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

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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. Our study suggests that reducing carbon emissions through increasing renewable energy investments requires a careful attention to the pricing policy and the market characteristics of each region.

Key words: Renewable Energy Investment, Electricity Pricing Policies, Carbon Emissions.

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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 2015), 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 2014a). 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 2015). 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 depend 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 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 paper is organized as follows. Section 2 summarizes the related literature. Section 3 provides preliminaries for the energy markets and utility firms. Section 4 analyzes the impact of pricing policies on the investment level of different energy sources, the carbon emission level, and the consumer surplus. Section 5 reports the impact of subsidies on the investment and carbon emission levels. Section 6 validates our findings by presenting a case study based on the Texas data. Section 7 discusses the extensions and Section 8 concludes. All proofs are given in Appendix B.

2 Literature Review

Our paper 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 paper 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 paper 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 paper 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.

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 off-peak demand period or the nighttime ($i = n$) and the second period is 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 $p_i \geq 0$ 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 $D_d\left(p_d, p_n\right) = a_d - \gamma p_d + \delta p_n$, and the nighttime demand is $D_n\left(p_n, p_d\right) = a_n - \gamma p_n + \delta p_d$, 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 $\tilde{q}_i$:

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

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 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 2015). 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 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

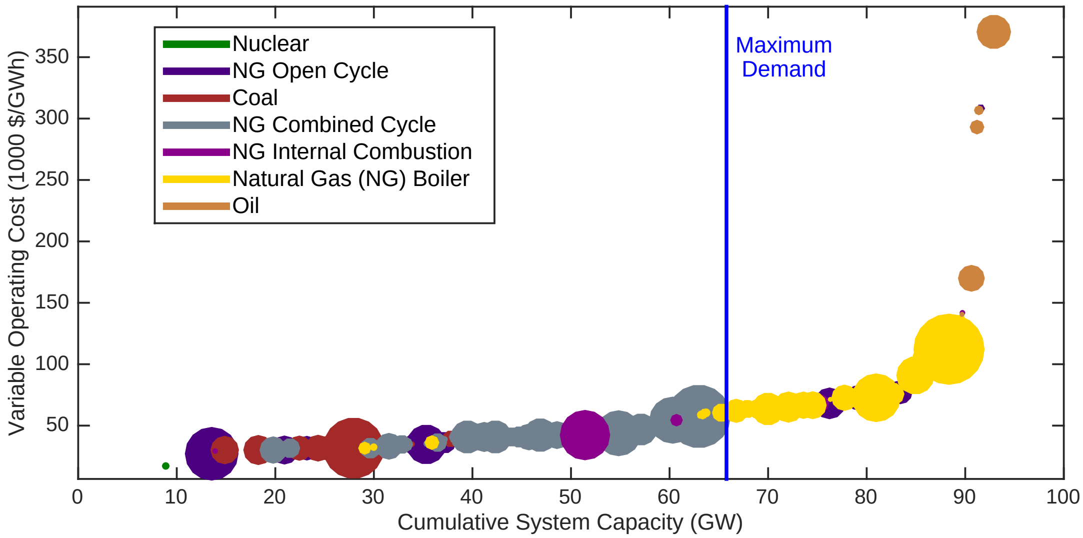


Figure 1: Variable Operating Costs of Power Plants in Texas Electricity System, 2010
Notes. Each circle in this graph represents one conventional power plant, where the size of the circle is proportional to the capacity of the plant.

about this graph. First, the 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 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

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

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 1). Thus, the generation cost is convex and increasing in the total capacity.

[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 1.

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.

We present the estimates of cost and intermittency parameters for various generation sources in Table 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 6. The estimation of the investment and generation cost rates are explained in Appendix D.

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 $e \leq 1$, 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

$$ECE = \sum_{i \in \{n,d\}} E_{\tilde{q}_i} \left[\left(D_i \left(p_i, p_{-i} \right) - k_c - k_r \tilde{q}_i \right)^+ + e \min \left(k_c, \left(D_i \left(p_i, p_{-i} \right) - k_r \tilde{q}_i \right)^+ \right) \right], \tag{3}$$

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

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 D for the estimation procedure of β and v.

Table 1: Model Parameters for Different Energy Sources

the second term is the expected emission amount from the new conventional source. In (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. A summary of notation and all proofs are given in Appendix A and B.

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:

$$\max_{k_r,k_c,p_n,p_d} \Pi\left(k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} E_{\tilde{q}_i}\Big[p_i D_i\left(p_i,p_{-i}\right) - g\Big(\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+\Big)$$
$$-v\min\Big(k_c,\left(D_i\left(p_i,p_{-i}\right)-k_r\tilde{q}_i\right)^+\Big)\Big] - \alpha_r\left(k_r\right) - \alpha_c\left(k_c\right). \quad (4)$$

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 paper.

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

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 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 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 (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 2015).

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 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 2011). Furthermore, Assumption 1 part (ii) ensures that the optimal daytime price is higher than the optimal nighttime price under both pricing policies, i.e., $p_d^* \geq p_n^*$. 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

[2]See the discussion following (3) for an explanation of the units for the argument of $g(\cdot)$.

price and daytime price, respectively, under the pricing policy $j \in \{\text{peak}, \text{flat}\}$.

Lemma 1. *The maximization problem in (4) is jointly concave in k_r, k_c, p_n, and p_d. Furthermore, at optimality*

$$p_n^{j*} + p_d^{j*} = \frac{a_n + a_d + (\gamma - \delta)(2v + \beta_c)}{2(\gamma - \delta)}, \qquad j \in \{peak, flat\}. \tag{5}$$

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).

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 1. *(i) If*

$$\frac{q_n}{q_d} \leq 1, \tag{6}$$

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

$$\frac{q_n}{q_d} \geq R_1 = \frac{C_1\left(f\left(\beta_r/q_n\right) + (a_d - a_n)\right) + C_2}{C_1\left(f\left(\beta_r/q_n\right) - (a_d - a_n)\right) + C_2}, \tag{7}$$

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

Proposition 1 compares the investment level of a renewable energy source between flat pricing and peak pricing. Proposition 1 (i) states that for a renewable source whose electricity output in the daytime is greater than that in the nighttime (i.e., $q_d \geq q_n$), 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 1 (ii), on the other hand, provides a condition that complements part (i). It is straightforward to show that $R_1 \geq 1$. Thus, Proposition 1 (ii) states that for a renewable source whose electricity output in the nighttime is sufficiently greater than that in the daytime (i.e., $q_n/q_d \geq R_1 \geq 1$), peak pricing leads to a higher investment level than flat pricing. As we state in Section 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 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 1. We shall see that flat pricing indeed increases wind energy investments in the Texas region.

Proposition 1 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 2. *(i) If*

$$\frac{1-q_n}{1-q_d} \leq 1, \tag{8}$$

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

$$\frac{1-q_n}{1-q_d} \geq R_2 = \frac{C_1\left(f\left(\beta_r/q_d\right)+\left(a_d-a_n\right)\right)+C_2}{C_1\left(f\left(\beta_r/q_d\right)-\left(a_d-a_n\right)\right)+C_2}, \tag{9}$$

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

Proposition 2 (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 2 (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.

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 (3) reduces to

$$ECE = \sum_{i\in\{n,d\}} \left[D_i\left(p_i, p_{-i}\right) - q_i k_r - (1-e)k_c\right], \tag{10}$$

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

Everything else being equal, (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

$$\bar{e} = \frac{2 - q_n - q_d}{2}. \tag{11}$$

This threshold value suggests that for the new conventional source whose emission intensity is sufficiently high, i.e., $e \geq \bar{e}$, 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 3 shows this comparison.

Proposition 3. *Suppose $e \geq \bar{e}$. (i) $ECE^{flat} \leq ECE^{peak}$ if $q_n/q_d \leq 1$. (ii) On the other hand, $ECE^{flat} \geq ECE^{peak}$ if $q_n/q_d \geq R_1$, where R_1 is defined in* (7)*. (iii) If $e < \bar{e}$, the statements in part (i) and (ii) might not hold.*

Proposition 3 (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 3 (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 3 (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 based on the parameters estimated from the Texas data in the case study of Section 6. Figure 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 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.

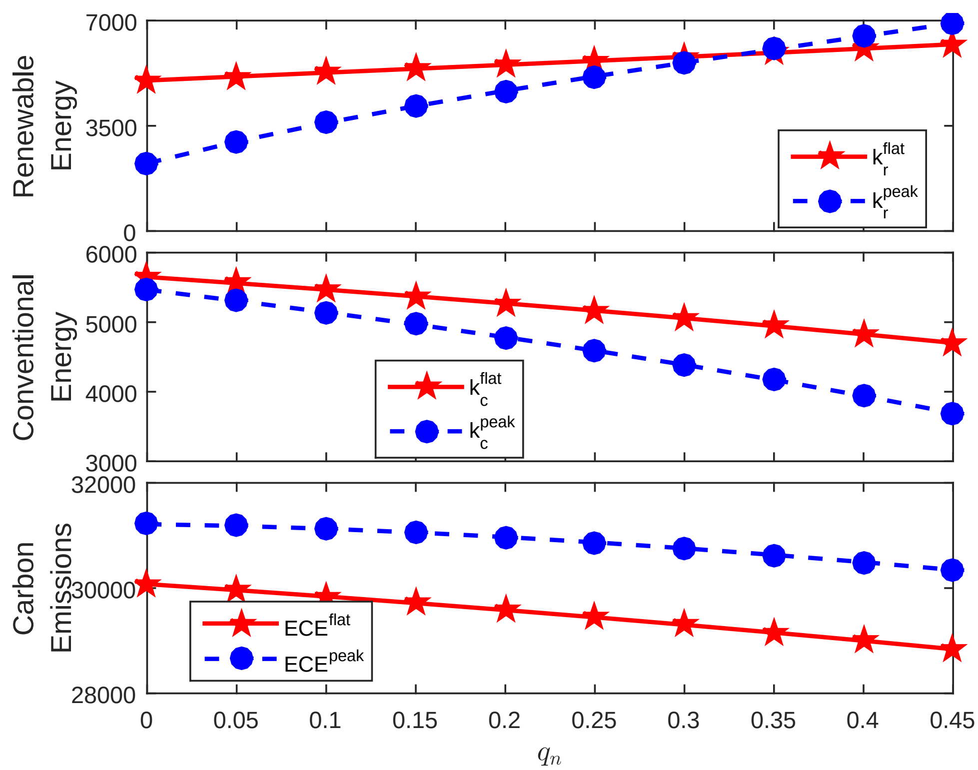
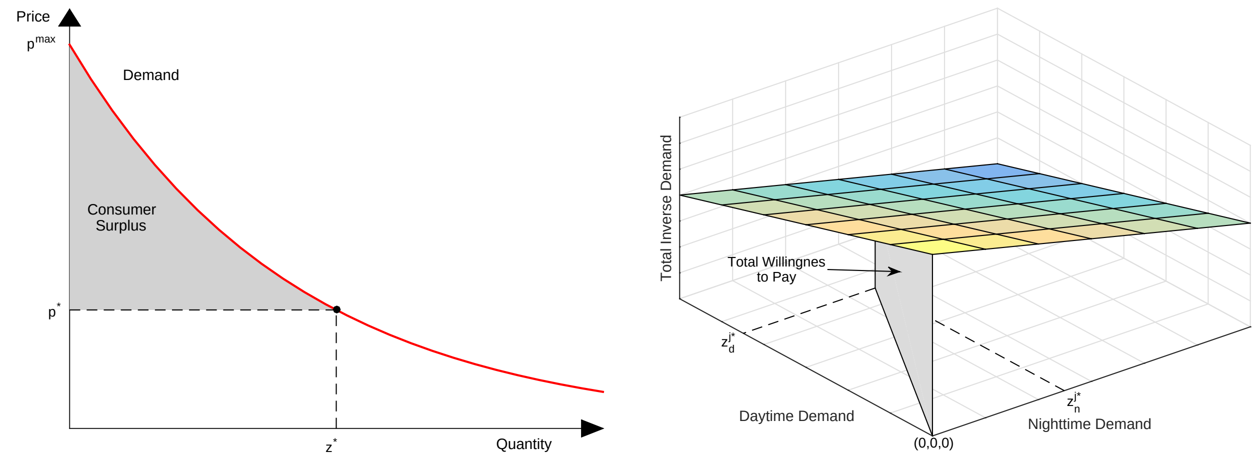


Figure 2: Investment Levels and Carbon Emissions

Notes. We use the following parameter values: $a_n = 30000$, $a_d = 40000$, $q_d = 0.28$, $C_1 = 10^{-6}$, and $C_2 = 10^{-2}$. These are in line with the real data used in the case study of Section 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 $e = 0$, $\beta_c = 161.1$, and $v = 141.6$. 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 $\beta_r = 62.3$.



(a) Single Product

(b) Two Products

Figure 3: Consumer Surplus

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 3a.

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

$$\xi_i\left(z_i, z_{-i}\right) = \frac{\gamma\left(a_i - z_i\right) + \delta\left(a_{-i} - z_{-i}\right)}{\gamma^2 - \delta^2}, \qquad i \in \{n, d\}, \tag{12}$$

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

$$CS^j = \oint_{C=(0,0)}^{(z_n^{j*}, z_d^{j*})} \xi_n (z_n, z_d)\, dz_n + \xi_d (z_d, z_n)\, dz_d - p_n^{j*} z_n^{j*} - p_d^{j*} z_d^{j*}, \tag{13}$$

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 3b. The line integral on the right hand side of (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 4. $CS^{flat} \geq CS^{peak}$.

According to Proposition 4, 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 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 E. 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.

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

5 Impact of Subsidies on Investment and Emissions

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 5.

(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 $e \geq \bar{e} = (2 - q_n - q_d)/2$*; 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 $e \geq \max\{\bar{e}, (\gamma + \delta)/2\gamma\}$*, where* γ *and* δ *are the price sensitivity parameters; otherwise, carbon emissions might decrease.*

Proposition 5 (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 4.2. We present an illustrative example of this case in Figure 4 by plotting the expected carbon emissions as a function of a cash grant for the renewable energy source. As seen in Figure 4, the amount of expected carbon emissions increases in the cash grant as long as the unit investment

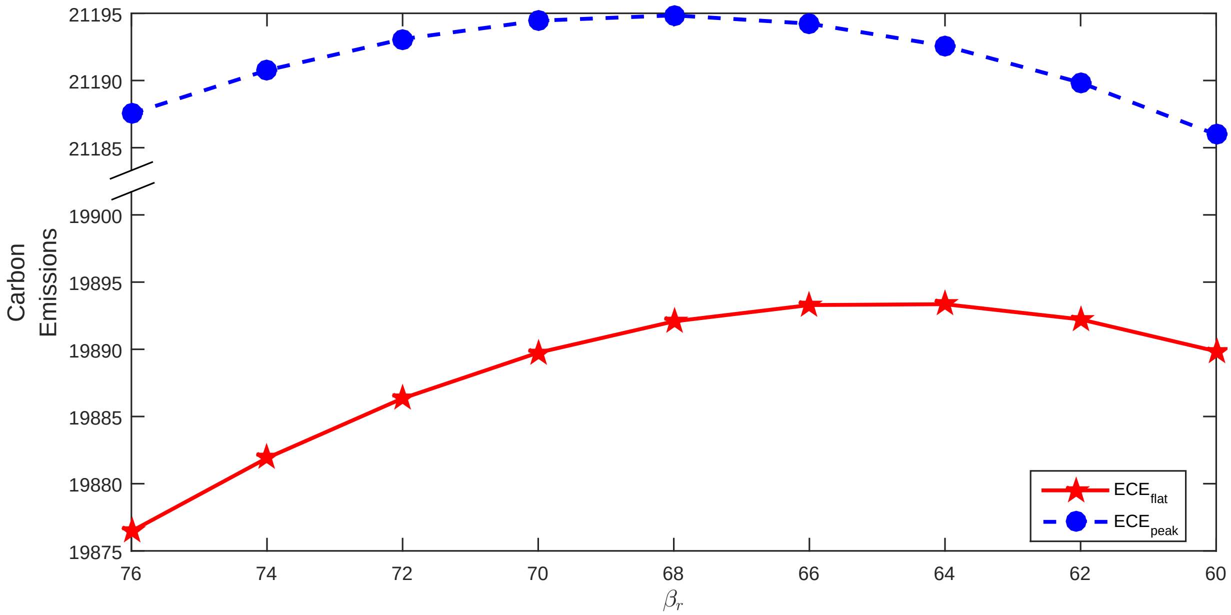


Figure 4: Effect of a Direct Subsidy on Expected Carbon Emissions
Notes. We use the same values for $a_n, a_d, C_1, C_2, \gamma, \delta, \beta_c, v$, and e as in Figure 2. We consider solar energy as the renewable source and use its intermittency and cost parameters reported in Table 1.

cost (β_r) is less than 68. Furthermore, flat pricing leads to lower emissions. This is because the renewable energy investment level is higher under flat pricing.

Proposition 5 (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.

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

$$\max_{k_r,k_c,p_n,p_d} \Pi\left(k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} E_{\tilde{q}_i}\Big[p_i D_i\left(p_i,p_{-i}\right) - g\left(\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+\right) - t\left(D_i\left(p_i,p_{-i}\right)-k_c-k_r\tilde{q}_i\right)^+$$
$$- \left(v+te\right)\min\left(k_c,\left(D_i\left(p_i,p_{-i}\right)-k_r\tilde{q}_i\right)^+\right)\Big] - \alpha_r\left(k_r\right) - \alpha_c\left(k_c\right). \tag{14}$$

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 6. *An indirect subsidy results in (i) higher renewable and lower conventional energy investments if* $e \geq \max\{\bar{e}, (\gamma+\delta)/2\gamma\}$*; 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 6 (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 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 6 (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).

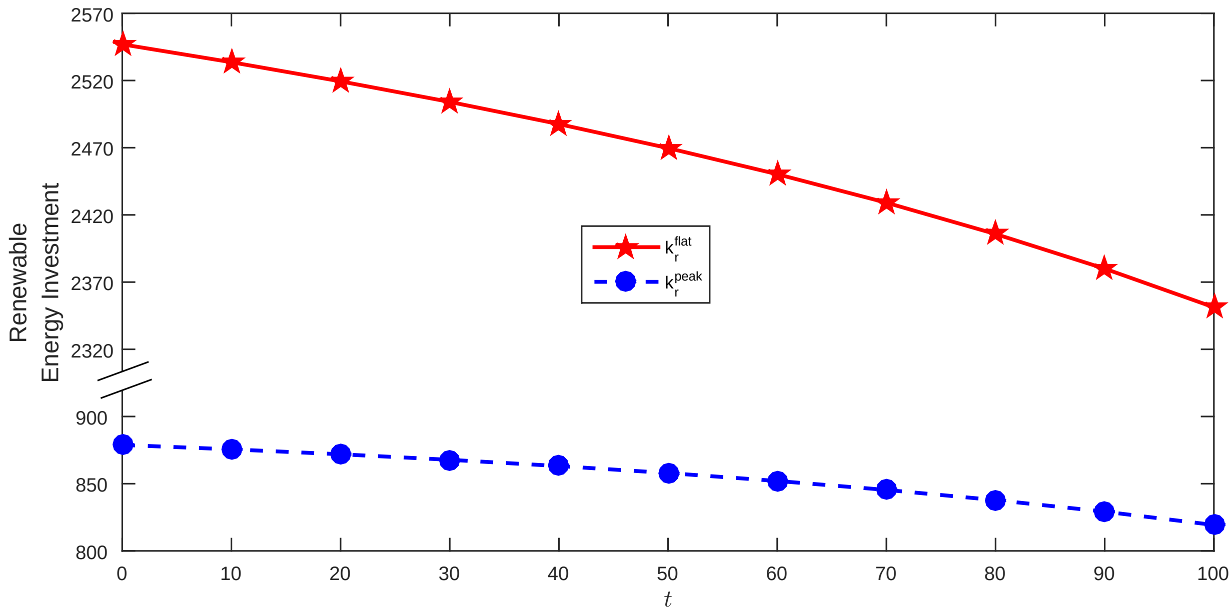


Figure 5: Effect of an Indirect Subsidy on Renewable Energy Investment Level

Notes. We use the same parameter values as in Figure 4.

6 Case Study: Texas Data

We use real electricity generation and demand data from the state of Texas in 2010 to validate Propositions 1 and 2.

Recall that our result is obtained by solving the problem in (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) operated 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 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 1 and 2.

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 paper, 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. One of the authors 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:

$$\max_{k_r, k_c} \Pi^j(k_r, k_c) = \mathit{Revenue}^j - G^j(k_r, k_c) - \alpha_r(k_r) - \alpha_c(k_c), \tag{15}$$

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 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:

$$\pi^j(k_r, k_c) = \Pi^j(k_r, k_c) - \Pi^j(0,0) = [G^j(0,0) - G^j(k_r, k_c)] + [\alpha_r(0) - \alpha_r(k_r)] + [\alpha_c(0) - \alpha_c(k_c)]. \tag{16}$$

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, $[\alpha_r(0)-\alpha_r(k)]$ and $[\alpha_c(0)-\alpha_c(k)]$, 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., $[G^j(0,0) - G^j(k_r, k_c)]$ 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:

$$[G^j(0,0) - G^j(k_r, k_c)] = l_r^j \times k_r + m_r^j \times \sqrt{k_r} + l_c^j \times k_c + m_c^j \times \sqrt{k_c}, \tag{17}$$

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 and 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 C.

	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: Case Study Results for Solar Energy

According to Table 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 this case, the new conventional

[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 1. This is consistent with the aforementioned investments in advanced coal units (Duke Energy 2015).

[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 and 3.

	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

Table 3: Case Study Results for Wind Energy

energy investment is lower under flat pricing. Table 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 1 and 2 predict.

Validation of Propositions 1 and 2. Proposition 1 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 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 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 $a_d = 40,834$ ($a_n = 32,003$, 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 1 (i) predicts that the investment in solar energy is higher under flat pricing. This is consistent with our numerical finding in Table 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. This numerical observation is consistent with the finding in Table 3 which also suggests that the investment in wind energy is higher under the flat pricing policy. This completes the validation of Proposition 1.

For the new conventional source, Proposition 2 states that if the renewable source satisfies $(1 - q_n)/(1 - q_d) \leq 1$, 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 and 3 are consistent with what Proposition 2 predicts. This completes the validation of Proposition 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

$$\theta \leq \bar{\theta} = \frac{q_n p_n + q_d p_d}{\beta_{\mathrm{DG}}}. \tag{18}$$

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 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:

$$\max_{k_r,k_c,p_n,p_d} \Pi\left(k_{DG},k_r,k_c,p_n,p_d\right) = \sum_{i\in\{n,d\}} E_{\tilde{q}_i}\Big[p_i\left(D_i\left(p_i,p_{-i}\right)-k_{DG}\tilde{q}_i\right) - g\Big(\left(D_i\left(p_i,p_{-i}\right)-k_c-\left(k_{DG}+k_r\right)\tilde{q}_i\right)^+\Big)$$

$$-v\min\Big(k_c,\left(D_i\left(p_i,p_{-i}\right)-\left(k_{DG}+k_r\right)\tilde{q}_i\right)^+\Big)\Big] - \alpha_r\left(k_r\right)-\alpha_c\left(k_c\right). \quad (19)$$

Proposition 7. *(i) The maximization problem in (19) is jointly concave in k_r, k_c, p_n, and p_d.* *(ii) If $q_n \geq q_d$, then $k_{DG}^{flat} \geq k_{DG}^{peak}$; otherwise, $k_{DG}^{flat} \leq k_{DG}^{peak}$.*

Proposition 7 states that flat pricing leads to a higher renewable energy investment for DGs if $q_n \geq q_d$, 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), and $\beta_r \geq \left(E\left[\tilde{q}_n\right]+E\left[\tilde{q}_d\right]\right)v+$ $\left(E\left[\tilde{q}_n\right]-E\left[\tilde{q}_n^2\right]-E\left[\tilde{q}_d^2\right]\right)g'\left(\left(3a_n-a_d\right)/4\right)+E\left[\tilde{q}_d\right]g'\left(\left(-a_n+3a_d\right)/4\right).$*

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 1, 2, and 3 in the following proposition.

Proposition 8. *Suppose that Assumption 2 holds. Consider the utility firm model in (4),*

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

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

Proposition 8 shows that flat pricing leads to a higher renewable energy investment, a lower conventional energy investment, and lower carbon emissions if $E[\tilde{q}_d] \geq E[\tilde{q}_n]$, i.e., when solar energy investments are considered. On the other hand, if wind energy investments (i.e., $E[\tilde{q}_d] \leq E[\tilde{q}_n]$) 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 (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 $\beta_r \geq q_n(v + g^{'}(L)) + q_d v + \max(q_n, q_d) g^{'}(a_d - a_n + L)$ and the $g(\cdot)$ function is quadratic, the results in Proposition 8 can be established. The proof is available from the authors.

8 Concluding Remarks

This paper 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 paper 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 paper 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 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.

[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 producer surplus as well as long-term implications of carbon emissions in our case.

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Online Appendix

A Summary of Notation

Notation	Explanation	Notation	Explanation
$i \in \{n, d\}$	subscript for period	q_i	probability that $\tilde{q}_i = 1$ when $\tilde{q}_i$ follows a two-point distribution
$j \in \{\text{flat}, \text{peak}\}$	superscript for pricing policy	$g(\cdot)$	generation cost function
p_i	price of electricity in period i	C_1, C_2, C_3, C_4	cost paramaters in $g(\cdot)$
$D_i(p_i, p_{-i})$	demand of electricity in period i	v	variable cost of the new conventional source
a_i	market size in period i	e	emission intensity of the new conventional source
γ	own-price sensitivity of demand	$\alpha_r(\cdot), \alpha_c(\cdot)$	investment cost function of renewable and conventional source, respectively
δ	cross-price sensitivity of demand	β_r, β_c	unit investment cost of renewable and conventional source, respectively
$\tilde{q}_i$	intermittency factor in period i	ECE^j	expected carbon emissions under pricing policy j
$\xi_i(\cdot, \cdot)$	inverse demand function in period i	CS^j	consumer surplus under pricing policy j

B 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 $\tilde{q}_i$, (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 $k_r + k_c \geq D_n$. There are two cases: first, assume that $k_r + k_c > D_d$. Then, the FOC with respect to (wrt) k_r is $\mathcal{F}(k_r,k_c,p_n,p_d) = q_n v 1_{k_r \leq D_n} + q_d v 1_{k_r \leq D_d} - \beta_r$, where 1. is the indicator function. By Assumption 1, $\beta_r \geq v(q_n + q_d)$, so this case cannot appear in the optimal solution. Second, assume that $k_r + k_c \leq D_d$. Then, the FOC wrt k_r is $\mathcal{F}(k_r,k_c,p_n,p_d) = q_n v 1_{k_r \leq D_n} + q_d g'(D_d - k_c - k_r) - \beta_r$. Note that this function can at most be $q_n v + q_d g'(a_d - a_n) - \beta_r \leq 0$ 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, $k_r + k_c \leq D_n$. 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 $\mathcal{I}(k_r,k_c,p_n,p_d)$:

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

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

$D_d\left(p_d^*, p_n^*\right) \geq D_n\left(p_n^*, p_d^*\right).$ $\square$

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

$$\begin{aligned} \frac{1 - q_n}{1 - q_d} &= \frac{g^{'}\left(D_d^{\text{flat}} - k_c^{\text{flat}}\right) - g^{'}\left(D_d^{\text{peak}} - k_c^{\text{peak}}\right)}{g^{'}\left(D_n^{\text{peak}} - k_c^{\text{peak}}\right) - g^{'}\left(D_n^{\text{flat}} - k_c^{\text{flat}}\right)} \\ &= \frac{\left(\tilde{D} - \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_d^{\text{flat}} - \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}}\right) + C_2\right)}{\left(\tilde{D} + \left(k_c^{\text{flat}} - k_c^{\text{peak}}\right)\right)\left(C_1\left(2D_n^{\text{flat}} + \tilde{D} - k_c^{\text{flat}} - k_c^{\text{peak}}\right) + C_2\right)} = R_c, \end{aligned} \tag{B.1}$$

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 $q_n/q_d \leq 1$, then $(1 - q_n)/(1 - q_d) \geq 1$ so that R_c is greater than R_k. Thus, $k_r^{\text{flat}} \geq k_r^{\text{peak}}$ because otherwise that would imply that R_c is less than R_k. (ii) We note that $k_r^{\text{peak}} \geq k_r^{\text{flat}}$ if $\mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{peak}}, p_n^{\text{peak}}, p_d^{\text{peak}}\right) \geq \mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{flat}}, p_n^{\text{flat}}, p_d^{\text{flat}}\right) = 0$, 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 $\mathcal{F}\left(k_r^{\text{flat}}, k_p^{\text{peak}}, p_n^{\text{peak}}, p_d^{\text{peak}}\right) \geq \mathcal{F}\left(k_r^{\text{flat}}, k_c^{\text{flat}}, p_n^{\text{flat}}, p_d^{\text{flat}}\right)$ if and only if

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

Next, we show that R_1 given in (7) is such that $R_1 \geq \underline{R}$ so that $q_n/q_d \geq R_1 > 1$ implies that $k_r^{\text{peak}} \geq k_r^{\text{flat}}$. Consider the following bound on $\underline{R}$

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

let the term on the right hand side be denoted by $\bar{R}$, where the inequality is due to the fact that $\tilde{D} \geq 0$ and $k_c^{\text{flat}} \geq k_c^{\text{peak}}$ assuming $q_n \geq q_d$ as shown in Proposition 2. 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 $k_c^{\text{flat}} + k_r^{\text{flat}} \leq D_n^{\text{flat}} - \epsilon$ for some $\epsilon \geq 0$. Define $R(\epsilon)$ as

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

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 $q_n/q_d \geq R(\epsilon)$, then $k_r^{\text{peak}} \geq k_r^{\text{flat}}$. 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 $k_c^{\text{flat}} + k_r^{\text{flat}} \leq D_n^{\text{flat}} - \epsilon$ holds if $q_n g'\left(D_n^{\text{flat}} - \left(D_n^{\text{flat}} - \epsilon\right)\right) + q_d g'\left(D_d^{\text{flat}} - \left(D_n^{\text{flat}} - \epsilon\right)\right) \leq \beta_r$. This inequality is valid if $\max(q_n, q_d)\, g'(a_d - a_n + 2\epsilon) \leq \beta_r$, where we use the fact that $g'(\cdot)$ is a convex function. Thus, we observe that

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

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 $q_n \geq q_d$. 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 $q_n/q_d \geq R_1 \geq 1$ implies $k_r^{\text{peak}} \geq k_r^{\text{flat}}$. □

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

Proof of Proposition 3. Based on (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 $e \geq \bar{e}$ as we assume so. (i) Note that $ECE^{\text{flat}} \leq ECE^{\text{peak}}$ if $k_r^{\text{flat}} \geq k_r^{\text{peak}}$ and $k_r^{\text{flat}} + k_c^{\text{flat}} \geq k_r^{\text{peak}} + k_c^{\text{peak}}$. The first condition holds due to Proposition 1 as long as $q_n/q_d \leq 1$. Thus, to prove this part of the proposition, we need to show that $k_r^{\text{flat}} + k_c^{\text{flat}} \geq k_r^{\text{peak}} + k_c^{\text{peak}}$. 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:

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

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

Proof of Proposition 4. Based on the definition of consumer surplus given in (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 $a_d - a_n \geq (\gamma+\delta)\Delta$. This holds because, as we show in the proof of Lemma 1, under Assumption 1, $(a_d - a_n)/(\gamma+\delta) \geq p_d^{\text{peak}} - p_n^{\text{peak}} = 2\Delta$. $\square$

Proof of Proposition 5. (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 $e \geq \bar{e}$. 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 $e \geq \bar{e}$. On the other hand, if $e < \bar{e}$, Figure 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. $\square$

Proof of Proposition 6. This proof is similar to that of Proposition 5. $\square$

Proof of Proposition 7. (i) It can be shown that the Hessian of (19) 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 $q_n \geq q_d$, then $q_n \Delta_n \geq q_d \Delta_d$, which, in turn, implies that $k_{DG}^{\text{flat}} \geq k_{DG}^{\text{peak}}$. 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

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

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

Proof of Proposition 8. The Hessian of the utility firm's profit maximization problem given in (4) is negative definite, and hence the FOCs are sufficient. Under Assumption 2, it can be shown that $k_r + k_c \leq D_n^j$ for $j \in \{\text{flat}, \text{peak}\}$. Furthermore, solving the FOCs simultaneously, we observe that $k_r^{\text{flat}} - k_r^{\text{peak}} = 2\tilde{D}\left(E[\tilde{q}_d] - E[\tilde{q}_n]\right)/A$, $k_c^{\text{flat}} - k_c^{\text{peak}} = \tilde{D}\left(-E[\tilde{q}_d]^2 + E[\tilde{q}_n]^2\right)/A$, and $ECE^{\text{flat}} - ECE^{\text{peak}} = 2\tilde{D}e\left(-E[\tilde{q}_d]^2 + E[\tilde{q}_n]^2\right)/A$, where $\tilde{D}$ is the difference between optimal demand levels under flat and peak pricing in a period and $A = Var[\tilde{q}_n] + Var[\tilde{q}_d] + E[\tilde{q}_n^2] + E[\tilde{q}_d^2] - 2E[\tilde{q}_n]E[\tilde{q}_d] \geq 0$. Hence, $k_r^{\text{flat}} \geq k_r^{\text{peak}}$, $k_c^{\text{peak}} \geq k_c^{\text{flat}}$ and $ECE^{\text{peak}} \geq ECE^{\text{flat}}$ if $E[\tilde{q}_d] \geq E[\tilde{q}_n]$, otherwise, all three inequalities are reversed. □

C Analysis of $\pi(k_r, k_j)$

We note that the benefit function is given as:

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

where we substitute (17) 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 (17) 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 4 and 5, and Figure 6 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 $\beta_r \geq l_r^j$ and $\beta_c \geq l_c^j$ under pricing policy $j \in \{\text{flat}, \text{peak}\}$. We report these optimal investment levels in Tables 2 and 3.

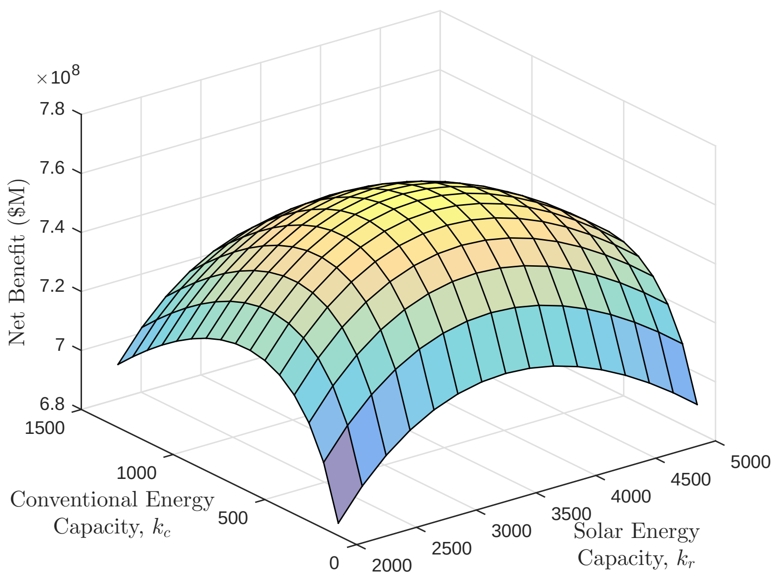

Figure 6: Net Benefit Function, $\pi(k_r, k_c)$, for Solar Energy under Flat Pricing

	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

Table 4: Parameter Estimates for Solar Energy

D 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 v for various electricity sources. We use cost estimates from the Transparent Cost

	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

Table 5: Parameter Estimates for Wind Energy

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, $\beta_r = \$1.57 \times 10^6$/MW/17.5years = \$249.2/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[8], 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 2014b 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 $\beta_c = 1,094,444 (= 1,970,000/1.8)$. 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 $\beta_c = 579,412$.

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

E Consumer Surplus and Utility

We first note that, in general, computing the line integral given in (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:

$$\begin{aligned}
&\max_{z_n, z_d} U(z_n, z_d) = m + \zeta_n z_n + \zeta_d z_d - \frac{\eta}{2}\left(z_n^2 + 2\lambda z_n z_d + z_d^2\right) \\
&\text{s.t. } p_n z_n + p_d z_d + m \leq I,
\end{aligned}$$

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:

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

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: $U(z_n, z_d) = m + \zeta_n z_n + \zeta_d z_d - \frac{\eta}{2}\left(z_n^2 + 2\lambda z_n z_d + z_d^2\right)$. We next compare the utility of consumers under flat and peak pricing. Note that $U\left(z_n^{\text{flat}*}, z_d^{\text{flat}*}\right) - \left(z_n^{\text{peak}*}, z_d^{\text{peak}*}\right) = (\delta + \gamma)\,\Delta^2 \geq 0$, 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 4.