase the capacity of natural gas by 5 GW so that the total capacity remains at 92GW. Under each of these generation mixes, the utility firm minimizes its generation and investment cost by determining its investment level in the renewable source:

$$\min_{k_R} \bar{\Pi}^j(k_R) = G^j(k_R) + \alpha_R(k_R), \tag{3.12}$$

where $G^j(k_R)$ corresponds to the output of the UCDM given renewable energy investment of k_R and generation mix j as either inflexible (denoted by "$j = I$") or flexible (denoted by "$j = F$"), finally $\alpha_R(k_R)$ is the investment cost. We note that we do not endogenize investments in the inflexible and flexible sources for tractability reasons. Nevertheless, we represent the effect of operational flexibility on optimal investments by considering two generation mixes with the same total capacity but different proportion of flexible and inflexible sources.

Given the above optimization problem for a utility firm, the benefit of making renewable energy investment for generation mix $j \in \{I, F\}$ can be defined as:

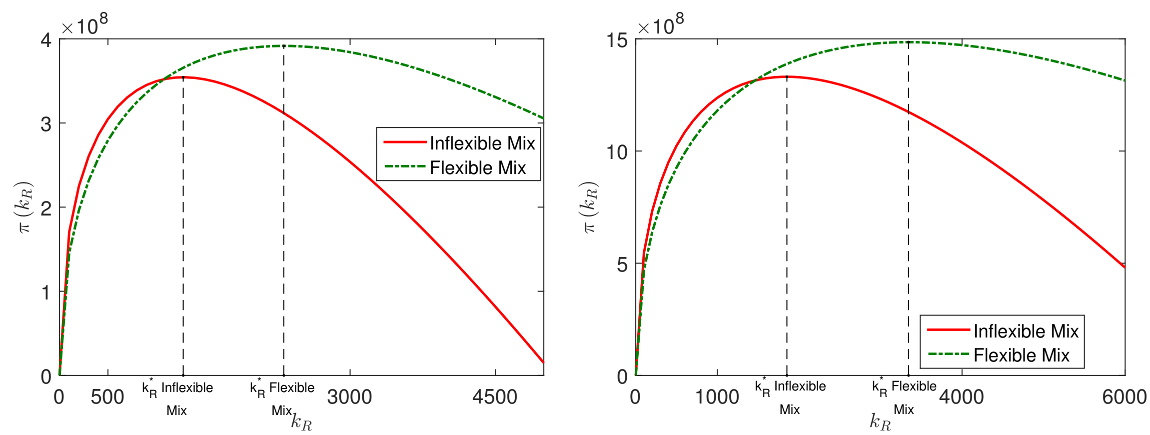
$$\pi^j(k_R) = \Pi^j(0) - \Pi^j(k_R) = \left[G^j(0) - G^j(k_R)\right] + [\alpha_R(0) - \alpha_R(k_R)]. \tag{3.13}$$

Here, the first bracket is positive as the generation cost becomes smaller after k_R MW of renewable investment is made. This is because renewable source can provide electricity at negligible cost. The second bracket represents the investment cost, which is negative. Thus, the utility firm finds its optimal investment level by maximizing its benefit, $\pi^j(k_R)$, for the generation mix $j \in \{I, F\}$.

To determine the optimal investment level, we next characterize the cost reduction in the UCDM, i.e., $[G^j(0) - G^j(k_R)]$. We solve the UCDM for each k_R level in $\{0, 5000, \ldots, 20000\}$ MW and fit the following function to the resulting cost reduction and investment level pairs:

$$\left[G^j(0) - G^j(k_R)\right] = a^j\sqrt{k_R} + b^j k_R, \quad j \in \{I, F\}. \tag{3.14}$$

We report estimated a^j and b^j values in Appendix B.3. We also plot the benefit function $\pi(k_R)$ for both generation mixes and renewable sources in Figure 3.5. As seen in



(a) Solar energy (b) Wind energy

Figure 3.5: Benefit function for inflexible and flexible generation mix

the figure, both solar and wind energy investment is higher when the generation mix is flexible. Table 3.3 presents the optimal investment levels by using these curves. First, note that the functional form in (3.14) provides a good fit indicated by very high adjusted R^2 values. Moreover, both solar and wind energy investments increase almost a thousand MW when the generation mix is flexible. As explained above, the difference of the flexible energy capacity between these two generaton mixes is about 5,000 MW. Thus, Table 3.3 indicates that for a five unit increase in the capacity of the flexible source, the renewable investment increases by more than a unit.

Table 3.3: Results of the case study

	Solar Energy		Wind Energy	
	k_R^*	Adjusted R^2	k_R^*	Adjusted R^2
Flexible Mix	2,316	0.99	3,344	0.99
Inflexible Mix	1,277	0.99	1,853	0.99

To sum, in this case study, we use a practical dispatch model to refine our definition of operational flexibility. We observe that our main insight still holds in this setting. That is, a utility firm increases its investment in the renewable source when its investment in the flexible source becomes higher.

3.8 Extensions

3.8.1 Spot Market

In our main model given in (3.3) to (3.6), we consider a vertically-integrated utility firm that does not participate in a spot market to buy or sell electricity. In practice, more than half of the U.S. utility firms use spot markets, such as the real-time Energy Imbalance Market in SPP (EIA 2011a). In this section, we consider the effect of a spot market on the capacity investments of a utility firm.

In an electricity market, a utility firm can procure electricity either from its own generation sources (self-schedule) or from other suppliers through bilateral contracts and spot markets (FERC 2015b, p. 62). The most common way for a utility firm to procure electricity is self-schedule. For example, in the biggest electricity market of the U.S. (PJM Interconnect), utility firms have generated more than 60% of their electricity from their own sources in 2014 (Monitoring Analytics 2015, p. 97). The remaining electricity can be purchased from a spot market in which the price varies stochastically during the day. Also, this market, such as the one in PJM, has a relatively thin volume so that the price might be affected by the amount of electricity traded. Considering these factors, we assume that the utility firm faces with the following price in the spot market:

$$p_S^n(\Gamma, q_S) = \Gamma + \frac{b_n}{2} q_S, \tag{3.15}$$

where Γ is a random variable representing price uncertainty, q_S is the amount of electricity bought by the utility firm, and $b_n > 0$ is the price responsiveness parameter in period n. We note that q_S is negative if the utility firm sells electricity in the market, which causes the market price to decrease. On the other hand, if the utility firm buys electricity from the market, q_S is positive, which causes the market price to increase. We note that our results hold for any positive b_n, that is, our results are robust to the magnitude of the impact of the utility firm on the market price. Similar models are considered for price formation in spot markets in the literature (c.f., Martínez-de-Albéniz and Simchi-Levi 2005).

In the presence of the spot market, we modify the second stage of the utility firm's problem as:

$$C_n\left(\boldsymbol{k}, \xi, \theta, \gamma\right) = \min_{q_R, q_F \geqslant 0, q_S \in \mathbb{R}} \quad c_F q_F + p_S^n\left(\gamma, q_S\right) q_S \tag{3.16}$$

$$\text{subject to} \quad q_R \leqslant \theta k_R \tag{3.17}$$

$$q_F \leqslant k_F \tag{3.18}$$

$$q_S = \xi - k_I - q_R - q_F. \tag{3.19}$$

Following Lemma 10 that it is optimal for the utility firm to dispatch the entire inflexible capacity at every period, the utility firm minimizes its generation and market transaction cost based on the dispatch levels of the renewable and flexible sources as well as the quantity traded in the spot market (q_S). In this stage, the utility firm observes the forecast of Γ as γ. Furthermore, q_S is defined in (3.19) as the difference between demand level and dispatched electricity from the utility firm's own investments. Recall that q_S is negative if the firm sells electricity in the market. In this case, the second term in (3.16) i.e., $p_S^n\left(\gamma, q_S\right) q_S$, is also negative, indicating a decrease in the cost for the utility firm. On the other hand, if q_S is positive, the utility firm buys electricity from the market, and the second term in (3.16) is positive, indicating an increase in the cost for the utility firm. With this per period cost, the first stage problem can be casted as:

$$\min_{\boldsymbol{k}\in\mathbb{R}^3_+} \bar{\Pi}\left(\boldsymbol{k}\right) = E\left[\sum_{n=1}^{N} C_n\left(\boldsymbol{k}, \epsilon_n, \Theta_n, \Gamma_n\right)\right] + \left(\alpha_I + c_I N\right) k_I + \alpha_F k_F + \alpha_R k_R. \quad (3.20)$$

We next derive the optimal dispatch policy. In this case, in addition to supply and demand uncertainities, we also consider a spot price uncertainty, which complicates our analysis considerably.

Lemma 18. *Consider the dispatch problem given in* (3.16)–(3.19)*. (i) The optimal dispatch policy is to set* $q_R^*\left(\boldsymbol{k}, \xi, \theta, \gamma\right) = \min\left(\theta k_R, \xi - k_I + \frac{\gamma}{b_n}\right)^+$ *and* $q_F^*\left(\boldsymbol{k}, \xi, \theta, \gamma\right) = \min\left(k_F, \xi - k_I - \theta k_R + \frac{\gamma - c_F}{b_n}\right)^+$*. (ii) The first stage problem given in* (3.20) *is convex in* $\boldsymbol{k}$*.*

Lemma 18 is the extension of Lemma 11 in the spot market setting. In this case, in addition to the demand and intermittency forecasts, the optimal dispatch levels also depend on the market price forecast. If the forecast of the market price is too low (γ is small), neither the renewable nor the flexible source is dispatched. That is, unlike the main model, the utility firm might find it optimal not to use all the renewable energy capacity in all periods. As the market price gets higher, the renewable source, followed by the flexible source is dispatched. We also note that the dispatch level of the inflexible source is equal to its capacity as in the main model.[3]

[3] Based on this optimal dispatch policy, optimal investment levels can be characterized similar to the multi-dimensional newsvendor solution in the main model. In addition, cross effects of subsidies are equivalent, i.e., $\frac{dk_i^*}{d\alpha_j} = \frac{dk_j^*}{d\alpha_i}, \forall i, j \in \{I, R, F\}$. Details of these proofs are available from the authors.

Next, we present our main result that identifies the interaction between energy sources in the spot market setting. We continue to consider the interior solution case (i.e., $\boldsymbol{k}^* > 0$) and impose Assumption 3 with a slight generalization in the first part. That is, we now consider that the three uncertainty sources (ϵ_n, Θ_n, Γ_n) are independent of each other. In addition, to identify the relationship between the renewable and flexible sources we require the following assumption.

Assumption 4. *(i) The utility firm dispatches all of its available renewable energy in each period, i.e., $q_R^* = \Theta k_R$. (ii) Demand distribution ϵ_n is bounded above by D_n. (iii) Market price uncertainty Γ_n follows a uniform distribution between L_n and U_n such that $L_n \leqslant -b_n D_n$.*

Part (i) of Assumption 4 ignores the possibility that the spot market price is too low so that the utility firm does not use (i.e., curtails) its renewable source. This is a good approximation of the practice because curtailment as a fraction of wind capacity is less than 4% in the U.S. in 2014 (Bird et al. 2014). Second part of the assumption bounds the demand distribution from above. This is also not very restrictive because such a distribution can be closely approximated by an unbounded random variable (e.g. Normal) as long as D_n is large enough compared to the variance (Petruzzi and Dada 1999). The last part of the assumption suggests that the market price follows a nonstationary uniform distribution and it can be negative. Note that negative prices are observed frequently in practice (c.f. Zhou et al. 2014a).

Proposition 19. *(i) The inflexible and renewable sources are substitutes. (ii) The inflexible and flexible sources are substitutes. (iii) Suppose Assumption 4 holds and Θ_n follows a stationary Bernoulli distribution, then the renewable and flexible sources are complements.*

Proposition 19 shows that our main insight also holds when a spot market is considered. That is, the relationship between a renewable and a conventional source is determined by the level of operational flexibility that the conventional source has. If the conventional source is inflexible it substitutes the renewable source, otherwise, it complements the renewable source.

3.8.2 Dual Sourcing

Throughout the essay, we assume that the triple sourcing strategy is optimal, i.e., $\boldsymbol{k}^* > 0$. In some cost parameters, a dual sourcing strategy may be optimal (e.g., $k_I^*, k_R^* > 0$ and $k_F^* = 0$). In any dual sourcing case, the two sources included in the optimal portfolio are substitutes. The details of the proof is available from the authors. We note that this conclusion is the same as that of the dual sourcing literature (c.f., Sting and Huchzermeier 2012).

3.8.3 General Intermittency Distribution

In Assumption 3, we impose a two-point intermittency distribution which helps us obtain analytical insights when the demand is nonstationary. If the demand is assumed stationary, i.e., $\epsilon_n = \epsilon$ for all n and ϵ has a log-concave density, our main results hold for a general intermittency distribution. In particular, Proposition 14 parts (i) - (iii) and Proposition 17 part (i) hold in this case. We show these generalizations in the proofs of the related propositions.

3.8.4 Energy Efficiency and Demand Response

Our model considers capacity investment in energy sources, which is related to managing the supply side of energy systems. Some of the incentives that reduce the demand, such as Energy Efficiency (EE) and Demand Response (DR), can be incorporated into the current model. Specifically, EE refers to the incentives that a utility firm provide to its customers so that the customers reduce their total electricity demand by using more efficient devices. For example, Duke Energy, through its Appliance Recycling Program, offers a rebate to those who want to replace their old refrigerators with more efficient ones (Duke Energy 2015a). DR aims to reduce the demand only during peak demand periods. For instance, MidWest Energy compensates farmers that curtail usage of water pumps upon a service call during high demand hours (Midwest Energy 2015).

From the perspective of a utility firm, EE is equivalent to the inflexible source and DR is equivalent to the flexible source. Specifically, the rebate paid to the customers under EE corresponds to the investment cost of the inflexible source and the curtailment payments made under the DR correspond to the generation cost of the flexible source. Furthermore, EE is used to reduce the baseload demand similar to nuclear energy, whereas DR is used to reduce demand at high demand periods similar to the natural gas. In terms of cost structures, the rebates given under EE are very costly similar to the high investment cost of the inflexible source. In contrast, DR involves a low initial cost but high curtailment payments similar to the high generation cost of the flexible source. Finally, similar to the flexible source, DR contracts are capable of curtailing demand within seconds because they involve automated response (DOE 2011). Thus, our model indicates that EE and renewable energy investment are substitutes, whereas DR and renewable investment are complements.

3.9 Conclusion

In this essay, we consider capacity investments of a utility firm in renewable and conventional energy sources with different levels of operational flexibility. We characterize the optimal investment levels and determine the role of operational flexibility in identifying the interaction (i.e., complement versus substitute) between energy sources. Specifically, a renewable and conventional source are substitutes (complements, respectively) if the conventional source is inflexible (flexible, respectively). We validate this result by using real electricity generation and demand data from Texas.

This essay has significant policy implications and it can provide guidelines for designing policies to promote renewables. First, we show that, from the perspective of a utility firm, the intermittency problem can be best alleviated by flexible energy sources, such as natural gas-fired power plants. Thus, to promote renewables, policymakers should keep natural gas prices low, for example, by investing in pipeline infrastructure and issuing more permits for drilling. Second, policymakers should refrain from providing a subsidy for an inflexible source (e.g., nuclear or coal power) because this subsidy leads to lower investment in renewables. Third, a carbon tax is only effective in increasing renewable investment if the inflexible source is carbon-intensive (e.g., coal power), otherwise, the tax actually leads the utility firm to decrease its investment in renewables. Finally, policymakers should introduce electricity spot markets that enable utility firms to procure electricity at low cost when their own capacity is not sufficient to meet the demand due to intermittency. Such markets can reduce the adverse effects of intermittency from the utility firm's perspective, thereby promoting investment in renewables.

4

Utility Death Spiral

4.1 Introduction

Capacity investment in rooftop solar panels has rapidly increased in recent years: as of 2016, there are more than 1 million rooftop solar panels in the U.S., up from 20,000 a decade earlier (UCS 2014, SEIA 2016b). The rapid increase in this new technology is attributed to the decreasing installation costs (Sweet 2016), diffusion of awareness about the panels (Bollinger and Gillingham 2012), and the governmental subsidy policies (Wang 2013). In particular, the net metering policy requires a utility firm to purchase the electricity produced by the panels at retail electricity price, effectively reducing the electricity demand of solar owners. According to The Wall Street Journal (Denning 2013), the increased investment in solar panels might lead to a "death spiral" for utility firms. As more customers adopt solar panels and produce their own electricity, the total demand of the utility firm decreases. The decrease in demand results in a higher electricity price as the fixed costs of grid maintenance is shared over less demand. Finally, higher electricity prices incentivize more customers to adopt solar panels in a vicious circle, i.e., the "utility death spiral." This phenomenon results in higher electricity prices and threatens the reliability of the grid by undermining utility firms. Hence, the policymakers and utility firms are actively seeking solutions to this "disruptive challenge" (EEI 2013): 97% of the utility executives, according to a recent survey (Utility Dive 2016), think that the regulations should change for their firms under pressure from new technologies, such as solar panels.

In this essay, we analyze the adoption process of rooftop solar panels from the perspective of a utility firm. Our main objective is to identify the conditions under which the utility death spiral effect may occur. We first focus on the commonly used rate-of-return regulation under which the electricity price is set so that the utility earns a prespecified return (e.g., 10%) over its fixed and variable costs (Cai et al. 2013). We explore the following research questions: Is the rate-of-return regulation susceptible to the utility death spiral effect? If so, can the death spiral be avoided by changing the rate-of-return regulation and allowing the utility firm to maximize its profit by setting the electricity price subject to a price cap? Finally, how do the characteristics of the adoption process, such as the parameters of adoption, affect the final adoption level?

We model the adoption process of solar panels as the diffusion of a new technology, similar to the classical Bass model. Specifically, in each period over an investment horizon, a portion of potential adopters install rooftop solar panels. The rate of diffusion is linear in the number of adopters as in the Bass model. The number of potential adopters depends on the current price of electricity: as the electricity price increases, more customers are inclined to install solar panels. Using this diffusion model, we compare the resulting electricity prices and adoption levels in two regulation frameworks. First, under the rate-of-return regulation, the electricity price is exogenously set so that the utility firm earns a specific profit over its variable and fixed costs. Second, we consider the case in which the utility firm maximizes its profit in a dynamic program. In this case, the state variable is the adoption level and the utility firm determines the electricity price subject to a price cap.

Our findings indicate that the rate-of-return regulation is prone to a death spiral for a utility firm. This is mainly because of the net metering policy as the utility firm is obligated to buy back the electricity produced from the solar panels at the same price that it sells electricity to its customers. That is, by using net metering, solar customers can reduce the total demand, which leads to an increase in the regulated price. Consequently, more customers adopt solar panels in line with the death spiral scenario.

One way to tackle the death spiral observed in the rate-of-return regulation is to allow a utility firm to maximize its profit by determining the electricity price subject to a price cap. On the one hand, the firm prefers to charge a high electricity price to earn a higher revenue, whereas, on the other hand, the firm prefers to keep the price low so that less customers adopt solar panels and produce their own electricity. Due to this tradeoff, we observe that the utility firm does not increase the price beyond a certain value. By doing so, the utility firm intuitively limits the number of solar panel adopters and maintains a large enough customer base. This result is due to the fact that the number of potential solar adopters is increasing in the price of electricity. Therefore, our results indicate that the death spiral can be eliminated by allowing a utility firm to determine the electricity price so as to maximize its profit.

We finally investigate the impact of the parameters of the diffusion process on the adoption dynamics. We particularly focus on the case in which the utility firm optimizes its profit. In this case, interestingly, we observe that greater diffusion parameters (implying faster diffusion speed all else being equal), might not lead to a higher final adoption level at the end of the problem horizon. This is because as the adoption speed increases, the utility firm acts proactively and keeps the price level low so that a lower level of adoption occurs.

The rest of the essay is organized as follows. Section 4.2 reviews the related literature on new product diffusion. Section 4.3 presents our model and Section 4.4 includes our findings. Section 4.5 concludes.

4.2 Literature Review

We study the diffusion process of a new product (solar panels) based on an extension of the cannonical Bass diffusion model (Bass 1969). In this model, the demand rate $d(t)$, i.e., the derivative of the total demand $D(t)$ with respect to time t, is given as:

$$d(t) = [M - D(t)]\,[a + bD(t)]\,. \tag{4.1}$$

Here, M is the market size; a and b are the diffusion parameters. The classical Bass model does not consider the impact of the marketing mix, e.g., pricing, promotion, and advertising, on the diffusion process. Several papers have extended the Bass model by incorporating these effects. For example, Robinson and Lakhani (1975) incorporate price as a multiplicative factor by letting $d(t) = [M - D(t)]\,[a + bD(t)]\,e^{-kP(t)}$, where k is a constant and $P(t)$ is the price level at time t. Another way to incorporate price is to let the potential market size depend on the current price level. For example, Feichtinger (1982) and Kalish (1985) assume that the market size depends on the price so that $d(t) = [M(P) - D(t)]\,[a + bD(t)]\,$. We also use this formulation because it better fits into our context: as the electricity price increases, more customers (with higher investment costs) consider installing rooftop solar panels, effectively increasing the market size.

In addition to pricing, capacity constraints have been incorporated into the classical Bass model. For instance, Shen et al. (2013) characterize the optimal capacity, pricing, and production decisions for a firm that introduces a new product under a capacity constraint. For various other extensions of the Bass model, see Mahajan et al. (1990). We also note that the Bass diffusion model has been used in explaining the diffusion of solar panels. For example, by using solar panel adoption data from California, Bollinger and Gillingham (2012) empirically investigate the social interaction effects in the adoption of solar panels. Specifically, they leverage the difference between the requested installation date and the actual installation date (after which peer effects appear) to identify the magnitude of peer effects. They show that an additional installation increases the probability of an adoption by 0.78 percentage points in a zip code.

The main difference between our setting and the above mentioned papers is as follows. In most product diffusion papers, a firm sets the price of a product so as to maximize its profit from the sales of that product. In our setting, the utility firm neither sets the price of solar panels nor collects revenue from these sales. Instead, the firm sets the price of electricity and it loses revenue from the diffusion of solar panels. In other words, the utility firm does not benefit from the adoption of solar panels by its customers.

4.3 Model

We model the diffusion process of rooftop solar panels from the perspective of a utility firm. We consider two regulation frameworks. First, under the rate-of-return regulation, the electricity price is exogenously set so that the utility firm earns a certain level of profit over its costs. Second, we let the utility firm to determine the electricity price subject to a price cap so as to maximize its profit. Under both regulation frameworks, solar panels diffuse according to the same diffusion process. Specifically, the customers adopt solar panels in accordance with the net metering policy. That is, the adopters of the solar panels can sell their excess generation back to the utility firm and earn the retail price per unit of electricity sold. For simplicity, we assume that each customer has one unit of demand. We further assume that the panels produce one unit of electricity, effectively canceling the utility bill of a customer once the customer adopts the panels. Below, we first describe the problem parameters commonly used in both regulation frameworks, followed by the price formation under each framework.

Formally, the firm has M customers and the price of electricity is p_t in period (e.g., a year) t. The problem horizon consists of T periods. Let N_t be the number of adopters of the rooftop solar panels in the beginning of period t. We explain the evolution of N_t in Section 4.3.1 below. Since each customer is assumed to have one unit of demand, the utility firm faces a total demand of $M - N_t$ during period t. Hence, the revenue of the utility firm is $p_t[M - N_t]$. The cost of the utility firm is given as $c(M-N_t)$ and it consists of a linear and a fixed component, i.e., $c(M-N_t) = C[M - N_t] + F$. The linear term represents the generation cost and the fixed term represents the fixed costs of grid maintenance.

Under the commonly used rate-of-return regulation, the price of electricity is exogenous set so that the utility firm earns a prespecified return α (e.g., 10%) over its fixed and variable costs (Cai et al. 2013). That is, the revenue of the utility firm is $(1+\alpha)$ times its total costs, i.e., $p_t[M-N_t] = (1+\alpha)c(M-N_t)$. Hence,

$$p_t = (1+\alpha)\left[\frac{F}{M-N_t} + C\right]. \qquad (4.2)$$

Under the profit maximization framework, the utility firm determines the price of electricity p_t so as to maximize its profit. In this case, the dynamic optimization problem of the utility firm can be casted as:

$$V_t\left(N_t\right) = \max_{p_t \leqslant p_{\max}} \left\{p_t\left[M-N_t\right] - c\left(M-N_t\right) + \gamma V_{t+1}\left(N_{t+1}\right)\right\} \quad 1 \leqslant t \leqslant T, \qquad (4.3)$$

where $V_{T+1}(\cdot) = 0$. Here, the price level is constrained by the maximum price $p_{\max}$, which is set by a regulator. Finally, γ is the discount factor.

4.3.1 Diffusion Process

We next explain the evolution of the state variable N_t, i.e., the diffusion level of solar panels. This diffusion process is common in both the rate-of-return and profit maximization cases. We consider the following state transition:

$$N_{t+1} = N_t + \left(a + bN_t\right)\left(m\left(p_t\right) - N_t\right)^{+} \quad 1 \leqslant t \leqslant T-1, \qquad (4.4)$$

where N_1 is the initial adoption level. This diffusion dynamic is based on the discrete version of the classical Bass diffusion model and it is also used by Feichtinger (1982) and Kalish (1985). Here, $m(p_t)$ represents the number of potential adopters in period t as a function of the current price of electricity p_t. Furthermore, $(m(p_t) - N_t)^+$ is the number of remaining potential adopters, if any, when price is p_t. Out of these customers a certain fraction decides to adopt at every period. The adoption rate, as in the classical Bass model, is a linear function of the current adoption level and given as $a + bN_t$.

The characterization of the $m(p_t)$ function is the main difference between our diffusion model and the diffusion models of Feichtinger (1982) and Kalish (1985) that also use (4.4). Similar to the majority of the marketing literature, in Feichtinger (1982) and Kalish (1985), a firm prices a product and collects revenue through sales, i.e., through diffusion into the market. However, in our case, the utility firm does not determine the price of solar panels and, moreover, the firm loses revenue from the diffusion of the panels. Due to this difference, our assumptions on the $m(p_t)$ function is the opposite of those of the Feichtinger (1982) and Kalish (1985). Specifically, we first assume that the potential market size for solar panels increases as the price of electricity increases, i.e., $m^{'}(p_t) > 0$. This is because as the electricity price goes up, more customers (with higher investment costs) will be inclined to invest in solar panels so that they can cancel out their utility bills. Second, we assume that the $m(p_t)$

function is convex, i.e., the rate of the increase in the market size increases with the price. Finally, we assume that if the utility firm sets the maximum price, the entire population becomes eligible for installing rooftop solar panels, i.e., $m(p_{\max}) = M$. Below, we summarize these assumptions.

Assumption 5. *$m'(p_t) > 0, m''(p_t) > 0,$ and $m(p_{\max}) = M$.*

In the subsequent analysis, to obtain numerical results, we use the following functional form

$$m(p_t) = M \frac{p_t^2}{p_{\max}^2}. \tag{4.5}$$

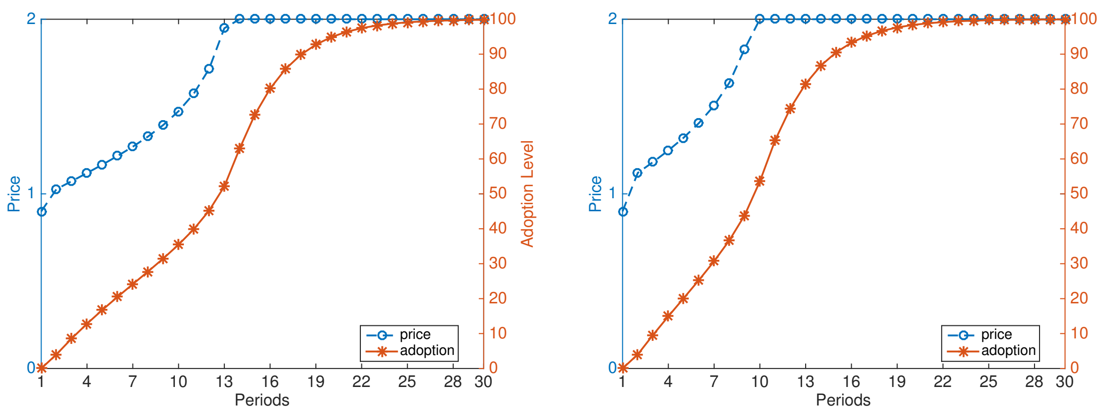
This function satisfies all conditions given in Assumption 5.

4.4 Numerical Observations

In this section, we describe the insights generated from our model. These insights are based on numerical examples, where problem parameters are chosen to represent a typical utility firm. Specifically, we assume a population of 100 customers with no initial adoption, i.e., $M = 100$ and $N_1 = 0$. Further, to represent a typical utility firm with high fixed cost and low variable cost, we set $F = 80$ and $C = 0.1$. The price cap is given as $p_{\max} = 2$, and the adoption parameters are set as 0.2 and 0.001 for a and b, respectively. We finally consider a 30 year investment horizon and 5% discount factor so that $T = 30$ and $\gamma = 0.95$.

4.4.1 Rate-of-Return Regulation

In most parts of the U.S., utility firms are regulated and the electricity price is set by a regulator so that the utility firm covers its expenses and earns a prespecified return. Under this form of regulation, we investigate whether or not the utility death spiral is likely to occur.



(a) $\alpha = 10\%$ (b) $\alpha = 20\%$

FIGURE 4.1: Rate-of-return regulation

In Figure 4.1, we plot the evolution of price and adoption levels on the left and right vertical axis, respectively, in each panel.[1] Specifically, we consider 10% rate-of-return in panel (a) and 20% rate-of-return in panel (b). We obtain two important insights from this figure. First, we observe that, in both cases, the price increases as the adoption level goes up. This is because, as more customers install rooftop solar panels, the fixed cost of the utility firm is shared among fewer customers. As a result, the electricity price increases and more customers are incentivized to install

[1] We restrict p_t to be less than $p_{\max}$ so that the cumulative adoption never exceeds M.

rooftop solar panels. Thus, rate-of-return regulation is prone to the utility death spiral. Our second finding from Figure 4.1 is that, compared to panel (a), in panel (b) the death spiral occurs faster. This is because as the rate-of-return increases, the aforementioned price increase occurs faster as well. We summarize these two findings below.

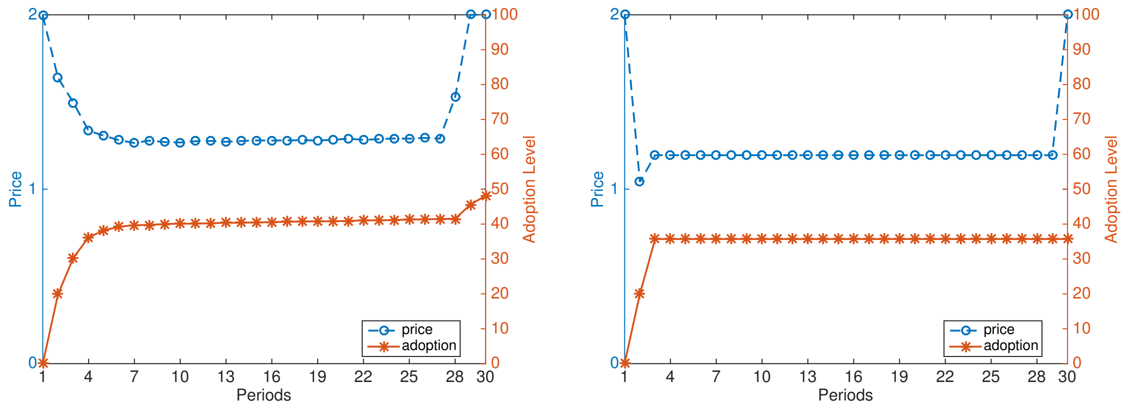
Observation 1. *(i) The rate-of-return regulation is prone to the utility death spiral. (ii) Furthermore, as the allowed rate of return increases, death spiral occurs more rapidly.*

4.4.2 Profit Maximization

We next investigate whether or not the utility death spiral occurs if the utility firm is allowed to maximize its profit. In particular, we solve the dynamic program described in (4.3)–(4.4) and plot the price and adoption levels in Figure 4.2. Observation 2 summarizes our findings.

Observation 2. *(i) If the utility firm is allowed to maximize its profit by solving* (4.3)–(4.4)*, the utility death spiral can be avoided. (ii) Furthermore, as the parameters of the diffusion process (a and b) increase, final adoption level might decrease.*

According to Observation 2 (i), by allowing the utility firm to maximize its profit, the death spiral can be avoided. This can be seen from both of the panels in Figure 4.2, where we plot the adoption and price levels for the base case and fast diffusion



(a) Base case: $a = 0.2$ and $b = 0.001$ (b) Fast diffusion: $a = 0.3$ and $b = 0.1$

FIGURE 4.2: Profit maximization

case. This result can be best explained by considering the optimal price path: First, the utility firm keeps the price high in order to collect high revenues. Then, after a certain level of adoption takes place, in order to limit the adoption level, the firm lowers the price. By doing so, the firm ensures that not many customers will adopt solar panels. Finally, at the end of the horizon, the firm increases prices again to gain high revenues as the problem horizon ends. This finding suggests that one way to avoid the death spiral is to allow the utility firm to maximize its profit.

Observation 2 (ii) compares the final adoption level in panels (a) and (b) in Figure 4.2. Specifically, despite the higher a and b parameters of the diffusion process, the diffusion level at the end of the horizon is lower in panel (b). This is a surprising result because, all else being equal, one would expect a higher final adoption level if the diffusion process is faster. The intuition behind this result is that the utility firm keeps the price lower in panel (b) in order to avoid a very rapid diffusion. As a result, the final diffusion level is lower in panel (b).

4.5 Conclusion and Future Research

In this essay, we study the utility death spiral which is characterized by increasing electricity prices due to higher investment in rooftop solar panels. We model the diffusion process of solar panels from the perspective of a utility firm. We observe that the current rate-of-return regulation may cause the death spiral. Furthermore, the death spiral can be reversed by allowing the utility firm to maximize its profit by setting the electricity price.

The above findings are based on numerical studies. As a future research direction, we aim to provide analytical results for these findings. In particular, we will first show that $V_t(N_t)$ function is concave and we will characterize the optimal price path p_t by demonstrating that it is unimodal. Furthermore, by using the dynamic programming formulation given in (4.3)–(4.4), we will test the effectiviness of other governmental policies aimed at reversing the death spiral. One promising direction is to consider a refined version of the net metering policy where the customers of the rooftop solar panels are paid a different price than the retail price for their electricity production. In essence, this price is the decision variable of a regulator that maximizes social welfare.

Another promising research direction is to use real data on the diffusion of solar panels to corroborate our findings. We will use the solar panel adoption data of the California Solar Initiative (CSI). This rich dataset contains detailed information regarding the installation of solar panels for over 600,000 households. Specifically, for each installation, the data includes the date and the zip code, quantity and brand of the solar panels, and the utility firm serving the customer. We will combine CSI data with the electricity prices of the utility firms from the Utility Rate Database (`http://en.openei.org/wiki/Utility_Rate_Database`). Our aim is to investigate whether or not the predictions of our model would be consistent with the real data as in Sections 2.6 and 3.7.

Appendix A

Appendices for Chapter 2

A.1 Proofs

In the following proofs, we suppress the arguments of the demand function for brevity whenever no confusion arises, i.e., we let $D_i^j = D_i^j(p_i, p_{-i})$ for $i \in \{n, d\}$ and $j \in \{\text{flat}, \text{peak}\}$. Also, to simplify notation, we drop the asterisk sign (*), e.g., we denote the optimal nighttime price under flat pricing as p_n^{flat} instead of $p_n^{\text{flat}*}$.

Proof of Lemma 1. Under the two point distribution assumption for $\tilde{q}_i$, (2.4) can be written as:

$$\max_{k_r, k_c, p_n, p_d} \Pi(k_r, k_c, p_n, p_d) = \sum_{i \in \{n,d\}} \Big[p_i D_i - (1 - q_i)\left(g\left((D_i - k_c)^+\right) + v \min(k_c, D_i)\right)$$
$$-q_i\left(g\left((D_i - k_r - k_c)^+\right) + v \min\left((k_c, D_i - k_r)^+\right)\right)\Big]$$
$$- \beta_c k_c - \beta_r k_r.$$

The hessian of this function is negative definite so that the First Order Conditions (FOCs) are sufficient. We first show that under Assumption 1, $k_r + k_c$ is always less than D_n. Suppose otherwise that $k_r + k_c \geqslant D_n$. There are two cases: first, assume that $k_r + k_c > D_d$. Then, the FOC with respect to (wrt) k_r is $\mathcal{F}(k_r, k_c, p_n, p_d) = q_n v 1_{k_r \leqslant D_n} + q_d v 1_{k_r \leqslant D_d} - \beta_r$, where 1. is the indicator function. By Assumption 1, $\beta_r \geqslant v(q_n + q_d)$, so this case cannot appear in the optimal solution. Second, assume that $k_r + k_c \leqslant D_d$. Then, the FOC wrt k_r is $\mathcal{F}(k_r, k_c, p_n, p_d) = q_n v 1_{k_r \leqslant D_n} + q_d g^{'}(D_d - k_c - k_r) - \beta_r$. Note that this function can at most be $q_n v + q_d g^{'}(a_d - a_n) - \beta_r \leqslant 0$ as $D_d - D_n = a_d - a_n - (\gamma + \delta)(p_d - p_n)$. By Assumption 1, this case cannot appear in the optimal solution either. Thus, at optimality, $k_r + k_c \leqslant D_n$. Next, consider the FOCs wrt k_c, p_n, and p_d given sequentially by $\mathcal{G}(k_r, k_c, p_n, p_d)$, $\mathcal{H}(k_r, k_c, p_n, p_d)$, and $\mathcal{I}(k_r, k_c, p_n, p_d)$:

$$\begin{aligned}
\mathcal{G}(k_r, k_c, p_n, p_d) &= (1 - q_n) g^{'}(D_n - k_c) + (1 - q_d) g^{'}(D_d - k_c) \\
&\quad + q_n g^{'}(D_n - k_c - k_r) + q_d g^{'}(D_d - k_c - k_r) - 2v - \beta_c \\
\mathcal{H}(k_r, k_c, p_n, p_d) &= a_n - 2\gamma p_n + 2\delta p_d + \gamma \Big((1 - q_n) g^{'}(D_n - k_c) + q_n g^{'}(D_n - k_c - k_r)\Big) \\
&\quad - \delta \Big((1 - q_d) g^{'}(D_d - k_c) + q_d g^{'}(D_d - k_c - k_r)\Big) \\
\mathcal{I}(k_r, k_c, p_n, p_d) &= a_d - 2\gamma p_d + 2\delta p_n - \delta \Big((1 - q_n) g^{'}(D_n - k_c) + q_n g^{'}(D_n - k_c - k_r)\Big) \\
&\quad + \gamma \Big((1 - q_d) g^{'}(D_d - k_c) + q_d g^{'}(D_d - k_c - k_r)\Big)
\end{aligned}$$

At optimality, $\mathcal{H}(k_r^*, k_c^*, p_n^*, p_d^*) + \mathcal{I}(k_r^*, k_c^*, p_n^*, p_d^*) = 0$ and incorporating the fact that $\mathcal{G}(k_r^*, k_c^*, p_n^*, p_d^*) = 0$, we observe that (2.5) holds true. This result implies that the sum of the nighttime and daytime demand is equal under both pricing policies as $D_n + D_d = a_n + a_d - (\gamma - \delta)(p_n + p_d)$.

Finally, we show that under Assumption 1 part (ii), $p_d^* \geqslant p_n^*$ and $p_d^* - p_n^* \leqslant \frac{a_d - a_n}{\gamma+\delta}$ under any pricing policy so that $D_d(p_d^*, p_n^*) - D_n(p_n^*, p_d^*) = a_d - a_n - (\gamma+\delta)(p_d^* - p_n^*) \geqslant 0$. This is because $a_d - a_n - (\gamma + \delta)(2(p_d^* - p_n^*) + 2v + \beta_c) \leqslant \mathcal{I}(k_r^*, k_c^*, p_n^*, p_d^*) - \mathcal{H}(k_r^*, k_c^*, p_n^*, p_d^*) = 0 \leqslant a_d - a_n - (\gamma + \delta)(2(p_d^* - p_n^*) - 2v - \beta_c)$, where we use that $\mathcal{G}(k_r^*, k_c^*, p_n^*, p_d^*) = 0$. Thus, under Assumption 1 part (ii), $0 \leqslant p_d^* - p_n^* \leqslant \frac{a_d - a_n + (\gamma+\delta)(2v+\beta_c)}{2(\gamma+\delta)}$, which is further lower than $\frac{a_d - a_n}{\gamma+\delta}$. This ensures that $D_d(p_d^*, p_n^*) \geqslant D_n(p_n^*, p_d^*)$. □

Proof of Proposition 2. (i) First, note that the FOC wrt k_r is given as $\mathcal{F}(k_r, k_c, p_n, p_d) = q_n g'(D_n - k_r - k_c) + q_d g'(D_d - k_r - k_c) - \beta_r$. Considering the FOCs wrt k_r and wrt k_c given above, we observe that at optimality $(1 - q_n) g'(D_n - k_c) + (1 - q_d) g'(D_d - k_c) = 2v + \beta_c - \beta_r$. Thus, considering this identity under flat and peak pricing, we can show that

$$\frac{1-q_n}{1-q_d} = \frac{g'\left(D_d^{\text{flat}} - k_c^{\text{flat}}\right) - g'\left(D_d^{\text{peak}} - k_c^{\text{peak}}\right)}{g'\left(D_n^{\text{peak}} - k_c^{\text{peak}}\right) - g'\left(D_n^{\text{flat}} - k_c^{\text{flat}}\right)}$$

$$= \frac{\left(\tilde{D} - \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_d^{\text{flat}} - \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}}\right) + C_2\right)}{\left(\tilde{D} + \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_n^{\text{flat}} + \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}}\right) + C_2\right)} = R_c, \tag{A.1}$$

where D_i^j is the demand corresponding to the optimal prices in period $i \in \{n, d\}$

under pricing policy $j \in \{\text{flat}, \text{peak}\}$ and $\tilde{D}$ is the difference between optimal demand levels under flat and peak pricing in a period. Considering the FOC wrt k_r, we similarly observe that

$$\frac{q_n}{q_d} = \frac{\left(\tilde{D} - \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right) - \left(k_r^{\text{flat}} - k_r^{\text{peak}}\right)\right)\left(C_1\left(2D_d^{\text{flat}} - \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}} - k_r^{\text{flat}} - k_r^{\text{peak}}\right) + C_2\right)}{\left(\tilde{D} + \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right) + \left(k_r^{\text{flat}} - k_r^{\text{peak}}\right)\right)\left(C_1\left(2D_n^{\text{flat}} + \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}} - k_r^{\text{flat}} - k_r^{\text{peak}}\right) + C_2\right)}$$
$$= R_k.$$

Suppose $q_n/q_d \leqslant 1$, then $(1-q_n)/(1-q_d) \geqslant 1$ so that R_c is greater than R_k. Thus, $k_r^{\text{flat}} \geqslant k_r^{\text{peak}}$ because otherwise that would imply that R_c is less than R_k. (ii) We note that $k_r^{\text{peak}} \geqslant k_r^{\text{flat}}$ if $\mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{peak}}, p_n^{\text{peak}}, p_d^{\text{peak}}\right) \geqslant \mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{flat}}, p_n^{\text{flat}}, p_d^{\text{flat}}\right) = 0$, where all arguments of the FOC wrt k_r are their respective optimal values. This is because $\mathcal{F}\left(k_r, k_c, p_n, p_d\right)$ is a decreasing function in k_r. We also note that $\mathcal{F}\left(k_r^{\text{flat}}, k_p^{\text{peak}}, p_n^{\text{peak}}, p_d^{\text{peak}}\right) \geqslant \mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{flat}}, p_n^{\text{flat}}, p_d^{\text{flat}}\right)$ if and only if

$$\frac{q_n}{q_d} \geqslant \underline{R} = \frac{g'\left(D_d^{\text{flat}} - k_c^{\text{flat}} - k_r^{\text{flat}}\right) - g'\left(D_d^{\text{peak}} - k_c^{\text{peak}} - k_r^{\text{flat}}\right)}{g'\left(D_n^{\text{peak}} - k_c^{\text{peak}} - k_r^{\text{flat}}\right) - g'\left(D_n^{\text{flat}} - k_c^{\text{flat}} - k_r^{\text{flat}}\right)}.$$

Next, we show that R_1 given in (2.7) is such that $R_1 \geqslant \underline{R}$ so that $q_n/q_d \geqslant R_1 > 1$ implies that $k_r^{\text{peak}} \geqslant k_r^{\text{flat}}$. Consider the following bound on $\underline{R}$

$$\underline{R} = \frac{\left(\tilde{D} - \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_d^{\text{flat}} - \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}} - 2k_r^{\text{flat}}\right) + C_2\right)}{\left(\tilde{D} + \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_n^{\text{flat}} + \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}} - 2k_r^{\text{flat}}\right) + C_2\right)}$$
$$\leqslant \frac{2C_1\left(D_d^{\text{flat}} - \left(k_c^{\text{flat}} + k_r^{\text{flat}}\right)\right) + C_2}{2C_1\left(D_n^{\text{flat}} - \left(k_c^{\text{flat}} + k_r^{\text{flat}}\right)\right) + C_2} = \bar{R},$$

where the inequality is due to the fact that $\tilde{D} \geqslant 0$ and $k_c^{\text{flat}} \geqslant k_c^{\text{peak}}$ assuming $q_n \geqslant q_d$ as shown in Proposition 3. At this point, $\underline{R}$ is bounded by $\bar{R}$ that involves the optimal values of the decision variables. Next, we will obtain an upper bound for $\bar{R}$ by assuming that $k_c^{\text{flat}} + k_r^{\text{flat}} \leqslant D_n^{\text{flat}} - \epsilon$ for some $\epsilon \geqslant 0$. Define $R(\epsilon)$ as

$$R(\epsilon) = \frac{2C_1(a_d - a_n + \epsilon) + C_2}{2C_1\epsilon + C_2} \geqslant \bar{R},$$

where we substitute $k_c^{\text{flat}} + k_r^{\text{flat}}$ with $D_n^{\text{flat}} - \epsilon$ in $\bar{R}$ and use the property that $D_d^{\text{flat}} - D_n^{\text{flat}} = a_d - a_n$. If $q_n/q_d \geqslant R(\epsilon)$, then $k_r^{\text{peak}} \geqslant k_r^{\text{flat}}$. Note that $R(\epsilon)$ decreases in ϵ and in order to characterize a greater portion of the q_n/q_d space, ϵ should be set to its maximum value. By examining the FOC wrt k_r, we observe that the assumption that $k_c^{\text{flat}} + k_r^{\text{flat}} \leqslant D_n^{\text{flat}} - \epsilon$ holds if $q_n g'\left(D_n^{\text{flat}} - \left(D_n^{\text{flat}} - \epsilon\right)\right) + q_d g'\left(D_d^{\text{flat}} - \left(D_n^{\text{flat}} - \epsilon\right)\right) \leqslant \beta_r$. This inequality is valid if $\max(q_n, q_d)\, g'(a_d - a_n + 2\epsilon) \leqslant \beta_r$, where we use the fact that $g'(\cdot)$ is a convex function. Thus, we observe that

$$\epsilon \leqslant \epsilon_{\max} = \frac{f(\beta_r/q_n) - (a_d - a_n)}{2},$$

where $f(\cdot)$ denotes the inverse of the derivative of the generation cost function, i.e., $f(\cdot) = \left(g'\right)^{-1}(\cdot)$, and we continue to assume that $q_n \geqslant q_d$. We note that $\epsilon_{\max}$ is positive by Assumption 1, and plugging it into $R(\epsilon)$, we observe that $R(\epsilon_{\max}) = R_1$ so that $q_n/q_d \geqslant R_1 \geqslant 1$ implies $k_r^{\text{peak}} \geqslant k_r^{\text{flat}}$. $\square$

Proof of Proposition 3. (i) Consider the relationship between FOCs wrt k_c given in (A.1). If $(1 - q_n)/(1 - q_d) \leqslant 1$, then $k_c^{\text{flat}} \geqslant k_c^{\text{peak}}$; otherwise R_c is greater than 1 contradicting the fact that $(1-q_n)/(1-q_d) \leqslant 1$. (ii) This part of the proof follows similar steps to the second part of the proof of Proposition 2 and hence is omitted. □

Proof of Proposition 4. Based on (2.10), $ECE^{\text{flat}} - ECE^{\text{peak}} = -2\left((1-e)\left(k_r^{\text{flat}} + k_c^{\text{flat}} - k_r^{\text{peak}} - k_c^{\text{peak}}\right) + (e-\bar{e})\left(k_r^{\text{flat}} - k_r^{\text{peak}}\right)\right)$, where $e \geqslant \bar{e}$ as we assume so. (i) Note that $ECE^{\text{flat}} \leqslant ECE^{\text{peak}}$ if $k_r^{\text{flat}} \geqslant k_r^{\text{peak}}$ and $k_r^{\text{flat}} + k_c^{\text{flat}} \geqslant k_r^{\text{peak}} + k_c^{\text{peak}}$. The first condition holds due to Proposition 2 as long as $q_n/q_d \leqslant 1$. Thus, to prove this part of the proposition, we need to show that $k_r^{\text{flat}} + k_c^{\text{flat}} \geqslant k_r^{\text{peak}} + k_c^{\text{peak}}$. To show this, consider the FOCs wrt k_r under flat and peak pricing by letting $k_r^j + k_c^j = k^j$ for $j \in \{\text{flat}, \text{peak}\}$ and observe that:

$$\begin{aligned}\frac{q_n}{q_d} &= \frac{g'\left(D_d^{\text{flat}} - k^{\text{flat}}\right) - g'\left(D_d^{\text{peak}} - k^{\text{peak}}\right)}{g'\left(D_n^{\text{peak}} - k^{\text{peak}}\right) - g'\left(D_n^{\text{flat}} - k^{\text{flat}}\right)} \\ &= \frac{\left(\tilde{D} - \left(k^{\text{flat}} - k^{\text{peak}}\right)\right)\left(C_1\left(2D_d^{\text{flat}} - \tilde{D} - k^{\text{flat}} - k^{\text{peak}}\right) + C_2\right)}{\left(\tilde{D} + \left(k^{\text{flat}} - k^{\text{peak}}\right)\right)\left(C_1\left(2D_n^{\text{flat}} + \tilde{D} - k^{\text{flat}} - k^{\text{peak}}\right) + C_2\right)}.\end{aligned}$$

Note that $q_n/q_d \leqslant 1$ implies that $k^{\text{flat}} \geqslant k^{\text{peak}}$, otherwise, the right hand side would be greater than 1, contradicting that $q_n/q_d \leqslant 1$. (ii) To prove this part, we first note that $ECE^{\text{flat}} \geqslant ECE^{\text{peak}}$ if $k_r^{\text{flat}} \leqslant k_r^{\text{peak}}$ and $k_r^{\text{flat}} + k_c^{\text{flat}} \leqslant k_r^{\text{peak}} + k_c^{\text{peak}}$. The first condition is given by Proposition 2 and the proof of the second condition follows similar steps to the part (ii) of the proof of Proposition 2 and hence is omitted. (iii) See Figure 2.2 for an example. □

Proof of Proposition 5. Based on the definition of consumer surplus given in (2.13),

$$CS^{\text{flat}} - CS^{\text{peak}} = \Delta \left(a_d - a_n - (\gamma + \delta)\, \Delta\right),$$

where Δ denotes the absolute difference in price levels between flat and peak pricing in a period. (Note that, by Lemma 1, this difference is the same for the nighttime and daytime.) Thus, consumer surplus is higher under flat pricing if and only if $a_d - a_n \geqslant (\gamma + \delta)\Delta$. This holds because, as we show in the proof of Lemma 1, under Assumption 1, $(a_d - a_n)/(\gamma + \delta) \geqslant p_d^{\text{peak}} - p_n^{\text{peak}} = 2\Delta$. □

Proof of Proposition 6. (i) Let (k_r, k_c, p_n, p_d) be the simultaneous solutions of the FOCs wrt k_r, k_c, p_n, and p_d, where the FOCs are given sequentially as $\mathcal{F}(k_r, k_c, p_n, p_d; \beta_r) = 0$, $\mathcal{G}(k_r, k_c, p_n, p_d; \beta_r) = 0$, $\mathcal{H}(k_r, k_c, p_n, p_d; \beta_r) = 0$, and $\mathcal{I}(k_r, k_c, p_n, p_d; \beta_r) = 0$. We show that $dk_r/d\beta_r$ is negative, $dk_c/d\beta_r$ is positive, and $dECE/d\beta_r$ is also positive if $e \geqslant \bar{e}$. By using implicit differentiation and Cramer's Rule, we can show that

$$\frac{dk_r}{d\beta_r} = \frac{\begin{vmatrix} -\frac{\partial \mathcal{F}}{\partial \beta_r} & \frac{\partial \mathcal{F}}{\partial k_c} & \frac{\partial \mathcal{F}}{\partial p_n} & \frac{\partial \mathcal{F}}{\partial p_d} \\ -\frac{\partial \mathcal{G}}{\partial \beta_r} & \frac{\partial \mathcal{G}}{\partial k_c} & \frac{\partial \mathcal{G}}{\partial p_n} & \frac{\partial \mathcal{G}}{\partial p_d} \\ -\frac{\partial \mathcal{H}}{\partial \beta_r} & \frac{\partial \mathcal{H}}{\partial k_c} & \frac{\partial \mathcal{H}}{\partial p_n} & \frac{\partial \mathcal{H}}{\partial p_d} \\ -\frac{\partial \mathcal{I}}{\partial \beta_r} & \frac{\partial \mathcal{I}}{\partial k_c} & \frac{\partial \mathcal{I}}{\partial p_n} & \frac{\partial \mathcal{I}}{\partial p_d} \end{vmatrix}}{H},$$

where $|\cdot|$ denotes the determinant operator and $H > 0$ is the determinant of the Hessian matrix. The numerator can be shown to be negative, hence, $dk_r/d\beta_r$ is negative. Similar steps prove that $dk_c/d\beta_r$ is positive, and $dECE/d\beta_r$ is also positive if $e \geqslant \bar{e}$. On the other hand, if $e < \bar{e}$, Figure 2.4 provides an example in which $dECE/d\beta_r$ is negative. (ii) This part is proved analogously to the previous part and omitted for brevity. □

Proof of Proposition 7. This proof is similar to that of Proposition 6. □

Proof of Proposition 8. (i) It can be shown that the Hessian of (2.18) is negative definite so that the FOCs are sufficient. (ii) We first note that $k_{DG}^{\text{flat}} - k_{DG}^{\text{peak}} = (q_n\Delta_n - q_d\Delta_d)/\beta_{DG}$, where Δ_i is the absolute value of the difference between price levels of flat and peak pricing in period $i \in \{n, d\}$. We first show that if $q_n \geqslant q_d$, then $q_n\Delta_n \geqslant q_d\Delta_d$, which, in turn, implies that $k_{DG}^{\text{flat}} \geqslant k_{DG}^{\text{peak}}$. By using the FOCs wrt k_r, k_c, p_n, and p_d, we prove that

$$\frac{\beta_{DG}}{2}\left(a_n + a_d + (\gamma - \delta)(2v + \beta_c) + \beta_r\left(\frac{q_n + q_d}{\beta_{DG}}\right)\right)$$

$$= \beta_{DG}(\gamma - \delta)(p_n + p_d) + (q_n + q_d)(q_n p_n + q_d p_d),$$

where the left hand side consists only of problem parameters. By using this relationship, we note that

$$\frac{-\Delta_n + \Delta_d}{q_n\Delta_n - q_d\Delta_d} = \frac{q_n + q_d}{\beta_{DG}(\gamma - \delta)}. \tag{A.2}$$

We now consider that $q_n \geqslant q_d$ and assume $\Delta_n \geqslant \Delta_d$ to prove by contradiction. In this case, the left hand side is negative in (A.2), which contradicts the fact that the right hand side is positive. Hence, $q_n \geqslant q_d$ implies $\Delta_d \geqslant \Delta_n$. Accordingly,

$q_n\Delta_n \geqslant q_d\Delta_d$ to ensure that the left hand side of (A.2) is positive. Thus, $q_n \geqslant q_d$ implies that $q_n\Delta_n \geqslant q_d\Delta_d$, and hence $k_{DG}^{\text{flat}} \geqslant k_{DG}^{\text{peak}}$. Next, consider that $q_d \geqslant q_n$. In this case, $\Delta_n \geqslant \Delta_d$ as otherwise there would be a contradiction in (A.2) as the left hand side would be negative whereas the right hand side is positive. Hence, $q_d \geqslant q_n$ implies that $\Delta_n \geqslant \Delta_d$, which, further implies $q_d\Delta_d \geqslant q_n\Delta_n$. Thus, if $q_d \geqslant q_n$, then $k_{DG}^{\text{peak}} \geqslant k_{DG}^{\text{flat}}$. □

Proof of Proposition 9. The Hessian of the utility firm's profit maximization problem given in (2.4) is negative definite, and hence the FOCs are sufficient. Under Assumption 2, it can be shown that $k_r + k_c \leqslant D_n^j$ for $j \in \{\text{flat}, \text{peak}\}$. Furthermore, solving the FOCs simultaneously, we observe that $k_r^{\text{flat}} - k_r^{\text{peak}} = 2\tilde{D}\left(E\left[\tilde{q}_d\right] - E\left[\tilde{q}_n\right]\right)/A$, $k_c^{\text{flat}} - k_c^{\text{peak}} = \tilde{D}\left(-E\left[\tilde{q}_d\right]^2 + E\left[\tilde{q}_n\right]^2\right)/A$, and $ECE^{\text{flat}} - ECE^{\text{peak}} = 2\tilde{D}e\left(-E\left[\tilde{q}_d\right]^2 + E\left[\tilde{q}_n\right]^2\right)/A$, where $\tilde{D}$ is the difference between optimal demand levels under flat and peak pricing in a period and $A = Var\left[\tilde{q}_n\right] + Var\left[\tilde{q}_d\right] + E\left[\tilde{q}_n^2\right] + E\left[\tilde{q}_d^2\right] - 2E\left[\tilde{q}_n\right]E\left[\tilde{q}_d\right] \geqslant 0$. Hence, $k_r^{\text{flat}} \geqslant k_r^{\text{peak}}$, $k_c^{\text{peak}} \geqslant k_c^{\text{flat}}$ and $ECE^{\text{peak}} \geqslant ECE^{\text{flat}}$ if $E\left[\tilde{q}_d\right] \geqslant E\left[\tilde{q}_n\right]$, otherwise, all three inequalities are reversed. □

A.2 Analysis of $\pi(k_r, k_j)$

We note that the benefit function is given as:

$$\pi^j(k_r, k_c) = [G^j(0,0) - G^j(k_r, k_c)] + [\alpha_r(0) - \alpha_r(k_r)] + [\alpha_c(0) - \alpha_c(k_c)].$$
$$= l_r^j k_r + m_r^j \sqrt{k_r} + l_c^j k_c + m_c^j \sqrt{k_c} - \beta_r k_r - \beta_c k_c,$$

where we substitute (2.16) for $[G^j(0,0) - G^j(k_r, k_c)]$, $\beta_r k_r$ for $\alpha_r(k_r)$, and $\beta_c k_c$ for $\alpha_c(k_c)$. We evaluate (2.16) for a renewable energy investment level up to 20,000MW, and a conventional energy investment level up to 5,000 MW. This difference is to account for the intermittency of renewables so that the actual generation from both sources would be approximately equal at these investment levels. We estimate l_r^j, m_r^j, l_c^j, and m_c^j parameters with our case study for $j \in \{\text{flat}, \text{peak}\}$. The estimated values are presented in Tables A.1 and A.2, and Figure A.1 plots this net benefit function for the estimated parameters and cost parameters described below. It is straightforward to show that $\pi^j(k_r, k_c)$ is jointly concave in k_r and k_c. The optimal investment levels are given as $k_r^j = \left(\frac{m_r^j}{2(\beta_r - l_r^j)}\right)^2$ and $k_c^j = \left(\frac{m_c^j}{2(\beta_c - l_c^j)}\right)^2$ as long as $\beta_r \geqslant l_r^j$ and $\beta_c \geqslant l_c^j$ under pricing policy $j \in \{\text{flat}, \text{peak}\}$. We report these optimal investment levels in Tables 2.2 and 2.3.

Table A.1: Parameter estimates for solar energy

	Response Level	m_c^j	m_r^j	l_c^j	l_r^j
Flat Pricing	N/A	10,120,131	21,908,656	889,002	1,436,892
Peak Pricing	Low (5%)	19,003,649	20,161,371	786,002	1,400,913
	Medium (10%)	17,504,077	23,126,617	838,970	1,323,337
	High (15%)	18,117,049	30,909,338	857,373	1,199,025

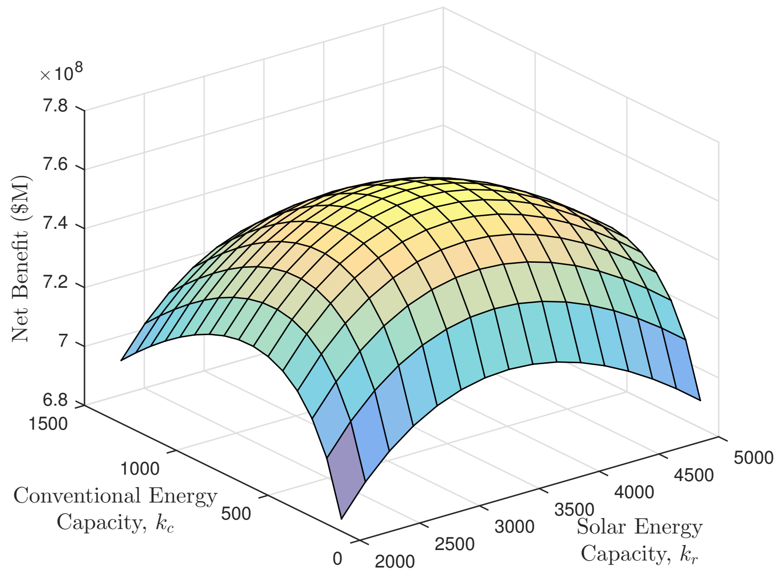


Figure A.1: Net benefit function, $\pi(k_r, k_c)$, for solar energy under flat pricing

Table A.2: Parameter estimates for wind energy

	Response Level	m_c^j	m_r^j	l_c^j	l_r^j
Flat Pricing	N/A	4,323,298	50,161,699	551,308	1,152,838
Peak Pricing	Low (5%)	9,706,227	54,680,383	490,897	1,095,233
	Medium (10%)	13,735,100	42,493,471	473,952	1,152,989
	High (15%)	13,081,120	30,448,889	490,256	1,214,981

A.3 Estimation of Cost Parameters

In this section, we describe the estimation procedure of investment and generation cost parameters, i.e., β_r, β_c, and υ for various electricity sources. We use cost estimates from the Transparent Cost Database (TCDB, `http://en.openei.org/apps/TCDB`), which is designed by National Renewable Energy Laboratory (NREL) to track publications that estimate cost parameters for renewable and conventional energy investments. In particular, to find β_r and β_c, we divide the overnight capital cost reported in TCDB with the useful economic lifetime of a source. Specifically, for wind energy, TCDB reports the median overnight capital cost as $\$1,570,000$/MW. The useful economic life for wind is estimated by NREL as 20 years although it is also reported that the lifetime is shorter (Gordon 2012). Thus, we consider wind lifetime as 15–20 years with an average value of 17.5 years. Hence, $\beta_r = \$1.57 \times 10^6/\text{MW}/17.5\text{years} = \$249.2/\text{MW}$ per day for wind energy. For solar energy, the cost estimates vary significantly between different studies and we consider the median of the most recent (from the year 2014) cost estimates for solar energy given as $\$1,625,000$/MW. According to NREL[1], solar panels last 25–40 years and we consider the lifetime of solar panels as 32.5 years (=(25+40)/2), hence $\beta_r = \$138.9$/MW per day. For coal energy, TCDB estimates useful life as 60 years so that we set $\beta_c = \$91.2$/MW per day. For nuclear and natural gas (combustion turbine) sources, TCDB estimates suggest that $\beta_c = \$161.1$/MW per day and $\beta_c = \$61.2$/MW per day. We take nuclear and natural gas lifetime as 60 and 30 years, respectively (see EIA 2014a and TCDB). The generation cost data for estimating v is taken from Energy Information Administration (EIA 2014c) for conventional sources.

In the case study, we focus on the entire lifetime of investments rather than a representative day. Thus, we use the above overnight capital cost estimates directly and account for the differences in lifetimes of energy sources while considering investment costs. Specifically, when solar energy and coal investments are considered simultaneously, we divide β_c by a factor of 1.8 (=60/32.5) and set $\beta_c = 1,094,444(=$

[1] See `http://www.nrel.gov/analysis/tech_footprint.html`

$1,970,000/1.8$). On the other hand, when wind and coal energy investments are considered, we divide β_c by a factor of 3.4(=60/17.5) and set $\beta_c = 579,412$.

A.4 Consumer Surplus and Utility

We first note that, in general, computing the line integral given in (2.13) is prone to the path dependency problem. Specifically, this integral may depend on the particular path on the (z_n, z_d) plane, with the starting point of $(0,0)$ and the ending point of (z_n^{j*}, z_d^{j*}). In our setting, this integral is path independent, i.e., computing it along any path that starts and ends at $(0,0)$ and (z_n^{j*}, z_d^{j*}) yields the same result. This is because the cross partial derivatives of the nighttime and daytime demand functions are equal to each other, i.e., $\frac{\partial^2 D_n(p_n,p_d)}{\partial p_n \partial p_d} = \frac{\partial^2 D_d(p_d,p_n)}{\partial p_d \partial p_n} = \delta$ (see Vives 2001 p.86 for a detailed discussion on the path dependency issue).

We next introduce the underlying utility maximization problem that is behind the linear demand model we use. Then, by using this utility function, we show that the utility of consumers is higher under flat pricing compared to peak pricing.

First, consider the following utility maximization problem subject to the budget constraint:

$$\max_{z_n, z_d} U(z_n, z_d) = m + \zeta_n z_n + \zeta_d z_d - \frac{\eta}{2}\left(z_n^2 + 2\lambda z_n z_d + z_d^2\right)$$

$$\text{s.t. } p_n z_n + p_d z_d + m \leqslant I,$$

where a representative agent maximizes its utility over its consumption levels z_n and

z_d in the nighttime and daytime periods, respectively. In this formulation, ζ_i, η, and λ represent parameters of the utility function, m is an outside good and I is the budget level. Similar utility maximization problems are considered in the literature (c.f., Shapley and Shubik 1969, Singh and Vives 1984, and Ledvina and Sircar 2012).

Solving this optimization problem, we observe that the optimal consumption level z_i^* in period $i \in \{n, d\}$ as a function of price levels p_i and p_{-i} is given as:

$$z_i^* \left(p_i, p_{-i}\right) = \frac{\zeta_i - \lambda \zeta_{-i}}{\eta \left(1 - \lambda^2\right)} - \frac{p_i}{\eta \left(1 - \lambda^2\right)} + \frac{\lambda p_{-i}}{\eta \left(1 - \lambda^2\right)}, \qquad i \in \{n, d\}.$$

Notice that letting $\frac{\zeta_i - \lambda \zeta_{-i}}{\eta(1-\lambda^2)} \equiv a_i$, $\frac{1}{\eta(1-\lambda^2)} \equiv \gamma$, $\frac{\lambda}{\eta(1-\lambda^2)} \equiv \delta$, the above demand function is equivalent to our demand model. Hence, we characterize the underlying utility formulation behind our linear demand function as: $U\left(z_n, z_d\right) = m + \zeta_n z_n + \zeta_d z_d - \frac{\eta}{2}\left(z_n^2 + 2\lambda z_n z_d + z_d^2\right)$. We next compare the utility of consumers under flat and peak pricing. Note that $U\left(z_n^{\text{flat}*}, z_d^{\text{flat}*}\right) - \left(z_n^{\text{peak}*}, z_d^{\text{peak}*}\right) = (\delta + \gamma)\,\Delta^2 \geqslant 0$, where Δ is the absolute difference between the price under flat pricing and the nighttime or daytime price under peak pricing. (By Lemma 1, both of these differences are equal to each other.) Thus, this result suggests that the utility of the consumers is higher under flat pricing, confirming the result given in Proposition 5.

Appendix B

Appendices for Chapter 3

B.1 Proofs

We first present the proofs of the Lemma 10 and 11.

Proof of Lemma 10. Let $q_I^* < k_I^*$ be the optimal solutions in (3.2). Let $\bar{k}_I = k_I^* - \epsilon$ for some $\epsilon > 0$ such that $q_I^* < \bar{k}_I$. Note that $\bar{k}_I$ is a feasible solution with a strictly lower cost, contradicting the optimality of k_I^*. □

Proof of Lemma 11. Considering (3.3), we observe that this function decreases in q_R at rate r, and it decreases in q_F at rate $r - c_F$. Hence, it is optimal to dispatch the renewable source first, followed by the flexible source, i.e., $q_R^* (\boldsymbol{k}, \xi, \theta) = \min (\theta k_R, \xi - k_I)^+$ and $q_F^* (\boldsymbol{k}, \xi, \theta) = \min (k_F, \xi - k_I - \theta k_R)^+$. □

Before proceeding to the proofs of the propositions, we introduce the following lemma to be used later on.

Lemma 20. *Consider a log-concave function $f(\cdot)$. Let x, y and z be positive scalars. Then, the following holds*

$$\frac{f(x+y)}{f(x)} \geqslant \frac{f(x+y+z)}{f(x+z)}. \tag{B.1}$$

Proof of Lemma 20. This inequality holds if and only if $\log f(x+y) + \log f(x+z) \geqslant \log f(x+y+z) + \log f(x)$. Let $\lambda = \frac{y}{y+z}$, by the definition of log-concavity:

$$\log f(\lambda(x+y+z) + (1-\lambda)x = x+y) \geqslant \lambda \log f(x+y+z) + (1-\lambda)\log f(x)$$

$$\log f((1-\lambda)(x+y+z) + \lambda x = x+z) \geqslant (1-\lambda)\log f(x+y+z) + \lambda \log f(x).$$

Adding these inequalities side by side, we observe that $\log f(x+y) + \log f(x+z) \geqslant \log f(x+y+z) + \log f(x)$. Hence, the inequality given in (B.1) holds. □

Proof of Proposition 12. This proof follows similar arguments as in Van Mieghem (1998) and Sting and Huchzermeier (2012). We first note that the dispatch problem given in (3.3)-(3.5) can be equivalently expressed as:

$$\begin{aligned} C(\boldsymbol{k}, \xi, \theta) = \min_{\boldsymbol{q} \in \mathbb{R}_+^2, s \in \mathbb{R}_+} \quad & c_F q_F + rs \\ \text{subject to} \quad & q_R \leqslant \theta k_R \leftarrow \lambda_R \\ & q_F \leqslant k_F \leftarrow \lambda_F \\ & -s - q_R - q_F \leqslant k_I - \xi \leftarrow \lambda_I, \end{aligned}$$

where λ_i's are the decision variables of the following dual problem:

$$\max_{\boldsymbol{\lambda} \in \mathbb{R}^3_+} (\xi - k_I)\, \lambda_I - k_R \lambda_R - k_F \lambda_F$$

$$\text{subject to} \quad \lambda_I \leqslant \frac{\lambda_R}{\theta}$$

$$\lambda_I \leqslant \lambda_F + c_F$$

$$\lambda_I \leqslant r.$$

Since $C(\cdot, \xi, \theta)$ is the minimal solution of a linear program, it is convex. Thus, $\bar{\Pi}(\cdot)$ is also convex because convexity is preserved under expectation and summation. Therefore, KKT conditions (3.7) and (3.8) are sufficient and necessary to identify the minimizer of $\bar{\Pi}(\cdot)$.

We next show that $E[C(\boldsymbol{k}, \xi, \theta)] = -E[\boldsymbol{\lambda}(\boldsymbol{k}, \xi, \theta)]$. First, we note that the primal problem is always finite as the demand and intermittency distributions are bounded. Hence, the dual problem and the primal has the same objective value when they are both optimal. Let $\boldsymbol{\lambda}^* (\boldsymbol{k}, \xi, \theta)$ be the optimal dual solution for given $\boldsymbol{k}, \xi$, and θ and fix some $\boldsymbol{k}^0 \in \mathbb{R}^3_+$. Then, for any $\boldsymbol{k} \in \mathbb{R}^3_+$: $C(\boldsymbol{k}, \xi, \theta) \geqslant \xi \lambda_I^* (\boldsymbol{k}^0, \xi, \theta) - \boldsymbol{k}' \boldsymbol{\lambda}^* (\boldsymbol{k}^0, \xi, \theta)$. Combining this with $C(\boldsymbol{k}^0, \xi, \theta) = \xi \lambda_I^* (\boldsymbol{k}^0, \xi, \theta) - \boldsymbol{k}^{0'} \boldsymbol{\lambda}^* (\boldsymbol{k}^0, \xi, \theta)$, we obtain that

$$-C(\boldsymbol{k}, \xi, \theta) \leqslant -C\left(\boldsymbol{k}^0, \xi, \theta\right) + \left(\boldsymbol{k} - \boldsymbol{k}^0\right)' \boldsymbol{\lambda}^* \left(\boldsymbol{k}^0, \xi, \theta\right).$$

Taking expectations of both sides, we observe that $E[\boldsymbol{\lambda}(\boldsymbol{k}, \epsilon, \Theta)]$ is a subgradient of $E[-C(\boldsymbol{k}, \epsilon, \Theta)]$ evaluated at $\boldsymbol{k}^0$. Because $C(\boldsymbol{k}, \epsilon, \Theta)$ is convex, it is differentiable almost everywhere (a.e.) except for a set whose Lebesgue mesaure is zero as demand and intermittency are continuous. Thus, $\nabla_{\boldsymbol{k}} C(\boldsymbol{k}, \epsilon, \Theta)$ is single-valued a.e. This implies that the subgradient is unique for any $\boldsymbol{k} \in \mathbb{R}_+^3$ and the KKT conditions given in (3.7) and (3.8) jointly define the optimal solution. $\square$

Proof of Proposition 13. Note that in the triple sourcing case (i.e., $\boldsymbol{k} > 0$), by expressing the demand and intermittency partitions explicitly, the FOCs with respect to (wrt) k_I, k_R, and k_F can be sequentially written as:

$$\mathcal{F}(\boldsymbol{k}) = -\sum_{n=1}^{N} \int_{\theta=0}^{1} \left[r - (r - c_F) F_{\epsilon_n|\Theta_n}(k_I + \theta k_R + k_F|\theta) - c_F F_{\epsilon_n|\Theta_n}(k_I + \theta k_R|\theta)\right] f_{\Theta_n}(\theta)\, d\theta$$

$$+ (\alpha_I + N c_I)$$

$$\mathcal{G}(\boldsymbol{k}) = -\sum_{n=1}^{N} \int_{\theta=0}^{1} \theta \left[r - (r - c_F) F_{\epsilon_n|\Theta_n}(k_I + \theta k_R + k_F|\theta) - c_F F_{\epsilon_n|\Theta_n}(k_I + \theta k_R|\theta)\right] f_{\Theta_n}(\theta)\, d\theta$$

$$+ \alpha_R$$

$$\mathcal{H}(\boldsymbol{k}) = -\sum_{n=1}^{N} \int_{\theta=0}^{1} (r - c_F)\left(1 - F_{\epsilon_n|\Theta_n}(k_I + \theta k_R + k_F|\theta)\right) f_{\Theta_n}(\theta)\, d\theta + \alpha_F.$$

In addition, we define two random variables for later use as

$X_n = (r - c_F) f_{\epsilon_n|\Theta_n}(k_I + \Theta_n k_R + k_F|\, \Theta_n)$ and $Y_n = c_F f_{\epsilon_n|\Theta_n}(k_I + \Theta_n k_R|\, \Theta_n)$. (i)

We first show that $\frac{dk_I^*}{d\alpha_I} \leqslant 0$. Using implicit differentiation and Cramer's rule, it can be shown that

$$\frac{dk_I^*}{d\alpha_I} = \frac{\begin{vmatrix} -\frac{\partial \mathcal{F}}{\partial \alpha_I} & \frac{\partial \mathcal{F}}{\partial k_R} & \frac{\partial \mathcal{F}}{\partial k_F} \\ -\frac{\partial \mathcal{G}}{\partial \alpha_I} & \frac{\partial \mathcal{G}}{\partial k_R} & \frac{\partial \mathcal{G}}{\partial k_F} \\ -\frac{\partial \mathcal{H}}{\partial \alpha_I} & \frac{\partial \mathcal{H}}{\partial k_R} & \frac{\partial \mathcal{H}}{\partial k_F} \end{vmatrix}}{H},$$

where we drop the arguments of the FOCs for notational simplicity and H is the determinant of the Hessian matrix which is positive. Thus, to show that $\frac{dk_I^*}{d\alpha_I} \leqslant 0$, it suffices to show that the numerator is negative. The numerator is given as $-E\left[\sum_{n=1}^N \Theta_n^2 (X_n + Y_n)\right] E\left[\sum_{n=1}^N X_n\right] + E\left[\sum_{n=1}^N \Theta_n X_n\right] E\left[\sum_{n=1}^N \Theta_n X_n\right]$, where X_n and Y_n are defined earlier. By Cauchy-Schwarz inequality, this is negative. Next, we consider $\frac{dk_R^*}{d\alpha_R}$ and following similar steps as above, one can show that this derivative is equal to $-E\left[\sum_{n=1}^N Y_n\right] E\left[\sum_{n=1}^N X_n\right]/H$, and hence negative. Finally, $\frac{dk_F^*}{d\alpha_F} =$
$-E\left[\sum_{n=1}^N (X_n + Y_n)\right] E\left[\sum_{n=1}^N \Theta_n^2 (X_n + Y_n)\right]/H+$
$E\left[\sum_{n=1}^N \Theta_n (X_n + Y_n)\right] E\left[\sum_{n=1}^N \Theta_n (X_n + Y_n)\right]/H$, which is also negative. (ii) Using a similar technique, it can be shown that $\frac{dk_i^*}{d\alpha_j} = \frac{dk_j^*}{d\alpha_i}$ for $i, j \in \{I, R, F\}$. □

Proof of Proposition 14. We evaluate these derivatives by using implicit differentiation. (i) One can show that $\frac{dk_I^*}{d\alpha_R} = \frac{dk_R^*}{d\alpha_I} = E\left[\sum_{n=1}^N X_n\right] E\left[\sum_{n=1}^N \Theta_n Y_n\right]/H \geqslant 0$. Hence, the inflexible source and the renewable source are substitutes. (ii) It can be shown that $\frac{dk_F^*}{d\alpha_I} = \frac{dk_I^*}{d\alpha_F} \geqslant Zc_F (r - c_F)/H$, where

$Z = \left(E\left[\sum_{n=1}^N X_n\right] E\left[\sum_{n=1}^N \Theta_n^2 Y_n\right] - E\left[\sum_{n=1}^N \Theta_n X_n\right] E\left[\sum_{n=1}^N \Theta_n Y_n\right]\right)/\left[c_F (r - c_F)\right]$.

Thus, to show that $\frac{dk_F^*}{d\alpha_I} \geqslant 0$, it sufficies to show that $Z \geqslant 0$. Using the definitions of

X_n and Y_n:

$$
\begin{aligned}
Z &= \sum_{n=1}^{N} \int_{\theta=0}^{1} f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) d\theta \times \sum_{n=1}^{N} \int_{\theta=0}^{1} \theta^2 f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\Theta_n}\left(\theta\right) d\theta \\
&- \sum_{n=1}^{N} \int_{\theta=0}^{1} \theta f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) d\theta \times \sum_{n=1}^{N} \int_{\theta=0}^{1} \theta f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\Theta_n}\left(\theta\right) d\theta \\
&= \sum_{n=1}^{N} \sum_{m=1}^{N} \int_{\theta=0}^{1} \left[\int_{\zeta=0}^{1} \theta\left(\theta-\zeta\right) f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\zeta\right] d\theta.
\end{aligned}
$$

This integral can also be expressed as

$\int_{\theta=0}^{1}\int_{\zeta=0}^{\theta} \theta\left(\theta-\zeta\right) f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\zeta d\theta +$ $\int_{\theta=0}^{1}\int_{\zeta=\theta}^{1} \theta\left(\theta-\zeta\right) f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\zeta d\theta$. The second integral is equivalent to $-\int_{\zeta=0}^{1}\int_{\theta=0}^{\zeta} \theta\left(\zeta-\theta\right) f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right) f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\theta d\zeta$. In this expression, renaming θ as ζ, m as n and vice-versa, we observe that

$$
\begin{aligned}
Z = \sum_{n=1}^{N} \sum_{m=1}^{N} \int_{\theta=0}^{1} \Bigg[\int_{\zeta=0}^{\theta} &\left(\theta-\zeta\right) \left\{\theta f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right)\right. \\
&\left. -\zeta f_{\epsilon_m}\left(k_I + \zeta k_R\right) f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right)\right\} f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\zeta\Bigg] d\theta.
\end{aligned}
$$

Thus, $Z \geqslant 0$ if

$$
\frac{\theta f_{\epsilon_n}\left(k_I + \theta k_R\right)}{\zeta f_{\epsilon_m}\left(k_I + \zeta k_R\right)} \geqslant \frac{f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right)}{f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right)},
$$

for $\theta > \zeta$ and $1 \leqslant n, m \leqslant N$. This condition is satisfied if Θ_n follows a two-point distribution. Furthermore, if $\epsilon_n = \epsilon$ for all n, i.e., ϵ_n is stationary, above inequality holds for any intermittency distribution as long as ϵ is log-concave by Lemma 20.

(iii) Finally, $\frac{dk_F^*}{d\alpha_R} = \frac{dk_R^*}{d\alpha_F} = -Tc_F\left(r - c_F\right)/H$, where

$$T = \left(E\left[\sum_{n=1}^{N} X_n\right] E\left[\sum_{n=1}^{N} \Theta_n Y_n\right] - E\left[\sum_{n=1}^{N} \Theta_n X_n\right] E\left[\sum_{n=1}^{N} Y_n\right]\right) / \left[c_F\left(r - c_F\right)\right]. \tag{B.2}$$

Thus, it is sufficient to show that $T \geqslant 0$ to prove that the flexible source and the renewable source are complements. Using a similar technique as above, one can show that

$$T = \sum_{n=1}^{N}\sum_{m=1}^{N}\int_{\theta=0}^{1}\left[\int_{\zeta=0}^{\theta}\left(\theta - \zeta\right)\left\{f_{\epsilon_n}\left(k_I + \theta k_R\right) f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right)\right.\right.$$

$$\left.\left. - f_{\epsilon_m}\left(k_I + \zeta k_R\right) f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right)\right\} f_{\Theta_n}\left(\theta\right) f_{\Theta_m}\left(\zeta\right) d\zeta\right] d\theta.$$

Thus, $T \geqslant 0$ if

$$\frac{f_{\epsilon_n}\left(k_I + \theta k_R\right)}{f_{\epsilon_m}\left(k_I + \zeta k_R\right)} \geqslant \frac{f_{\epsilon_n}\left(k_I + \theta k_R + k_F\right)}{f_{\epsilon_m}\left(k_I + \zeta k_R + k_F\right)},$$

for $\theta > \zeta$ and $1 \leqslant n, m \leqslant N$. This condition is satisfied if $\epsilon_n = \epsilon$ for all n, and the density function of ϵ is log-concave. Next, consider that Θ_n follows a two point distribution as in Assumption 3 and $q_n = q$ for all n. Then, $T = \sum_{n=1}^{N}\sum_{m=1}^{N} q\left(1 - q\right)\left(f_{\epsilon_n}\left(k_I + k_R\right) f_{\epsilon_m}\left(k_I + k_F\right) - f_{\epsilon_m}\left(k_I\right) f_{\epsilon_n}\left(k_I + k_R + k_F\right)\right)$, which is positive if

$$\frac{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I + k_F\right)}{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I\right)} = \frac{g\left(k_I + k_F\right)}{g\left(k_I\right)} \geqslant \frac{g\left(k_I + k_R + k_F\right)}{g\left(k_I + k_R\right)} = \frac{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I + k_R + k_F\right)}{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I + k_R\right)},$$

i.e., as long as $g\left(\cdot\right)$ is log-concave by Lemma 20. $\square$

Proof of Proposition 15. (i) Since c_I is charged to the entire capacity k_I, the effect of c_I on investment levels is the same as that of α_I. (ii) Consider Assumption 1. It can be shown that $\frac{dk_I^*}{dc_F} \times H = A_1 A_2 \left[N - \sum_n q_n F_{3,n} - \sum_n (1-q_n) F_{4,n}\right] + A_1 B_1 \left[\sum_n (1-q_n) F_{2,n} - \sum_n (1-q_n) F_{4,n}\right] + A_2 B_1 \left[N - \sum_n (1-q_n) F_{4,n} - \sum_n q_n F_{1,n}\right]$, where H is the determinant of the Hessian matrix, $A_1 = \sum_n q_n (r - c_F) f_{\epsilon_n}(k_I + k_R + k_F)$, $A_2 = \sum_n (1-q_n)(r - c_F) f_{\epsilon_n}(k_I + k_F)$, $B_1 = \sum_n q_n c_F f_{\epsilon_n}(k_I + k_R)$, $B_2 = \sum_n (1-q_n) c_F f_{\epsilon_n}(k_I)$, $F_{1,n} = F_{\epsilon_n}(k_I + k_R + k_F)$, $F_{2,n} = F_{\epsilon_n}(k_I + k_F)$, $F_{3,n} = F_{\epsilon_n}(k_I + k_R)$ and $F_{4,n} = F_{\epsilon_n}(k_I)$. Hence, $\frac{dk_I^*}{dc_F} \geqslant 0$, indicating that a generation subsidy for the flexible source leads to a lower investment in the inflexible source. Furthermore, $\frac{dk_F^*}{dc_F} \times H = -A_1 A_2 \left[N - \sum_n q_n F_{3,n} - \sum_n (1-q_n) F_{4,n}\right] - A_1 B_2 \left[N - \sum_n q_n F_{3,n} - \sum_n (1-q_n) F_{2,n}\right] - A_2 B_1 \left[N - \sum_n q_n F_{1,n} - \sum_n (1-q_n) F_{4,n}\right] - B_1 B_2 \left[N - \sum_n q_n F_{1,n} - \sum_n (1-q_n) F_{2,n}\right]$, which is negative. Thus, a generation subsidy for the flexible source leads to a higher investment in the flexible source. □

Proof of Proposition 16. Defining $\bar{c}_i = c_i + te_i$ for $i \in \{I, R, F\}$, one can show that this problem is jointly convex in its arguments. Furthermore, suppose $e_I = 0$. Then, $\frac{\partial \mathcal{F}(k_I,k_R,k_F)}{\partial t} = e_F \frac{\partial \mathcal{F}(k_I,k_R,k_F)}{\partial c_F}$, where $\mathcal{F}(k_I, k_R, k_F)$ is the FOC wrt k_I. Similar relationships also hold for the FOCs wrt k_R and k_F. Thus, through implicit differentiation it can be shown that $\frac{dk_i^*}{dt}$ has the same sign as $\frac{dk_i^*}{dc_F}$. □

Proof of Proposition 17. (i) We first consider $\frac{dk_I^*}{dr}$ for a general intermittency distribution. By using implicit differentiation, it can be shown that $\frac{dk_I^*}{dr} =$

$E\left[\sum_{n=1}^{N}\Theta_n Y_n\right] R\left(r-c_F\right)/H$, where

$R = \left(E\left[\sum_{n=1}^{N}\Theta_n X_n\right] E\left[\sum_{n=1}^{N} Z_n\right] - E\left[\sum_{n=1}^{N} X_n\right] E\left[\sum_{n=1}^{N}\Theta_n Z_n\right]\right)/\left(r-c_F\right)$ and $Z_n = \bar{F}_{\epsilon_n}\left(k_I+\Theta_n k_R+k_F\right)$. By using a similar strategy as in the proof of Proposition 3, one can show that

$$R = \sum_{n=1}^{N}\sum_{m=1}^{N}\int_{\theta=0}^{1}\int_{\zeta=0}^{\theta}\left(\theta-\zeta\right)\left[f_{\epsilon_m}\left(k_I+\theta k_R+k_F\right)\bar{F}_{\epsilon_n}\left(k_I+\zeta k_R+k_F\right)-\right.$$

$$\left. f_{\epsilon_n}\left(k_I+\zeta k_R+k_F\right)\bar{F}_{\epsilon_m}\left(k_I+\theta k_R+k_F\right)\right] f_{\Theta_n}\left(\zeta\right) f_{\Theta_m}\left(\theta\right) d\zeta d\theta.$$

Notice that $R \geqslant 0$ if

$$\frac{f_{\epsilon_m}\left(k_I+\theta k_R+k_F\right)}{\bar{F}_{\epsilon_m}\left(k_I+\theta k_R+k_F\right)} \geqslant \frac{f_{\epsilon_n}\left(k_I+\zeta k_R+k_F\right)}{\bar{F}_{\epsilon_n}\left(k_I+\zeta k_R+k_F\right)},$$

for $\theta > \zeta$ and $1 < n, m < N$. If demand distribution is stationary, i.e., $\epsilon_n = \epsilon$ for all n, this condition is satisfied as long as ϵ is log-concave, which implies that the failure rate is increasing (see Bagnoli and Bergstrom 2005, Corollary 2). Furthermore, consider that the intermittency follows a two-point distribution as given in (3.9) and $q_n = q$ for all n, then

$R = \sum_{n=1}^{N}\sum_{m=1}^{N} q\left(1-q\right)\left[f_{\epsilon_m}\left(k_I+k_R+k_F\right)\bar{F}_{\epsilon_n}\left(k_I+k_F\right) - f_{\epsilon_n}\left(k_I+k_F\right)\bar{F}_{\epsilon_m}\left(k_I+k_R+k_F\right)\right].$

In this case, $R \geqslant 0$ if

$$\frac{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I+k_R+k_F\right)}{\sum_{n=1}^{N}\bar{F}_{\epsilon_n}\left(k_I+k_R+k_F\right)} = \frac{g\left(k_I+k_R+k_F\right)}{\bar{G}\left(k_I+k_R+k_F\right)} \geqslant \frac{g\left(k_I+k_F\right)}{\bar{G}\left(k_I+k_F\right)} = \frac{\sum_{n=1}^{N} f_{\epsilon_n}\left(k_I+k_F\right)}{\sum_{n=1}^{N}\bar{F}_{\epsilon_n}\left(k_I+k_F\right)},$$

where we define $\bar{G}\left(x\right) = \sum_{n=1}^{N}\bar{F}_{\epsilon_n}\left(x\right)$. We next show that this inequality holds if

$g(x)$ is log-concave. As long as $g(x)$ is log-concave, $\bar{G}(x)$ is also log-concave. This can be seen from Bagnoli and Bergstrom 2005, Lemma 4 because $d\bar{G}(x)/dx = -g(x)$. Due to log-concavity of $\bar{G}(x)$ and $g(x)$, the ratio $g(x)/\bar{G}(x)$ (hazard rate) is increasing as shown in Bagnoli and Bergstrom 2005, Corollary 2. Hence, the inequlity above holds if $g(x)$ is a log-concave function. This proves that $R \geqslant 0$, implying that $\frac{dk_I^*}{dr} \geqslant 0$. We next consider the flexible source and note that $\frac{dk_F^*}{dr} \geqslant \left(E\left[\sum_{n=1}^N Z_n\right] U + E\left[\sum_{n=1}^N \Theta_n Z_n\right] T\right) c_F\left(r - c_F\right)/H$, where
$U = \left(E\left[\sum_{n=1}^N \Theta_n^2 X_n\right] E\left[\sum_{n=1}^N Y_n\right] - E\left[\sum_{n=1}^N \Theta_n X_n\right] E\left[\sum_{n=1}^N \Theta_n Y_n\right]\right)/\left[c_F\left(r - c_F\right)\right]$,
and T is defined in (A.3) and shown to be positive if Θ_n follows a stationary two-point distribution and $g(\cdot)$ is log-concave. Hence, it sufficies to show that $U \geqslant 0$, to prove that $\frac{dk_F^*}{dr} \geqslant 0$. Under Assumption 1,
$U = \sum_{n=1}^N \sum_{m=1}^N q_n\left(1 - q_m\right)\left(r - c_F\right) c_F f_{\epsilon_n}\left(k_I + k_R + k_F\right) f_{\epsilon_m}\left(k_I\right) \geqslant 0$. Therefore, $\frac{dk_F^*}{dr} \geqslant 0$. (ii) We finally consider $\frac{dk_R^*}{dr} = -E\left[\sum_{n=1}^N Y_n\right] R\left(r - c_F\right)/H$. We already show the conditions that ensure $R \geqslant 0$. Hence, whenever $\frac{dk_I^*}{dr}$ is positive, $\frac{dk_R^*}{dr}$ is negative. □

Proof of Lemma 18. (i) By plugging q_S into the objective function in (3.16), we define $\bar{C}_n(\boldsymbol{k}, \xi, \theta, \gamma) = c_F q_F + \left(\gamma + \frac{b_n}{2}\left(\xi - k_I - q_R - q_F\right)\right)\left(\xi - k_I - q_R - q_F\right)$, where its derivative wrt q_R and q_F is given as $-\gamma + b_n\left(k_I + q_R + q_F - \xi\right)$ and $c_F - \gamma + b_n\left(k_I + q_R + q_F - \xi\right)$, respectively. To determine optimal dispatch policy, we consider five cases. Case 1: $\gamma \leqslant b_n\left(k_I - \xi\right)$, $\frac{\partial \bar{C}_n}{\partial q_R} \geqslant 0$ and $\frac{\partial \bar{C}_n}{\partial q_F} \geqslant 0$, hence $q_R^* = q_F^* = 0$. Case 2:

$b_n(k_I-\xi) \leqslant \gamma \leqslant b_n(k_I+\theta k_R-\xi)$, $q_R^* = \xi - k_I + \frac{\gamma}{b_n}$ so that $\frac{\partial \bar{C}_n}{\partial q_R} = 0$, and $q_F^* = 0$ as $\frac{\partial \bar{C}_n}{\partial q_F} \geqslant 0$. Case 3: $b_n(k_I+\theta k_R-\xi) \leqslant \gamma \leqslant c_F + b_n(k_I+\theta k_R-\xi)$, $q_R^* = \theta k_R$ so that $\frac{\partial \bar{C}_n}{\partial q_R}$ can be as close to 0 as possible subject to the constraint (3.17) and $q_F^* = 0$ as $\frac{\partial \bar{C}_n}{\partial q_F}$ is still positive. Case 4: $c_F + b_n(k_I+\theta k_R-\xi) \leqslant \gamma \leqslant c_F + b_n(k_I+\theta k_R+k_F-\xi)$, similar to the previous case $q_R^* = \theta k_R$ but in this case $q_F^* = \xi - k_I - \theta k_R + \frac{\gamma - c_F}{b_n}$. Case 5: $c_F + b_n(k_I+\theta k_R+k_F-\xi) \leqslant \gamma$, q_R^* remains to be θk_R and $q_F^* = k_F$ so that $\frac{\partial \bar{C}_n}{\partial q_F}$ can be as close to 0 as possible subject to the constraint (3.18). This optimal dispatch policy can be defined as $q_R^*(\boldsymbol{k},\xi,\theta,\gamma) = \min\left(\theta k_R, \xi - k_I + \frac{\gamma}{b_n}\right)^+$ and $q_F^*(\boldsymbol{k},\xi,\theta,\gamma) = \min\left(k_F, \xi - k_I - \theta k_R + \frac{\gamma - c_F}{b_n}\right)^+$. (ii) With this optimal dispatch policy, the Hessian of the first stage problem can be shown to be positive so that the problem is jointly convex in its arguments. □

Proof of Proposition 19. We first define two random variables:

$$X_n^{'} = b_n E\left[\bar{F}_{\Gamma_n|\epsilon_n,\Theta_n}\left(c_F + b_n(k_I+\Theta_n k_R + k_F - \epsilon_n)|\epsilon_n,\Theta_n\right)\right]$$

$$Y_n^{'} = b_n E\left[F_{\Gamma_n|\epsilon_n,\Theta_n}\left(c_F + b_n(k_I+\Theta_n k_R - \epsilon_n)|\epsilon_n,\Theta_n\right) - F_{\Gamma_n|\epsilon_n,\Theta_n}\left(b_n(k_I+\Theta_n k_R - \epsilon_n)|\epsilon_n,\Theta_n\right)\right].$$

(i) As in the proof of Proposition 13, we use implicit differentiation to evaluate these derivatives. $\frac{dk_I^*}{d\alpha_R} = \frac{dk_R^*}{d\alpha_I} = E\left[\sum_{n=1}^N X_n^{'}\right] E\left[\sum_{n=1}^N \Theta_n Y_n^{'}\right]/H^{'}$, where $H^{'}$ is the determinant of the Hessian (which is positive). Thus, $\frac{dk_I^*}{d\alpha_R} \geqslant 0$, indicating that the inflexible and renewable sources are substitutes. (ii) $\frac{dk_I^*}{d\alpha_F} = \frac{dk_F^*}{d\alpha_I} \geqslant Z/H$, where $Z = E\left[\sum_{n=1}^N X_n^{'}\right] E\left[\sum_{n=1}^N \Theta_n^2 Y_n^{'}\right] - E\left[\sum_{n=1}^N \Theta_n X_n^{'}\right] E\left[\sum_{n=1}^N \Theta_n Y_n^{'}\right]$. It can be shown that $Z = \left[\sum_{n=1}^N b_n(1-q_n)\int_{\xi=0}^{\infty}\left[\int_{\gamma=c_F+b_n(k_I+k_F-\xi)}^{\infty} f_{\Gamma_n}(\gamma)\,d\gamma\right] f_{\epsilon_n}(\xi)\,d\xi\right]$

$\times \left[\sum_{n=1}^{N} b_n q_n \int_{\xi=0}^{\infty} \left[\int_{\gamma=b_n(k_I+k_R-\xi)}^{c_F+b_n(k_I+k_R-\xi)} f_{\Gamma_n}(\gamma)\, d\gamma \right] f_{\epsilon_n}(\xi)\, d\xi \right]$ under the Bernoulli intermittency assumption. Hence, Z is positive so that the inflexible and flexible sources are substitutes as well. (iii) Finally, considering Assumption 2, $\frac{dk_R^*}{d\alpha_F} = \frac{dk_F^*}{d\alpha_R} = -T/H$, where $T = E\left[\sum_{n=1}^{N} X_n'\right] E\left[\sum_{n=1}^{N} \Theta_n Y_n'\right] - E\left[\sum_{n=1}^{N} \Theta_n X_n'\right] E\left[\sum_{n=1}^{N} Y_n'\right]$. Under the Bernoulli intermittency distribution with $q_n = q$ for all n,

$T = q(1-q)\left[\sum_{n=1}^{N} b_n c_F \frac{1}{U_n - L_n}\right] \left[\sum_{n=1}^{N} b_n \int_{\xi=0}^{\infty} \int_{\gamma=c_F+b_n(k_I+k_F-\xi)}^{c_F+b_n(k_I+k_R+k_F-\xi)} f_{\Gamma_n}(\gamma) f_{\epsilon_n}(\xi)\, d\gamma d\xi\right]$.

Since T is positive, $\frac{dk_R^*}{d\alpha_F} \leqslant 0$, hence the renewable and flexible sources are complements. □

B.2 Estimation of Cost Parameters

We first note that α_i for $i \in \{I, R, F\}$ is given in dollars per megawatt (MW, unit for the capacity of power plants) per day as we focus on a daily cost for a utility firm. The generation costs c_I and c_F, on the other hand, are given in dollars per MWperiod, where period refers to a 5-min length operating period. To estimate these parameters, we adopt a similar approach as in Appendix A.3 by using the Transparent Cost Database (TCDB, http://en.openei.org/apps/TCDB/), which tracks various publications that estimate cost figures for power plants. The median estimate for the overnight capital cost of coal power plants (inflexible source) is \$1.97M per MW. Dividing this cost by the median useful life of these plants (60 years as reported in TCDB), we find that α_I = \$91 per MW per day. For the renewable source, we consider wind energy. According to TCDB, median overnight capital cost in this case is \$1.57M per MW and the economic life of wind plants is 30 years, hence α_R = \$145 per MW per day. For the flexible source, we consider natural gas with combustion turbine whose median overnight capital cost is \$0.61M and economic life is 30 years, indicating that α_F = \$56 per MW per day. Finally, based on TCDB, c_I = \$0.3 per MWperiod and c_F = \$0.6 per MWperiod.

B.3 Analysis of $\pi(k_R)$

We note that the benefit function is given as:

$$\pi^j(k_R) = \Pi^j(0) - \Pi^j(k_R) = \left[G^j(0) - G^j(k_R)\right] + [\alpha_R(0) - \alpha_R(k_R)] = a^j\sqrt{k_R} + b^j k_R - \beta_R k_R. \tag{B.3}$$

Thus, the optimal investment level is $k_R^* = \left(\frac{a^j}{2(\beta_R - b^j)}\right)^2$ as long as $\beta_R > b^j$ for each $j \in \{I, F\}$. We report our estimates of a^j and b^j along with the adjusted R^2 values in Table B.1.

Table B.1: Parameter estimates in the case study

	Solar Energy			Wind Energy		
	a^j	b^j	Adjusted R^2	a^j	b^j	Adjusted R^2
Flexible Mix	16,274,584	1,455,910	0.9999	51,365,257	1,125,873	0.9969
Inflexible Mix	19,832,058	1,347,503	0.9995	61,843,458	851,651	0.9951

Finally, we note that, in the case study, we do not consider a representative day.

Instead, our time horizon is the entire economic life of solar and wind energy. Thus, for wind energy we use β_r = \$1.57M per MW as explained above. For solar energy, we use β_r = \$1.625M per MW. This value is the median of overnight capital costs for solar energy in 2014 (the most recent year) in TCDB.

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