Information and Rivalry: How Do Firms Respond to Competitors' Investment Decision under Environmental Uncertainty? -- Evidence from the U.S. Electric Utility Companies' Adoption of Solar Energy

Shaohua Lu*
Fisher College of Business
Ohio State University
256A Fisher Hall 2100 Neil Avenue
Columbus, OH 43210
Tel: (614)-292-5317
E-mail: lu_492@fisher.osu.edu

Jaideep Anand
Fisher College of Business
Ohio State University
836 Fisher Hall 2100 Neil Avenue
Columbus, OH 43210
Tel: (614)-247-6851
Fax: (614)-764-2557
E-mail: anand_18@osu.edu

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Abstract

A broad literature in strategy examines how competitors' presence affects the focal firm's strategic decision making. This stream of research identifies imitation and deterrence as two distinct patterns, and concludes with an inverted U-shaped relationship. Yet, we propose in this study that under environmental uncertainty competition could both strengthen and undermine the benefits of imitation, and consequently lead to a U-shaped relationship. Combining both information- and competition-based theories, we develop stylized models of how firms update their beliefs and make strategic decision under environmental uncertainty. The analytical results suggest a U-shaped relationship, and we find empirical evidence consistent with our predictions using data on the U.S. electric utility companies' commitment to develop utility-scale solar projects.

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Strategy is about the choice of direction of firms (Rumelt, 1994: 42). A broad literature examines how competitor's prior choices affect the focal firm's decision making, and identifies imitation and avoidance as two distinct decision-making patterns concluding with an inverted U-shaped association. Specifically, the benefits of imitation induce firms to make similar strategic choices; as the intensity of competition increases, it countervails such benefits and leads to avoidance in firms' decision-making (e.g., Lieberman & Asaba, 2006; Anand, *et al*, 2009; Koçak, & Özcan, 2013; Alcácer, *et al,* 2015). We posit in this study, however, that competition could also strengthen the benefits of imitation and thus generate imitative decision making under environmental uncertainty. Combining information- and competition-based theories, we develop stylized models of how firms update their beliefs and make strategic decisions in a highly uncertain environment. The analytical results suggest a U-shaped relationship: avoidance is followed by imitation as the intensity of competition increases. Using data on the U.S. electric utility companies' commitment to develop utility-scale solar projects, we find supporting evidence for our predictions.

Imitation is a common observation of how firms respond to competitors' strategic decisions under uncertainty (please see Lieberman & Asaba, 2006 for a comprehensive review). The rationale behind imitation includes reducing the cost of searching, legitimation benefits, positive externality such as knowledge spillovers and access to resources, and serving as an external information source. Meanwhile, competitors' decision might have a structural impact on the focal firm's decision-making (Bain, 1959; Tirole, 1988). In an oligopolistic market, one firm's payoffs depend on the strategic choices made by competitors. Specifically, competitors' action enhances the intensity of competition, which in turn reduces the benefits of imitation and hinders the focal firm from making the same choice. Combining the two-fold impact of competitors' action, the extent studies have identified an inverted U-shaped relationship: firms tend to imitate first, but avoid later taking the same action with intensifying competition. While our work is closely related to the conventional wisdom on the dual role of competitors' prior choice, we recognize that in a highly uncertain environment these two mechanisms might not independently affect how firms respond to competitors' presence. In addition to the countervailing effect, increasing competition could also affect firms' decision making by reinforcing the information-based benefits of imitation.

We anchor our formal analysis on both Bayesian observational leaning models in the herd behavior literature (also known as information cascades) and competitive rivalry in Industrial Organization (IO) theory, and propose a U-shaped relationship concerning how competitors' presence affects firms' decision-making under environmental uncertainty. The analytical results show that, consistent with previous observations, imitation is likely to take place when the intensity of competition is low and the avoidance becomes salient as the structural impact of competitors' presence increases. Nevertheless, our formal modeling efforts also indicate that firms tend to imitate at a high level of rivalry because competitors' action reveals extremely optimistic information about future payoffs from investing in a novel market. We conduct empirical analysis using data on the U.S. utility companies' construction of large-scale solar projects. The results lend support to our predictions. This research contributes to the literature on firms' decision making under uncertainty. We focus on the highly uncertain environmental in which it is difficult for all firms to predict future performance, and endeavor to untangle how firms make decision under such uncertain situations. It responds to the call for studies that "use environmental conditions to distinguish among theories" (Lieberman & Asaba, 2006: 376). In addition, our empirical examination enhances our understanding of how utility companies commit to novel energy sources.

The remainder of the paper is organized as follows. We begin with a discussion of theoretical background, and proceeds to the basic model structure and extended analytical models. We then describe the empirical context and develop hypotheses concerning utility companies' decision on building large-scale solar projects. The empirical analysis results are followed by discussion of implications and opportunities for future work.

THEORETICAL BACKGROUND

Making strategic decisions is fundamentally characterized by uncertainty given the inherently stochastic state of world. Uncertainty reflects an inability of a firm to predict the range of possible outcomes associated with a particular action or behavior (Knight, 1921; Milliken, 1987). It is generally defined as a lack of information regarding how to specify a unique distribution appropriate for a given situation (Mosakowski, 1997). Future payoffs from investing in the novel business domain hinge upon the realization of the state of the world, when firms are confronted with environmental uncertainty, e.g., disturbances caused by the shift in customer demands or diminishing marginal utility of incremental product improvement (Christensen & Bower, 1996; Adner, 2002; Adner and Zemsky, 2005), or the emergence of new technologies (Dosi, 1982; Tushman and Anderson, 1986; Anderson & Tushman, 1990; Henderson and Clark, 1990). Hence, it is difficult for all firms to predict the consequences of taking a certain action (Lieberman & Asaba, 2006). Environmental uncertainty is also analogous to the notion of "market uncertainty", which refers to volatility in market conditions and therefore affects all firms' decision making to the same degree (Beckman, et al, 2004; Gaba & Terlaak, 2013).

A common justification for firms' decision making under uncertainty is that they tend to imitate the choices made by competitors (Lieberman & Asaba, 2006). Small and medium-sized commercial banks, for instance, tend to follow large banks into new geographic markets and mimic their new products and service offerings (Koçak & Özcan, 2013). A variety of theoretical perspectives offer explanations for firms' imitation. Specifically, it can reduce the cost of searching. Drawing insights from Cyert and March (1963), Dimaggio and Powell (1983), for example, argue that imitation is an inexpensive search yielding "a viable solution with little expense" when "the environment creates symbolic uncertainty" (1983: 151). Moreover, firms gain legitimation benefits from imitation by conforming to audience expectations, (e.g., Hannan & Freeman, 1977, 1984; Carroll & Hannan, 2000). Furthermore, firms tend to imitate because of positive externalities, e.g., technological spillovers and access to specialized labor and intermediate inputs (Marshall, 1892). In addition, the herd behavior literature draws attention to the information component of strategic choices; the key idea is that "actions reflect information" (e.g., Bikhchandani, Hirshleifer, & Wlech, 1992, 1998; Kennedy, 2002; Hirshleifer & Teoh, 2003). Hence, imitation is a common observation concerning how competitors' presence affects firms' decision making.

The broad range of research on imitation can be organized into two categories based on the underlying information assumption. One stream of research assumes that the early movers' choices are seen as successful. Firms that first make investment choice are aware of the unique, stochastic causal structure between inputs and outputs, whereas others are in the state of ignorance. It is thus straightforward that firms are expected to imitate competitors' prior investment decisions. Alternatively, under environmental uncertainty, no firms are able to predict the consequences of taking a certain action. The herd behavior literature suggests that while firms observe information from the environment, update their beliefs, and make decisions, their actions reveal to other firms the private information they observe from the environment. "Information cascades", for instance, occur when firms make decision based on others' actions and without regard to its own observation (Bikhchandani, Hirshleifer, & Wlech, 1992). Our study focuses on the environmental uncertainty, and thus more related to the information-based argument in the herd behavior literature.

There is an alternative view of how firms' decision-making is affected by competitors' prior choices, one that has its root in the IO economics literature and focuses on the structural impact of competitors' presence. Specifically, the classical Structure-Conduct-Performance (SCP) paradigm suggests that firms' conduct is a function of industry structure (Bain, 1959; Tirole, 1988). In an oligopolistic market, for instance, firms no longer encounter a passive environment as in a perfectly competitive market. One firm's investment decision would influence the demand and product price, and ultimately affect others' expected returns for investing in the same domain.

The concept of competitive interaction depicts the interdependence between competing firms. It has two important implications for how competitors' presence affects firm's decision making. Firstly, rivalry influences a firm's estimation on its future investment return. Firms might choose differentiation strategies as a response designed to attenuating the intensity of competition. Japanese automotive suppliers, for example, are less likely to enter the North American market when there are a large number suppliers competing in the market, but the likelihood of entry increases when the number of existing suppliers is small (Martin, *et al*, 1998). Secondly, anticipating its influence on other firms' strategic choices, first movers would exploit the possibility to their advantages. This idea brings about firms' reaction functions that generate the best choice for each possible action taken by competitors. Excess capacity, for example, represents one of the structural entry barriers that allow incumbent firms to deter potential entrants[1] (Bain, 1954; Spence, 1977).

Combining the dual role of competitors' prior choice, the extent literature has identified an inverted U-shaped relationship concerning how firms' decision making is affected by competitors' presence. Specifically, firms tend to imitate competitors' choice with low competitive intensity. Nevertheless, increasing competition would countervail the benefits of imitation, and ultimately lead to avoidance in firms' decision making. The implicit assumption here is that competition has an independent, negative effect on firms' decision making. However, in a highly uncertain environment, the dual role that competitors' action plays in firms' decision making might not be isolated, though in different directions. We argue that the rising level of competition could also strengthen the role of

[1] This argument has been well developed in industrial economics theory, but lacks empirical evidence. Lieberman (1987), for example, investigates thirty-eight chemical product industries and finds out that the incumbent firms rarely build excess capacity to deter potential entrants.

competitors' prior choices as an external information source and thus enhance the benefits of imitation.

To examine the association between competitors' presence and firms' decision-making, we formally model the process of how firms make investment decisions when it is difficult for all firms to predict the payoffs to taking a certain action. In particular, we focus on the selection activity in the behavioral decision-making framework (Cyert & March, 1963; Nelson & Winter, 1982). Nelson and Winter (1982), for example, formally develop the "search and selection" framework when they interpret long-run productivity as "moving along" an existing production function and "shifting" to a new one. Their work has inspired an exploration of studies on search activities that apply "NK" model of evolutionary biology to firm-level adaptation in a complex environment (e.g., Levinthal, 1997; Rivkin, 2000; Gavetti, Levinthal, & Rivkin, 2005; Ghemawat & Levinthal, 2008). Nevertheless, insufficient attention has been drawn to the selection process that becomes prominent in the uncertain environment. A general selection process specifies "the benefits and costs that are weighted by the organizations that will decide to adopt or not to adopt a new innovation" (Nelson & Winter, 1982: 262). Previous studies on technology and innovation, for example, have shown that incumbent firms have appropriation advantage by possessing complementary assets when facing disruptive technologies (e.g., Teece, 1986; Helfat, 1994; Tripsas, 1997; Rothaermel & Hill, 2005). Yet firms need to find it worthwhile or profitable before choosing to utilize the assets and seek cooperation with technology start-ups. We build our formal analysis based on the selection activity.

In the next section, we first introduce the basic model structure of firms' decision-making under uncertainty and then proceed to the analytic models that incorporate both information- and rivalry-based impact of competitors' presence.

MODEL STRUCTURE

We develop in this section a prototypical model with simplistic structure. It allows us to demonstrate the basic intuitions behind the decision-making process. Consider firms' making investment decisions in a novel domain. In accordance with the general selection process, firms evaluate future payoffs and make a decision only when it is perceived as worthwhile. In other words, profit function specifies the investment decision rule. At time *t* firm *i*'s profits from investing in the new area is denoted as $\pi_{i,t}$. Assuming a downward demand function and a monotonically-increasing production function of investment, we model a firm's profits as a function of investment:

$$\pi_{i,t} = \mu I_{i,t} - \frac{1}{2} {I_{i,t}}^2, \tag{1}$$

where $I_{i,t}$ is the investment choice made by firm *i* at time *t*, and μ is productivity parameter[2]. The profit function is concave in investment. It exhibits properties that we can generalize the results to more broad cases, e.g., diminishing marginal investment return and inefficient phase of overinvestment.

Productivity parameter, μ, carries the uncertainty of decision-making. If the value of μ is known *ex ante* when firms make investment decisions, firm *i* can choose the amount of investment that maximizes its profits. The first order condition by differentiating expression (1) with regard to investment $I_{i,t}$ shows that firm *i* would choose the amount given by ${I^*}_{i,t} = \mu$. The optimal investment choice derived here is consistent with findings in an empirical study conducted by Knott (2008) that firms with higher productivity tend to invest more.

To reflect uncertainty inherent in the decision-making process, assume that the value of μ is fixed but not completely known when firms make decisions. The profit function with unknown productivity parameter is specified as

$$\pi_{i,t} = \mu I_{i,t} - \frac{1}{2} {I_{i,t}}^2 + \varepsilon, \tag{2}$$

[2] To simplify the calculation, we assign 1/2 as the coefficient of the squared term in the profit function. In this way, the optimal investment choice equals to productivity parameter, μ, i.e., $I_{i,t} = \mu$. The results can be generalized to other forms of concave profit function.

where ε is the stochastic noise term. Assume that ε follows a normal distribution with zero mean and precision h (equal to the inverse of variance), i.e., $\varepsilon \sim N(0, h)$. Firm *i* thus chooses the investment that maximizes its expected profits. Take expectation on both side of expression (2), and the first order condition yields $I^*_{i,t} = E_{i,t}(\mu)$, where $E_{i,t}(\mu)$ is firm *i*'s estimate of μ at time *t*. As suggested by this optimal investment condition under uncertainty, firm *i* relies on its beliefs to make an investment decision. High expectations or optimal beliefs increase the likelihood of investment.

Firm *i* updates its beliefs about investment return $E_{i,t}(\mu)$ when additional information is revealed from the environment. In accordance with Bayesian statistical decision theory (DeGroot, 1970), we model the belief updating as a convex combination of a firm's prior beliefs and the information it observes from the environment. Specifically, let each firm's prior belief be given by a normal distribution of μ with mean $m_{i,0}$ and precision $h_{i,0}$, i.e., $\mu \sim N(m_{i,0}, h_{i,0})$. The prior mean, $m_{i,0}$, describes firm *i*'s expected payoffs before it perceives information from the environment. A larger value of $m_{i,0}$ indicates that firm *i* considers the investment as more profitable. The precision $h_{i,0}$ is equal to the inverse of variance of firm *i*'s prior belief. A larger value of $h_{i,0}$ implies more confidence of firm *i* in its prior beliefs.

Information about the distribution of μ is disclosed over time. Suppose at time *t* the information that firm *i* observes is given by,

$$z_{i,t} = \mu + \varepsilon_{i,t} + \varepsilon_t \tag{3}$$

where $\varepsilon_{i,t}$ and ε_t are stochastic noise terms. ε_t reflects environmental disturbance; it shapes the information perceived by all firms attempting to enter the novel area. $\varepsilon_{i,t}$, on the contrary, is firm-specific, and characterizes the variance in observed information associated with heterogeneity of firm resources and capabilities. Assume that ε_t's and $\varepsilon_{i,t}$'s are independent and normally distributed with zero mean and precision h_ε and $h_{i,\varepsilon}$, respectively (i.e., $\varepsilon_t \sim N(0, h_\varepsilon)$, and $\varepsilon_{i,t} \sim N(0, h_{i,\varepsilon})$). A smaller precision value of h_ε indicates a larger variance of information perceived from the environment, and thus implies a more disruptive technological change. In contrast, a smaller value of $h_{i,\varepsilon}$, or equivalently a larger value of variance, suggest that firm *i* is deemed low capability of cumulating related knowledge. Given that $\varepsilon_{i,t}$ and ε_t are normally distributed and independence, the information $z_{i,t}$ that firm *i* observes from the environment at time t stays normal with mean μ and precision h_i given by $h_i = \frac{1}{\frac{1}{h_\epsilon}+\frac{1}{h_{i,\epsilon}}} = \frac{h_\epsilon h_{i,\epsilon}}{h_\epsilon+h_{i,\epsilon}}$.

Given the normality and independence assumptions of $\varepsilon_{i,t}$ and ε_t, firm *i*'s estimate of posterior distribution of μ at time *t* follows normal distribution with mean $\hat{\mu}_{i,t}$ and precision $h_{i,t}$ given by,

$$\begin{aligned}\hat{\mu}_{i,t} &= E\left(\mu \middle| \hat{\mu}_{i,t-1}, h_{1,t-1}, z_{i,t}, h_i\right)\\ &= \frac{h_{i,t-1}\hat{\mu}_{i,t-1}+h_i z_{i,t}}{h_{i,t-1}+h_i} = \frac{h_{i,t-1}}{h_{i,t-1}+h_i}\hat{\mu}_{i,t-1} + \frac{h_i}{h_{i,t-1}+h_i} z_{i,t}\\ &= \frac{h_{i,0}m_{i,0}+h_i\sum_{s=1}^{t} z_{i,s}}{h_{i,0}+th_i} = \frac{h_{i,0}}{h_{i,0}+th_i} m_{i,0} + \frac{h_i}{h_{i,0}+th_i}\sum_{s=1}^{t} z_{i,s} \qquad (4)\end{aligned}$$

$$h_{i,t} = h_{i,t-1} + h_i = h_{i,0} + th_i \qquad (5)$$

As shown by expression (4), firm *i*'s estimation of posterior distribution of μ is a weighted average of its prior and external information; the weight assigned to prior belief is $\frac{h_{i,0}}{h_{i,0}+th_i}$ (or, $\frac{h_{i,t-1}}{h_{i,t-1}+h_i}$, for a two-stage learning model), and the weight to external information is $\frac{h_i}{h_{i,0}+th_i}$. Observe that the precision of firm *i*'s posterior distribution of μ increases by h_i in each period of time. In other words, firm *i*'s capability of predicting future investment payoffs improves over time as more information is revealed from the environment. The Bayesian inference process demonstrates that in the limit the value of μ will become fully known. Furthermore, the learning process corroborates findings in empirical studies about the competitive dynamics between incumbent firms and new entrants. An established firm, for instance, tends to place more emphasis on prior beliefs reflected by a large $h_{i,0}$. When facing disruptive changes characterized by a small h_ϵ (or equivalently small h_i), it would be less motivated to invest in the new technological domain.

Analysis of Competitor's Presence as Both External Information and Rivalry

To demonstrate how competitors' prior investment affects the focal firm's decision-making, we consider a Stackelberg competition in which the leader firm 1 and the follower firm 2 provide identical products and compete on quantity. Firm *i*'s profit function is generalized as

$$E(\pi_{i,t}) = E_{i,t}(\mu)I_{i,t} - \frac{1}{2}{I_{i,t}}^2 - \gamma I_{i,t}I_{j,t},\ i = 1,2, j \neq i,$$

where γ denotes the type and the intensity of rivalry.[3] If products are (imperfect) substitutes, for example, the value of γ is greater than zero, i.e., $\gamma > 0$. The cross partial derivative of firm *i*'s profits with respect to firm *j*'s investment is negative (i.e., $\frac{\partial \pi_{i,t}}{\partial I_{j,t}} < 0$), which means a firm *i*'s profits would decline with rival firm *j*'s investments. The sign of second-order cross partial derivative is also negative (i.e., $\frac{\partial^2 \pi_{i,t}}{\partial I_{i,t} \partial I_{j,t}} < 0$), which means firm *i*'s marginal return on investment decreases with firm *j*'s investment[4].

Let firm 1 receive a private observation from the environment, $z_{1,t}$, in the beginning of time period *t*. Firm 1 then updates its beliefs about the distribution of μ, and makes an investment $I_{1,t}$ at the end of time *t* after perceives the investment as profitable based on the posterior distribution of μ. Meanwhile, firm 1 is aware that firm 2 observes its choice, and that its investment choice reveals information about μ to firm 2. Because firm 2's investment influences its investment return, firm 1 would exploit the possibility to its advantages. Hence, we specify firm 1's estimation about future payoffs at time *t* as follows,

$$E(\pi_{1,t}) = E_{1,t}\left(\mu \middle| \hat{\mu}_{1,t-1}, h_{1,t-1}, z_{1,t}, h_1\right)I_{1,t} - \frac{1}{2}{I_{1,t}}^2 - \gamma I_{1,t} \cdot I_{2,t}\left(I_{1,t}\right), \tag{6}$$

where $I_{2,t}\left(I_{1,t}\right)$ is firm 2's investment after it observes firm 1's investment and its own private information from the environment. In accordance with equation (4), firm 1's posterior estimation is

[3] Please see Appendix A for a detailed derivation of profit function with the presence of competitive interaction.

[4] We only consider γ taking positive value, i.e., $\gamma > 0$, in our model; nonetheless, the results can be applied to the case of complements, i.e., $\gamma < 0$.

given as $E_{1,t}\left(\mu \middle| \hat{\mu}_{1,t-1}, h_{1,t-1}, z_{1,t}, h_1\right) = (1-\lambda_1)\hat{\mu}_{1,t-1} + \lambda_1 z_{1,t}$, where $\lambda_1 = \frac{h_1}{h_{1,t-1}+h_1}$ represents the extent to which firm 1 relies on external information when firm 1 forms its posterior estimation of μ. Differentiating Equation (6) with respect to firm 1's investment and solving the first order condition, we have firm 1's optimal investment specified as follows,

$$
\begin{aligned}
I_{1,t} &= \frac{h_{1,t-1}}{h_{1,t-1}+h_1}\hat{\mu}_{1,t-1} + \frac{h_1}{h_{1,t-1}+h_1} z_{1,t} - \gamma I_{2,t}\left(I_{1,t}\right) - \gamma I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} \\
&= (1-\lambda_1)\hat{\mu}_{1,t-1} + \lambda_1 z_{1,t} - \gamma I_{2,t}\left(I_{1,t}\right) - \gamma I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}}, \qquad (7)
\end{aligned}
$$

Firm 2 observes firm 1's investment, $I_{1,t}$, and perceives private information $z_{2,t+1}$ in the next period of time. Similar to the prior analysis, firm 2's posterior estimate of μ is a combination of its prior beliefs and the average of external information. The expected profit function of firm 2 is described as

$$E(\pi_{2,t+1}) = E_{2,t+1}\left(\mu \middle| \hat{\mu}_{2,t}, h_{2,t}, z_{2,t+1}, z_{1,t}, h_2\right) I_{2,t+1} - \frac{1}{2}{I_{2,t+1}}^2 - \gamma I_{1,t+1} I_{2,t+1}. \qquad (8)$$

Firm 2 chooses the amount of investment that maximizes its expected profits at the end of time *t+1*. Differentiate equation (8) with respect to $I_{2,t}$, and assuming $I_{i,t} = I_{i,t+1}$ $(i = 1,2)$ we have:

$$\omega I_{2,t} = (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{\lambda_2}{2\lambda_1} I_{1,t} + \frac{\lambda_2\gamma}{2\lambda_1}\frac{\partial I_{2,t}}{\partial I_{1,t}} I_{1,t} - \gamma I_{1,t} - \frac{\lambda_2(1-\lambda_1)}{2\lambda_1}\hat{\mu}_{1,t-1}, \qquad (9)$$

where $\omega = 1 - \frac{\lambda_2\gamma}{2\lambda_1}$, and $\lambda_i = \frac{2h_i}{h_{i,t}+2h_i}$ (i=1,2) denotes the extent to which firm *i* relies on external information when forming its posterior estimate about μ (See Appendix B for the proof).

The sign of first-order derivative of $I_{2,t}$ with respect of $I_{1,t}$ (i.e., $\frac{\partial I_{2,t}}{\partial I_{1,t}}$) reflects the overall impact of rival firms' investments on the firm's incentive for investment. Differentiating equation (9) with respect to firm 1's investment yields:

$$\frac{\partial I_{2,t}}{\partial I_{1,t}} = \frac{1}{2}\frac{\lambda_2 - 2\gamma\lambda_1}{\lambda_1 - \gamma\lambda_2}. \qquad (10)$$

As shown in expression (9), the sign of $\frac{\partial I_{2,t}}{\partial I_{1,t}}$ is contingent upon parameter γ given λ_1 and λ_2. To illustrate the overall impact of firm 1's investment on firm 2's investment, we use the following five examples in which γ takes on different values, i.e., $\gamma = 0.15$, $\gamma = 0.4$, $\gamma = 1/\sqrt{2} = 0.707$, $\gamma = 0.9$, and $\gamma = 1.5$. When $\gamma = 1/\sqrt{2}$, the first-order derivative of $I_{2,t}$ with respect of $I_{1,t}$ equals $-1/\sqrt{2}$, i.e., $\frac{\partial I_{2,t}}{\partial I_{1,t}} = -1/\sqrt{2}$. In other words, firm 2 would choose to avoid investing in the same area after observing firm 1's investment (Figure 1).

For $\gamma < 1/\sqrt{2}$, we use two examples, i.e., $\gamma = 0.15$ and $\gamma = 0.4$, to illustrate the effect of competitors' presence on the focal firms' decision-making. As shown in Figure 2 and 3, firm 2 would be more likely to follow firm 1's investment decision as the value of γ decreases. As a matter of fact, $\gamma = 0$ is a special case in which firm 1's investment merely serves as an external information source heralding attractive investment opportunity.

Insert Figure 1 and 2 here

The intuitive interpretation is straightforward. The role of competitors' prior investments as an external source of information dominates the role as competitive rivalry if it has little structural impacts on a firm's profits. The extreme case is that firms choose to make the same investment decision as their competitors. Yet, as the level of rivalry increases, it countervails the positive impact of competitors' prior investment as an external information source. When parameter γ reaches the value $1/\sqrt{2}$, rivals' investments would intimidate all potential entry. We thus develop the following proposition:

> **PROPOSITION 1**: All other things being equal, for $\gamma < 1/\sqrt{2}$, the smaller γ is, the more likely competitors' investment is to have a positive effect on the focal firm's incentive to invest in the novel business area, i.e., $\frac{\partial I_{2,t}}{\partial I_{1,t}} > 0$.

For $\gamma > 1/\sqrt{2}$, we use two examples, i.e., $\gamma = 0.9$, and $\gamma = 1.5$, to illustrate the effect of competitors' presence on the focal firms' decision-making. As shown in Figure 4 and 5, firm 2 is more likely to follow firm 1' investment decision as the value of γ increases.

Insert Figure 3 here

The rationality behind this result is that competitors' investments imply particularly favorable information on investment return. The fact that firm 1 chooses to invest in the new area regardless of vigorous rivalry indicates that the information it perceives from the environment is sufficiently favorable to justify its investment decision. Based on the analytical result, we develop the following proposition:

> **PROPOSITION 2**: All other things being equal, for $\gamma > 1/\sqrt{2}$, the larger γ is, the more likely competitors' investment is to have a positive effect on the focal firm's incentive to invest in the novel area, i.e., $\frac{\partial I_{2,t}}{\partial I_{1,t}} < 0$.

To illustrate the overall effect of competitors' investments on the focal firm's investment incentive, we use the following numerical example in which $\lambda_1 = 0.4$ and $\lambda_2 = 0.2$. The first derivative of firm 2's investment with regard to firm 1's investment as a function of γ, the intensity of rivalry, is given in figure 4.

Insert Figure 4 here

As seen from figure 4, in which imitation is most likely to take place when the intensity of competitive rivalry is low or high. If we regress the incidence of competitors' prior investment on the likelihood of the focal firms' investment in the same domain, the coefficient of competitors' prior entries are expected to be U-shaped holding other factors constant. In the next section, we will introduce the empirical context and develop specific hypotheses.

Empirical Context and Hypotheses

To provide a suitable context to test the predictions derived from the analytical models, we study the U.S. electric utility companies' commitment to develop utility-scale solar projects. The majority of prior studies focus on the implications of regulatory environment for the renewable energy adoption in the electric utility sector (e.g., Delmas et al, 2007; Kim, 2013; Fremeth & Shaver, 2014). In this study, we look into utility companies' decision to adopt one particular type of renewable energy, i.e., solar power. The uncertainty associated with investing in solar technology allows us to empirically examine the effect of competitors' prior decision on the focal firm's investment when it is difficult for all firms to predict future returns.

While solar generation capacity dramatically increased in the first decade of this century, the development of solar energy is still subject to technological and operational uncertainties. Terrestrial solar power applications have a history of less than fifty years. To capture the sun's radiation and convert it into electricity, companies can use four major technologies, i.e., crystalline silicon, thin film, concentrated photovoltaic, and concentrated solar power. Yet, for each solar technology, utility companies face uncertainties associated with integration between different subsystems, e.g., solar modules, mounting system, grid interaction and curtailment, and connection arrangements. Variability in solar radiation level is another factor of uncertainty associated with solar energy investment. Utility companies can roughly predict sunlight level based on historical data, but the data need to be collected from a measuring station quite near to the solar project site. Notwithstanding the data accuracy, additional uncertainty exists in terms of converting the data to radiation in the angle of the solar array[5]. Take TECO Energy, Inc., a utility company based in Florida, for example. While Charles Hinson, vice president of state and community relations at TECO, expressed their confidence on natural gas, he doubted the future of renewable energy technologies: "other clean power generation like wind and solar are yet to be reliable"[6].

In addition, the fact that electric utility companies can choose from a variety of renewable technologies to meet the renewable energy policy requirement aggravates the uncertainty in

[5] Please see detailed introduction in Wolfe, P. 2013. *Solar photovoltaic projects in the mainstream power market*. Routledge.
[6] Erny Zah. "TECO buys New Mexico Gas Company for $950 million". *The Daily Times*, 10 July 2014.

estimating returns from developing solar energy[7]. Renewable energy resources include electricity produced from water, wind, solar thermal/PV, geothermal energy, and biomass (e.g., biofuels, waste, and wood and derived fuels). The federal Energy Policy Act of 2005 requests that the total amount of renewable electric energy consumed by the federal government during 2013 and thereafter should not be less than 7.5%, and provide load guarantees for entities that develop or use innovative green technologies. Even before the Energy Policy Act of 2005, state governments have established their own renewable portfolio standards (RPS) that utility companies are required to meet. The state of California, for example, enacted legislation in 2002 that requires electric utilities to have 33% of their retail sales derived from eligible renewable resources in 2010 and all subsequent years. Among all renewable energy technologies, wind power has particularly made substantial advances in reliability improvement and cost reduction in recent decades. Some utility companies think that wind technology offers the most promise for meeting the RPS requirement. For example, company executive of Black Hills Corporation, an energy company based in South Dakota, said:

> "Among all (of the renewable energy sources), wind is clearly more cost-effective than solar, so we're looking closely at wind."[8]

Xcel Energy, on the contrary, invested in a number of renewable technologies. It claimed itself as the nation's No.1 wind power provider for the past decade, and meanwhile made a statement about solar technology on its webpage: "We believe in the power of the sun. In a big way." Hence, given the inherent environmental uncertainty in solar and other renewable energy technologies, it is difficult for utility companies to predict the nature of solar technology development and returns for investing in this new area.

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[7] 28 states specify minimum solar energy requirement of renewable portfolio standard (RPS). Nonetheless, utility companies can meet the requirement via, for example, home or business owner rebate incentive program, rather than investing in building utility-scale solar projects.

[8] Patrick Malone. "Black Hills files renewable plan; Key questions linger over state's tougher energy mandates" The Pueblo Chieftain, 10 Nov 2010.

To isolate utility companies' solar energy investment decision from their experimental investment, we focus on the utility-scale solar projects. The term "utility-scale" is used for large-scale grid connected photovoltaic generation. Utility-scale solar power generation is designed for feeding electric energy into the grid. Alternatively, electric utility companies can meet the RPS requirement by developing distributed solar solutions that connect small solar power generation equipment to the utility distribution system or where the energy is used. Duke Energy, for instance, formed a partnership with Integrys Energy Services to jointly develop rooftop and small ground-mounted photovoltaic solar projects that serve a local energy user or distributed power application. Green Mountain Power Corporation, on the contrary, began investing in utility-scale solar farms after a series of small-scale solar farms.

Hypotheses

In accordance with propositions derived from the analytical models, we posit a U-shaped relationship between competitors' presence and the focal firms' investment in utility-scale solar projects. Nevertheless, because we see utility companies' investment in large-scale solar project as a sign of commitment to solar technology, it would cause at least a modest level of rivalry and countervail the benefits of imitation. For this reason, we expect utility companies to first avoid building large-scale solar projects as more competitors invest in solar technology. Yet, at a high level of expected competition, the rivalry effect of competitors' presence would be dominated by the information effect because the investment choice made by competitors reveals particularly optimistic information about the nature of solar power development and returns for investing in this novel area. We thus expect that the likelihood of utility companies investing in large-scale solar projects increases with competitors' presence at a higher level of rivalry. Formally stated:

> **Hypothesis 1A**: All else being equal, the likelihood that electric utilities invest in large-scale solar projects will first decrease and then increase (the U-shaped effect) as more competitors invest in solar technology.

We estimate the U-shaped effect of competitors' presence in different types of electricity suppliers. The U.S electric utility industry consists of traditional utilities and independent power producers (IPP). Traditional utilities possess transmission facilities and sell power in any retail service territory where they have a franchise. IPPs, also known as non-utility generators, own facilities to generate electric power for sale to utility companies and end users. The literature on strategic groups suggests that firms tend to respond to competitors that follow similar strategies (Caves & Porter, 1977). Likewise, the resource-based scholars argue that resource similarity is the basis for firm interdependencies. The previous literature offers empirical evidence that firms tend to respond to most relevant competitors, e.g., firms in a focal area or within neighboring areas (Greve, 2002; Cattani, et al, 2003).Therefore, we expect to find the U-shaped relationship within the group of direct competitors.

> **Hypothesis 1B**: All else being equal, the likelihood that electric utilities invest in large-scale solar projects will first decrease and then increase as more direct competitors invest in solar technology.

While we predict in Hypothesis 1B that electric suppliers tend to respond to the presence of direct competitors, electric utility companies might see indirect electric utility competitors as potential cooperative partners. This particularly holds true in the U.S. electric utility industry. IPPs are potential partners of traditional utilities companies to generate electricity from renewable energy sources. IPPs have developed with institutional support since 1978 when the idea of competition was introduced into the traditionally regulated industry. The Public Utility Regulatory Policies Act of 1978, for example, required electric utilities to purchase electricity from IPPs (Kim, 2013). Traditional utility companies own transmission facilities, whereas IPPs typically generate energy using renewable technologies at a small scale. Hence, we expect to find the following:

> **Hypothesis 2**: All else being equal, the likelihood that electric utilities invest in large-scale solar projects will decrease more with the capacity of IPPs' solar projects.

In addition to the U-shaped effect of competitors' presence, our analytical models shed light on how utility companies' inclination toward alternative energy sources (prior beliefs) affects their decision to develop solar energy. In the electric power industry, fossil fuels are the primary energy supply for electricity generation. In particular, coal, oil, and natural gas are three kinds of fossil fuels that we rely most on for our energy needs. Yet, fossil fuels are non-renewable; they are limited in supply and will one day be depleted. Moreover, fossil fuels are the major sources of greenhouse gases, accounting for approximately 35 percent of the total emission in the U.S. Thus, the past decades of years have witnessed the continuous pursuit of alternative energy sources in electric utility industry. Nuclear power, for example, gained momentum as a novel alternative technology during the time period between the 1960s and late 1980s. Our formal analysis suggests that utility companies with high inclination toward alternative energy sources tend to adopt novel technologies early. Because nuclear power and solar power use different technologies for electricity generation—one from splitting atoms and the other converting sunlight into electricity—we contend that the timing of adopting nuclear power embodies utility companies' inclination toward alternative energy sources, which in turn affects their commitment to solar energy.

> **Hypothesis 3**: All else being equal, the likelihood that electric utilities invest in large-scale solar projects will increase as a function of the timing of nuclear power adoption.

In sum, we develop hypotheses in this section based on the analytical results of formal modeling. Hypothesis 1A and 1B predict a U-shaped relationship between competitors' presence and firms' decision on investing in large-scale solar projects. Hypothesis 2 extends the first two hypotheses regarding strategic similarity (dissimilarity) among competing companies. Hypothesis 3 summarizes the effect of firms' prior beliefs on their investment decisions. In the next section, we will describe the sample and method of analysis.

Data and Estimation

Sample and Data

The sample in this study consists of all holding companies of investor-owned electric utilities (IOUs) in the U.S from 2002 to 2013. Adopting a new energy generation technology is a strategic decision concerning the direction of the whole company as opposed to routinized decisions that can be decentralized to utility subsidiaries. Solar power plants are mostly owned and operated by a renewable-energy subsidiary under the utility parent company. MidAmerican Renewable, LLC, for instance, is a subsidiary of MidAmerican Energy Holding Company[9]; it operates wind, hydro, geothermal, and solar projects. Hence, we use utility holding company as the basic unit of analysis in this study.

Twelve years of electric utility data were manually collected from a variety of public sources. The main data source is U.S. Energy Information Administration (EIA). In particular, the plant-level survey data were collected from Form EIA-860, and utility-level data from Form EIA-861. Other data sources include Database of State Incentives for Renewables & Efficiency (DSIRE), Hoover's database, Bloomberg's database, Plunkett's Energy Industry Almanac, Platt's Energy Trader, and utility companies' websites. The construction time of utility companies' first large-scale solar project, for instance, was gathered from Form EIA-860, utility companies' website, and public announcements in the form of company press releases and news releases.

Our sample is based on all parent companies of investor-owned utilities (IOUs) in the U.S. IOUs are the largest players in the U.S. electric utility sector, providing services to around two thirds (68.5%) of customers in the U.S., although they comprise only a small portion of the total number of utility companies (5.8% in 2014) [10]. According to the EIA-861 Annual Electric Power Industry Report, 176 investor-owned utilities (IOUs) operated in every state except Alaska in 2012. We collected information on the subsidiary status of each IOU via Hoover's and Bloomberg's database.

[9] MidAmerican Energy Holding Company changed its name to Berkshire Hathaway Energy in April 2014

[10] Please see APPA (American Public Power Association) U.S. Electric Utility Industry Statistical Report.

The 176 IOUs are affiliated to 81 electric utility's parent companies. Further, we explore our argument during the time period from 2002 to 2013. The earliest utility-scale solar farm was developed in 1984; Edison International, headquartered in Rosemead, CA, built Solar Energy Generating System I (SEGS I), a 13.8MW concentrated solar power (CSP) project in Daggett, California. Nonetheless, there were in total 16 solar projects established in the U.S. before 2002, and only two IOUs invested in utility-scale solar farms during that time period. After 2002, the first adoption by building utility-scale solar project in our sample took place in 2004, and two more utility holding companies decided to do so in 2006 and 2007, respectively. The first few years after 2002 thus retained a similar solar energy development pattern as before 2002. Thus, the time period between 2002 and 2013 allows us to fully capture the trend of solar energy adoption in the electric utility sector.

Dependent Variable and Method of Analysis

Our hypotheses relate to the likelihood that utility companies adopt solar energy by building utility-scale solar farms. There are variations in the capacity of solar plants that are qualified as "utility-scale", ranging from 25 kilowatts to tens of megawatts; a widely adopted capacity level is 5 or 10 megawatts (MW). The number of solar plants increases if we drop the capacity threshold value. To improve the comprehensiveness of our study, we use 1 MW as the "utility-scale" capacity threshold value. Among the 81 holding companies of IOUs, 29 built utility-scale solar plants during the time period from 2002 to 2013.

The time of solar farm construction is measured in discrete units (i.e., years in this study). Because the units are large relative to the total period of observation and the rate of event occurrence, we estimate the adoption likelihood using models of non-repeated events with discrete-time data. The discrete time hazard is defined as $h_t = \frac{P_t}{1-P_t}$, where $P_t = \Pr(T = t|T > t)$ and T is an integer-valued random variable. P_t refers to the probability that an event occurs at time t given that it has not already occurred.

Further, time-variant fuel prices affect utility companies' incentive to develop renewable energy because electricity generated from renewable sources can be perfectly substituted by coal, natural gas, and other fuel sources. In other words, the adoption likelihood would change as a function of time. To allow for arbitrary changes in the hazard with time, we use both maximum partial likelihood, i.e., semiparametric proportional hazard models (Cox, 1975), and maximum likelihood, i.e., logistic regression for non-repeated events. Specifically, the proportional hazard model is specified as follows:

$$h_{it}\big(\boldsymbol{X_i}(t)\big) = h_t exp(\beta' \boldsymbol{X_i}(t)),$$

where $h_t = exp(\alpha_t) = exp(\alpha_0 + \alpha_1 t)$ allows for a linear effect of time. Alternatively, we converted each utility parent company's event history into a set of distinct observations, and then pooled these observations and estimated a logistic regression model with time as an explanatory variable.

Independent Variables

Competitors' presence. We count the number of utility companies that (1) conducted operating activities in the same geographic areas as the focal firm and (2) completed construction of solar projects in a certain year. Based on the type of competitors, we developed two measures for competitors' presence: *IOU competitors* and *IPP competitors*. IOU competitors consist of all traditional utility companies, including municipal departments and power agencies, cooperatives, political subdivisions, State agencies and power pools, marketing agencies, and power marketers. In addition to independent power producers, industrial and commercial plants, including those that are owned or partly owned by traditional utilities, are also included in the count of IPP competitors. The average number of IOU competitors is 0.78 with a maximum of 9. The average number of IPP competitors is 7.28 with a maximum of 71.

IPP Capacity. IPP capacity is calculated as the total capacity of solar plants installed in a certain year by IPP competitors operating in the same geographic regions. The average capacity of IPP competitors' solar projects is 97.45 MW with a maximum of 3165.1 MW.

Nuclear power. We construct a variable of "nuclear power" as a proxy for utility companies' inclination toward alternative energy sources. The first commercial nuclear plant was opened in the U.S. on May 26, 1958. Since then, nuclear power had expanded throughout the 1960s and the early 1970s. The Three Mile Island accident in 1979, however, intensified the opposition of developing nuclear power plants. The 1980s witnessed nuclear power reactor cancellation and construction halt. We thus created three dummy variables to distinguish how early utility companies invested in nuclear power technology. Specifically, Nuke 1 takes a value of one if utility companies' first nuclear reactor is built in 1960s, Nuke 2 takes a value of one if utility companies' first nuclear reactor is built in 1970s, and Nuke 3 takes a value of one if utility companies' first nuclear reactor is built in 1980s; the baseline group comprises those that never developed nuclear plants.

Control Variables

Geographic regions. We control for geographic regions in which the holding electric companies conduct operations. It partly captures the effect of external information that utility companies perceive from the environment. We employ North American Electric Reliability Corporation (NERC) geographic classifications. NERC works with eight regional entities to improve the reliability of the bulk power system, i.e., Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), ReliabilityFirst Corporation (RFC), Southeastern Electric Reliability Council (SERC), Southwest Power Pool (SPP), Texas Regional Entity (TRE), and Western Electric Coordinating Council (WECC). These entities cover the whole geographic territory of the U.S. We created eight dummy variables that take a value of 1 if the electric company conducts operational activities in a particular NERC area. In the sample, 16 holding companies operate in multiple NERC geographic regions.

RPS Policy. State governments play an important role in supporting the development of renewable technologies. As of 2013, 28 states in the U.S. have established an RPS that requires a certain percentage of electric power suppliers' sales come from renewable resources; among them, 15 states have issued specific requirements that a certain percentage of the RPS be met using solar energy. The state of California, for example, is among the first adopting a renewable portfolio standard. The standard was originally issued in 2002. After amended, it requires that 25% of retail sales should be derived from renewable energy by 2016 and 33% by 2020; renewable technologies including solar, wind, biomass, geothermal, and certain hydroelectric electric are all eligible for the RPS. Arizona, on the other hand, established in 2006 a renewable energy standard of 6% by 2016 and 10% by 2020; meanwhile, it specified 3% generated with solar technology.

To control for the regulatory information, we develop two measures: (1) *RPS policy* measured the maximum renewables portfolio standard issued within the electric companies' geographic regions each year from 2002 to 2013, and (2) *RPS 2015 target* measured the maximum RPS requirement in 2015. We also identified (3) *solar policy*, the maximum solar curve-outs within the electric companies' geographic regions each year from 2002 to 2013, and (4) *2015 solar target*, the maximum solar requirement in 2015 as alternative measures.

Wind power. Wind power has been the fastest-growing source of new electric power generation for years. Though solar power development picked up momentum and exceeded a 50% growth rate since 2010, wind technology has accounted for the largest share of renewable electric generation (54.84% excluding hydropower in 2012). We created the dummy variable *wind* that takes a value of 1 if an electric power company owned a wind farm during the time period from 2002 to 2013.

Revenue and operating activities. We also control for the scale effect that large companies have slack resources and therefore might be more likely to invest in new technology. The variable *Firm size* is calculated as the logarithm of the total revenue in a certain year. In addition, we control for operating activities of electric power companies. Consistent with EIA classification, we categorized operating activities into *generation*, *transmission*, *distribution*, *wholesale marketing*, *retail marketing*, and *bundled*. Utility companies might involve multiple operating activities. We created six dummy variables that take a value of 1 if the electric company conducts a particular activity.

Results

In Table 1, we summarize descriptive statistics for the variables used in the analyses. The correlations between first order variables are small to modest, suggesting that multicollinearity is not a serious problem.

Insert Table 1 and 2 here

We present in Table 2 the regression coefficient estimate results from Cox models that estimate the hazard of investor-owned utility holding companies' development of utility-scale solar projects. Model 2.1 includes all control variables and the variable "Nuclear power". As expected, utility companies that build wind power projects are less likely to commit a large investment to solar power technology. It indicates the underlying substitution among different types of renewable technologies when utility companies choose to develop alternative energy sources. Regulatory policy also exhibits significant effect on utility companies' decision on building large-scale solar projects. We include two variables that control for RPS policy: the constant variable "*RPS 2015 target*" and the time-varying variable "*RPS policy*". The positive coefficient of "*RPS 2015 target*" suggests that utility companies are forward-looking when choose to invest in solar energy as a response to regulatory policy. The effect of regulatory policy, however, decreases over time as suggested by the negative coefficient of "*RPS policy* ".

In Model 2.2-2.6, we tested hypothesis 1A and 1B. These two hypotheses predicted a U-shaped relationship between the presence of competitors and the likelihood of utility companies' investing in large-scale solar projects. Hypothesis 1B further specified that the U-shaped relationship exists for competitors in the same electric utility group, i.e., traditional utility (IOU) competitors. We first estimated coefficients in the linear function of *IOU competitors* in Model 2.2; the effect is insignificant. Model 2.3 is the quadratic model of *IOU competitors*, and the coefficient of the squared *IOU competitors* is positive and significant at the 0.1 level. Though the coefficient of the linear term is insignificant, the sign is negative as expected. Likewise, we ran the same analysis in models 2.4-2.5 for *IPP competitors*; neither the coefficient of *IPP competitors* nor the coefficient of the squared *IPP competitors* is significant. In Model 2.6, we included both types of competitors, and only found significant coefficients of *IOU competitors*. In particular, the positive coefficient of the quadratic term and the negative coefficient of the linear term point to a U-shaped relationship between competitors' presence and the propensity of utility companies to build large-scale solar projects (figure 5). These results provide support to hypothesis 1A and 1B.

Hypothesis 2 predicted that utility companies' propensity to invest in large-scale solar projects would decrease more with the total capacity of independent power producers' newly added solar projects. We tested this hypothesis in model 2.7 by observing whether IPP capacity had an impact on how utility companies respond to the presence of competitors. As can be seen in Table 2, the coefficient of the interaction term between "*IOU competitors*" and "*IPP capacity*" is significantly negative (figure 6). The result is in line with our prediction that independent power producers are potential cooperative partners rather than direct competitors to investor-owned utility companies.

To correctly interpret the finding of U-shaped relationship, we assess the magnitude of coefficient estimates and plot the models within the range of our data. In figure 5, we draw the curve based on the coefficient estimates in model 2.7 that reflects the effect of IOU competitors on the likelihood that the focal electric utility company invests in building large-scale solar projects. The inflection point is approximately where the variable, *IOU competitors*, takes the value 2. In other words, the curve decreases at a decreasing rate until the inflection point, and then increases as *IOU competitors* takes larger values. Furthermore, we illustrate in figure 6 how the U-shaped relationship between IOU competitors' presence and the focal utility company's investment decision is modified by IPP competitors' newly added solar capacity (IPP capacity). The graph was drawn based on the coefficient estimates in model 2.7 and the range of independent variables. As shown in figure 6, IPP capacity extends the negative effect of IOU competitors on the focal utility company's propensity to invest in large-scale solar projects.

Insert Figure 5 and 6 here

Hypothesis 3 delineates how utility companies' inclination (prior beliefs) toward alternative energy source affected their decision on investing in large-scale solar projects. We included dummy variables of "Nuclear power" in all models. As shown in Table 2, the coefficient of variable "Nuke 1 (1960s)" is significantly positive in all estimations using Cox models. We draw graphs of hazard functions for utility companies that developed nuclear plants in 1960s (nuke_earlybird) and for the counterpart group that developed later or didn't develop nuclear plants (Figure 7). Figure 7 illustrates distinct difference between these two groups. This finding is in line with hypothesis 3. It suggests that utility companies that first developed nuclear energy tend to have strong beliefs on alternative energy sources and thus are likely to commit a large investment to solar energy.

Insert Figure 7 here

Robustness Test

We conduct robust tests using maximum likelihood methods to identify the shape of the relationship between competitors' presence and utility companies' large-scale solar energy investment decision. To eliminate spurious correlation in Model 2.2-2.7 caused by changes in fuel prices over time, we allowed for arbitrary changes in the baseline hazard with time in our models. Assuming the underlying continuous-time models, we use exact partial likelihood method to estimate results using Cox models. Nevertheless, the method only allows for a linear effect of time. We draw in figure 8 the hazard function of IOU investing in utility-scale solar projects, and it exhibits association with time. In particular, as shown in figure 8b, the smoothed hazard estimate is a curvilinear function.

Similar to the long-form dataset structure employed in the partial likelihood method, we break each utility company's event history into a set of distinct observations, one for each year until censoring or an event occurred (utility company-years). For each of these observations, we coded the dependent variable as one if an event occurred, otherwise as zero. We then pooled these observations and estimate a logistic regression, or a complementary log-log model, by maximum likelihood method. These approaches allow for great flexibility in specifying the time function and utilizing advanced econometrics methods for panel data analysis.

Insert Figure 8 and Table 3 here

The estimate results are presented in Table 3. In Model 3.1 and 3.2, we include both the linear and the squared terms of '*Year*" in logistic and complementary log-log regression. All coefficient estimates stay consistent with those in model 2.7. We estimate the random effect model to control for unobserved heterogeneity in Model 3.3. The estimation results are quite similar to model 3.1. In model 3.4, we use generalized estimating equations (GEE) with robust standard errors to generate efficient estimates of coefficients. As expected, the coefficient estimates are downscaled in GEE model compared to other estimation models, but the results are consistent with other models. In sum, the maximum likelihood methods did not materially change the results.

Discussion

In this study, we identify with formal analytical models a U-shaped relationship between competitors' presence and the focal firm's decision-making. Using data of electric utility companies' investment in utility-scale solar plants, we find empirical evidence for our predications: utility companies tend to avoid investing in a novel area as more competitors appear; yet as the intensity of competition further increases, their reactions turn into imitation.

Our arguments center on the dual role that competitors' prior action plays in the focal firm's belief updating and decision making under uncertainty: information and competition. On the one hand, it heralds an attractive opportunity of taking a certain choice, and on the other hand, lowers expectations on future returns because of intensified competition. Consistent with previous studies, we find that competition leads to avoidance in the focal firm's decision making. Yet we also find that, in a highly uncertain environment, the twofold roles interact in determining how firms respond to competitors' prior action. Specifically, in addition to a separate, negative effect on future investment returns, competition affects a firm's decision making by strengthening the positive informational cues of competitors' presence in a highly uncertain market. In other words, investment decision made by competitors at a high level of rivalry implies particularly optimistic information about the new investment opportunity. As such, the benefits of imitation would not be outweighed by the countervailing effect of competition, which ultimately leads to imitation at a high level of competition and generates a U-shaped relationship.

This paper has significant implications for the literature on firms' strategic decision making under uncertainty, e.g., investment in novel technologies, entry to a new product market, or expansion into foreign markets. It is well known in the extant studies that there are two distinct decision-making patterns: imitation and avoidance. When multimarket competition takes place in the novel markets, for example, firms exhibit mimetic behavior instead of mutual forbearance because uncertainty causes them to rely on competitors' action to estimate the investment opportunity (Anand, *et al*, 2009). Yet, competition countervails the benefits of imitation, and therefore weakens the incentive for investment. For this reason, the previous literature suggests an inverted U-shaped relationship: firms imitate initially competitors' action and avoid later making the same decision as the competitive intensity increases (e.g., Lieberman & Asaba, 2006; Koçak, & Özcan, 2013; Alcácer, *et al,* 2015). The underlying assumption, however, is that the dual role of competitors' presence has independent effects, though in opposite directions, on the focal firms' future payoffs from investing in a novel area. Overlooking the link between these two mechanisms could mislead us into drawing an incomplete conclusion about how firms respond to competitors' presence in a novel market.

Moreover, our research responds to the call for studies that link theories to environmental conditions where they are most applicable (Lieberman & Asaba, 2006). We focuses in this study on one particular type of uncertainty, i.e., environmental or market uncertainty (Lieberman & Asaba, 2006; Gaba & Terlaak 2013). It is characterized by a lack of information that makes it difficult for all firms to predict the future payoffs from taking a certain action. We aim to open the black box of how firms make strategic decisions under such uncertain situations. Behavioral decision making model advanced by Cyert and March (1963) has provoked a broad research interest in "search activities". In this paper, we take a different route to untangle the question. Drawing insights on the selection activity from Nelson and Winter (1982), we build stylized decision making models, and discern a strengthening effect of intensified competition on the information role of competitor's prior action. The results reiterate the importance of environmental conditions, and demonstrate that uncertainty engenders a certain type of competitive dynamics between competing firms. The condition of environmental uncertainty delineates the circumspect conditions for this study. We should emphasize that, throughout the analysis in this study, uncertainty does not resolve when firms invest in a novel market. This attribute of environmental uncertainty has important implications for modeling firms' decision-making. Specifically, it undermines the first-mover advantage and incentives for preemption investment (Lieberman & Montgomery, 1988). Moreover, it distinguishes from real options investments that are characterized by sequential investment decisions, in which future investment opportunities are contingent on firms' prior investment commitments (McGrath, 1997; Adner & Levinthal, 2004; Folta & O'Brien, 2004).

Our study also has important implications for practice. Firms exhibit different decision-making patterns in a highly uncertain environment compared to a relatively mature phase of an industry. In the latter case, taking imitative decision-making pattern is straightforward because competitors are seen to provide superior products, process, and organizational system; competition, however, countervails the benefits of imitation. In the former case where it is difficult for all firms to predict future payoffs from investing in the novel market, our analysis shows that first-movers would initially attract new entrants because their actions reveal optimistic information about future development. As more competitors appear, firms would be less likely to make same decisions as their competitors do. Yet imitative moves become the decision-making pattern again as the intensity of competition further increases. The different competitive dynamics indicates that firms' competitive advantage would be less likely to be eroded by new entrants if they enter the new market at the right time. Moreover, we develop several additional hypotheses based both on the analytical results and on the specific features of the empirical context. The empirical examination enhances our understanding of the underlying mechanism of solar energy adoption in the U.S. electric utility industry.

Several limitations apply to this research. First, our study captures a certain stage of industry evolution, e.g., environmental disturbance caused by, for instance, new technological changes. It is not our primary interest in this paper to provide a comprehensive understanding of how firms respond to competitors' presence along the continuum of uncertainty as a market or an industry evolves. Yet it would be an interesting research project to look into the differences in firms' decision making patterns across various stages. Second, we use the U.S. electric utility companies' commitment to develop utility-scale solar projects as an appropriate context for empirical examination. Our empirical examination is limited to the U.S. utility electric companies. Nevertheless, our formal models are applicable to a wide variety of strategic decision-making scenarios. We believe that further research could test the predictions in other proper contexts.

Conclusion

This paper theoretically and empirically investigates the effect of competitors' prior action on firms' decision-making under environmental disturbance. Unlike the inverted U-shaped relationship in previous studies, we propose a U-shaped relationship between competitors' presence in a novel market and the focal firm's decision-making. Results from our models suggest that two mechanisms, i.e., learning (information) and competition, interact to determine how competitors' presence affects a firm's decision making. Competition can strengthen the information role of competitors' prior action, as well as countervailing the favorable information revealed from competitors' action. We choose utility companies' investment decision to build large-scale solar projects as the context for empirical examination, and find empirical support to our predictions. This study contributes to a broad array of literature on strategic decision making under uncertainty. It helps us identify the causal mechanisms underlying firms' decision making in a highly uncertain environment. In particular, we emphasize the environmental conditions, and formally establish more precise boundary conditions for various theoretical perspectives of firms' decision-making under uncertainty. Understanding how firms make strategic decision is a critical task in Strategy. We believe that this study takes researcher one more step closer to understanding the fundamental question.

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Table 1: Summary Statistics and Correlations

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. *IOU competitors*	0.78	1.53	0	9	1.00											
2.*IOU competitors (squared)*	2.94	9.94	0	81	0.90	1.00										
3. *IPP competitors*	7.28	12.16	0	71	0.79	0.68	1.00									
4. *IPP competitors (squared)*	200.77	523.65	0	5041	0.76	0.74	0.93	1.00								
5. *IPP capacity*	97.45	399.60	0	3165	0.60	0.58	0.62	0.67	1.00							
6. *Nuke 1 (1960s)*	0.12	0.33	0	1	-0.07	-0.07	-0.09	0.09	-0.07	1.00						
7. *Nuke 2 (1970s)*	0.21	0.41	0	1	-0.04	-0.04	0.03	0.02	-0.04	-0.19	1.00					
8. *Nuke 3 (1980s)*	0.09	0.29	0	1	0.07	0.06	0.05	0.04	0.07	-0.12	-0.16	1.00				
9. *RPS 2015 target*	9.52	9.50	0	38	-0.07	-0.07	-0.12	-0.11	-0.10	0.17	-0.22	0.08	1.00			
10. *RPS policy*	3.87	7.28	0	36	0.05	0.03	0.03	0.01	-0.01	0.15	-0.19	0.07	0.81	1.00		
11. *Wind energy*	0.25	0.43	0	1	0.12	0.09	0.14	0.13	0.08	0.04	0.23	0.04	-0.04	-0.10	1.00	
12. *Geographic region NERC_TRE*	0.09	0.29	0	1	-0.01	-0.02	0.04	0.06	-0.01	-0.12	0.16	0.03	-0.24	-0.15	-0.07	1.00
13. *Geographic region NERC_FRCC*	0.04	0.19	0	1	-0.07	-0.05	-0.07	-0.05	-0.04	-0.07	0.02	-0.06	-0.20	-0.10	-0.11	-0.06
14. *Geographic region NERC_RFC*	0.29	0.45	0	1	-0.02	-0.04	0.13	0.08	-0.08	0.01	0.29	-0.08	0.07	0.00	0.18	0.10
15. *Geographic region NERC_SERC*	0.17	0.38	0	1	-0.10	-0.08	0.01	0.03	-0.06	0.01	0.24	0.04	-0.33	-0.22	-0.18	0.21
16. *Geographic region NERC_SPP*	0.10	0.31	0	1	0.09	0.04	0.14	0.13	0.10	-0.05	-0.07	0.05	-0.27	-0.17	0.17	0.37
17. *Geographic region NERC_WECC*	0.24	0.43	0	1	0.33	0.27	0.22	0.20	0.21	-0.01	-0.15	0.20	0.04	-0.06	0.14	-0.09
18. *Revenue (logarithm)*	13.59	2.81	0	20.74	0.02	-0.01	0.04	0.01	-0.02	0.22	0.34	0.06	0.10	0.06	0.11	0.09
19. *Operating activity_generation*	0.75	0.43	0	1	0.07	0.04	0.06	0.06	0.05	0.07	0.22	0.18	-0.11	-0.07	0.33	-0.16
20. *Operating activity_transmission*	0.73	0.45	0	1	0.00	0.01	-0.03	0.00	0.03	0.04	-0.06	0.19	-0.09	-0.05	-0.07	0.08
21. *Operating activity_wholesale mkt*	0.57	0.50	0	1	0.04	0.01	0.02	0.03	0.02	0.12	0.07	0.27	-0.03	-0.08	0.25	-0.02
22. *Operating activity_retailing mkt*	0.21	0.41	0	1	-0.02	-0.03	-0.03	-0.03	-0.04	0.13	0.04	0.04	0.14	0.05	0.21	-0.16
23. *Operating activity_bundled*	0.37	0.48	0	1	-0.05	-0.03	-0.02	-0.01	-0.04	0.07	-0.01	0.14	0.13	0.09	0.12	-0.06

Variable	13	14	15	16	17	18	19	20	21	22	23
13. *Geographic region NERC_FRCC*	1.00										
14. *Geographic region NERC_RFC*	-0.13	1.00									
15. *Geographic region NERC_SERC*	0.11	-0.04	1.00								
16. *Geographic region NERC_SPP*	-0.07	-0.02	0.08	1.00							
17. *Geographic region NERC_WECC*	-0.11	-0.30	-0.25	-0.13	1.00						
18. *Revenue (logarithm)*	0.00	0.26	0.07	-0.03	0.05	1.00					
19. *Operating activity_generation*	-0.06	-0.01	0.09	0.09	0.18	0.26	1.00				
20. *Operating activity_transmission*	0.12	-0.29	0.20	0.21	0.14	0.37	0.28	1.00			
21. *Operating activity_wholesale mkt*	0.02	0.01	0.02	0.21	0.06	0.32	0.47	0.39	1.00		
22. *Operating activity_retailing mkt*	-0.10	0.16	-0.13	-0.07	0.06	0.15	0.17	0.09	0.20	1.00	
23. *Operating activity_bundled*	0.00	0.17	0.11	-0.11	0.02	0.22	0.24	0.08	0.29	0.06	1.00

Table 2: Examining predictions of electric power companies' decision of building solar plants

Variables	Cox Regression – Exact Marginal Likelihood						
	2.1	2. 2	2. 3	2.4	2.5	2.6	2.7
RPS 2015 target	0.235***	0.238***	0.246***	0.236***	0.247***	0.263***	0.224***
	(0.078)	(0.078)	(0.080)	(0.078)	(0.080)	(0.084)	(0.082)
RPS policy	-0.196**	-0.199**	-0.208**	-0.197**	-0.211**	-0.227***	-0.204**
	(0.081)	(0.080)	(0.082)	(0.081)	(0.083)	(0.886)	(0.084)
Wind energy	-3.239***	-3.225***	-3.314***	-3.248***	-3.603***	-3.603***	-3.016***
	(1.041)	(1.034)	(1.049)	(1.046)	(1.131)	(1.136)	(1.091)
Geographic region NERC_TRE	-0.367	-0.371	-0.529	-0.377	-0.573	-0.748	-1.001
	(0.973)	(0.976)	(0.993)	(0.977)	(0.995)	(1.001)	(1.127)
Geographic region NERC_FRCC	2.242*	2.299*	2.322*	2.247*	2.416*	2.488**	1.988
	(1.231)	(1.241)	(1.241)	(1.231)	(1.243)	(1.250)	(1.233)
Geographic region NERC_RFC	0.754	0.694	0.874	0.818	1.287	1.727*	0.954
	(0.586)	(0.600)	(0.611)	(0.810)	(0.900)	(0.943)	(0.639)
Geographic region NERC_SERC	1.318*	1.309*	1.350*	1.342*	1.493*	1.693**	0.928
	(0.749)	(0.752)	(0.759)	(0.777)	(0.792)	(0.819)	(0.780)
Geographic region NERC_SPP	1.130	1.112	1.509	1.177	1.594	2.236	1.733
	(1.354)	(1.348)	(1.351)	(1.1.416)	(1.508)	(1.505)	(1.324)
Geographic region NERC_WECC	2.256***	2.095***	2.356***	2.336***	2.987***	3.470***	2.501***
	(0.677)	(0.755)	(1.773)	(0.973)	(1.137)	(1.257)	(0.810)
Annual Revenue (logarithm)	0.138	0.144	0.158	0.137	0.148	0.164	0.196
	(0.130)	(0.133)	(0.136)	(0.130)	(0.134)	(0.138)	(0.142)
Operating activity_Generation	-0.564	-0.559	-0.544	-0.563	-0.574	-0.540	-0.424
	(0.692)	(0.691)	(0.709)	(0.691)	(0.697)	(0.706)	(0.731)
Operating activity_Transmission	0.485	0.491	0.549	0.479	0.308	0.398	1.061
	(0.902)	(0.902)	(0.921)	(0.904)	(0.925)	(0.944)	(1.065)
Operating activity_Wholesale mkt	0.128	0.090	0.172	0.129	0.031	0.126	0.133
	(0.558)	(0.564)	(0.574)	(0.558)	(0.566)	(0.578)	(0.595)
Operating activity_Retailing mkt	1.428**	1.430**	1.434**	1.429**	1.466**	1.470**	1.302**
	(0.576)	(0.576)	(0.582)	(0.576)	(0.592)	(0.590)	(0.578)
Operating activity_Bundled	0.480	0.490	0.443	0.476	0.429	0.376	0.334
	(0.488)	(0.491)	(0.498)	(0.489)	(0.496)	(0.501)	(0.510)
Nuke 1 (1960s)	1.767**	1.770**	1.887**	1.771**	1.847**	1.964**	1.989***
	(0.743)	(0.742)	(0.758)	(0.744)	(0.764)	(0.775)	(0.763)
Nuke 2 (1970s)	1.806**	1.798**	1.850**	1.809**	2.063**	2.006**	1.529
	(0.887)	(0.890)	(0.918)	(0.888)	(0.935)	(0.957)	(0.951)
Nuke 3 (1980s)	0.462	0.465	0.419	0.468	0.704	0.583	0.668
	(0.798)	(0.797)	(0.793)	(0.800)	(0.832)	(0.826)	(0.811)
IOU competitors		-0.073	-0.544			-0.597*	-1.033**
		(0.150)	(0.339)			(0.354)	(0.415)
IOU competitors (squared)			0.092*			0.104*	0.247***
			(0.046)			(0.054)	(0.861)
IPP competitors				-0.004	-0.075	-0.073	
				(0.032)	(0.064)	(0.067)	
IPP competitors (squared)					0.001	0.001	
					(0.001)	(0.001)	
IOU competitors × IPP capacity							-0.001*
							(0.001)
Log likelihood	-69.09	-63.98	-61.81	-64.09	-63.21	-61.05	-58.00
LR χ^2 against null model	62.58	62.81	67.14	62.59	64.34	68.66	74.76

*Notes. N = 867. Standard errors are in parentheses. LR, likelihood ratio. *p<0.10; **p<0.05; ***p<0.01*

Table 3: Examining predictions of electric power companies' decision of building solar plants

Variables	Models			
	3.1 Logistic Regression	3.2 Complementary log-log	3.3 Random Effect	3.4 GEE (population-averaged)
RPS 2015 target	0.218**	0.208***	0.218**	0.187***
	(0.085)	(0.077)	(0.085)	(0.065)
RPS policy	-0.197**	-0.187**	-0.197**	-0.173***
	(0.088)	(0.077)	(0.088)	(0.063)
Wind energy	-2.884***	-2.663***	-2.884***	-2.489***
	(1.082)	(0.993)	(1.082)	(0.730)
Geographic region NERC_TRE	-1.091	-0.978	-1.091	-1.268*
	(1.156)	(1.068)	(1.156)	(0.753)
Geographic region NERC_FRCC	1.889	1.757	1.889	1.586
	(1.285)	(1.216)	(1.285)	(1.331)
Geographic region NERC_RFC	0.931	0.907	0.931	0.716
	(0.702)	(0.624)	(0.702)	(0.569)
Geographic region NERC_SERC	0.984	0.913	0.984	0.807
	(0.832)	(0.771)	(0.832)	(0.746)
Geographic region NERC_SPP	1.741**	1.652	1.741**	1.533
	(1.347)	(1.306)	(1.347)	(1.200)
Geographic region NERC_WECC	2.667***	2.412***	2.667***	2.208***
	(0.894)	(0.769)	(0.894)	(0.642)
Annual Revenue (logarithm)	0.227	0.205	0.227	0.199**
	(0.148)	(0.137)	(0.148)	(0.099)
Operating activity_Generation	-0.378	-0.389	-0.378	-0.347
	(0.772)	(0.708)	(0.772)	(0.553)
Operating activity_Transmission	1.175	1.206	1.175	0.994
	(1.129)	(1.035)	(1.129)	(1.041)
Operating activity_Wholesale mkt	0.262*	0.173	0.262*	0.225**
	(0.633)	(0.574)	(0.633)	(0.605)
Operating activity_Retailing mkt	1.233**	1.130**	1.233**	0.941*
	(0.601)	(0.552)	(0.601)	(0.568)
Operating activity_Bundled	0.257	0.285	0.257	0.218
	(0.538)	(0.497)	(0.538)	(0.441)
Nuke 1 (1960s)	1.976**	1.831**	1.976**	1.577**
	(0.764)	(0.718)	(0.764)	(0.651)
Nuke 2 (1970s)	1.436	1.337	1.436	1.147
	(0.947)	(0.888)	(0.947)	(0.783)
Nuke 3 (1980s)	0.658	0.694	0.658	0.640
	(0.873)	(0.790)	(0.873)	(0.748)
IOU competitors	-0.998**	-0.904**	-0.998**	-0.782***
	(0.442)	(0.384)	(0.442)	(0.293)
IOU competitors (squared)	0.269***	-0.244***	0.269***	-0.202***
	(0.092)	(0.077)	(0.092)	(0.048)
IOU competitors × IPP capacity	-0.001**	-0.001**	-0.001**	-0.001***
	(0.001)	(0.000)	(0.001)	(0.000)
Year	2.486***	2.356***	2.486***	2.058**
	(0.825)	(0.783)	(0.825)	(0.805)
Year (squared)	-0.102**	-0.097**	-0.102**	-0.084*
	(0.046)	(0.044)	(0.046)	(0.047)
Log likelihood	-74.53	-73.84	-74.53	
LR/Wald χ^2 against null model	105.03	106.40	44.76	177.18

*Notes. N = 867. Standard errors are in parentheses. LR, likelihood ratio. *p<0.10; **p<0.05; ***p<0.01*

Figure 1: The impact of firm 1's investment on firm 2's incentive to invest in the same domain given that $= 1/\sqrt{2}, (1/\sqrt{2} = 0.707)$.

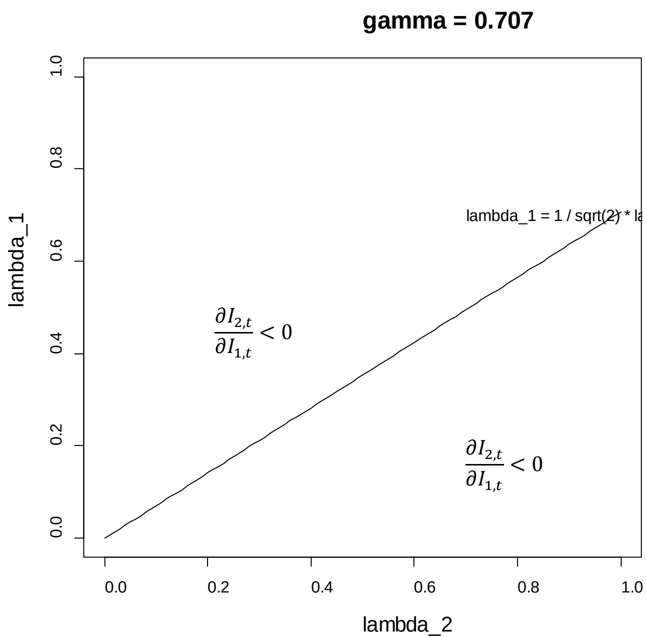


Figure 2: Two numerical examples concerning the impact of firm 1's investment on firm 2's incentive to invest in the same domain given that $\gamma < 1/\sqrt{2}$, i.e., $\gamma = 0.15$ and $\gamma = 0.4$.

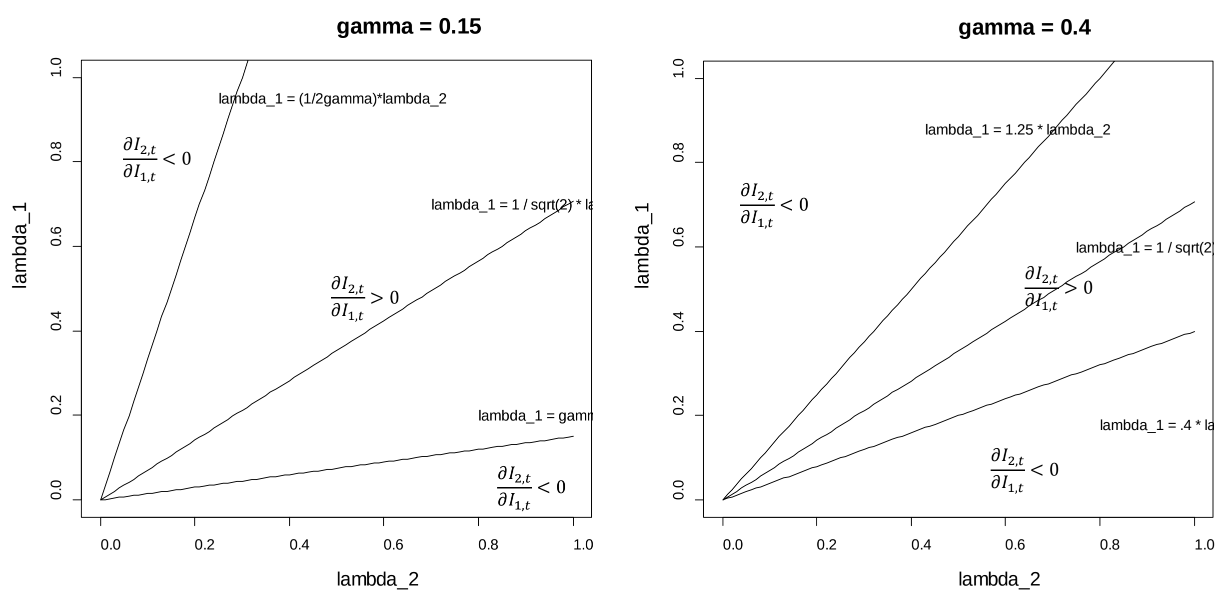
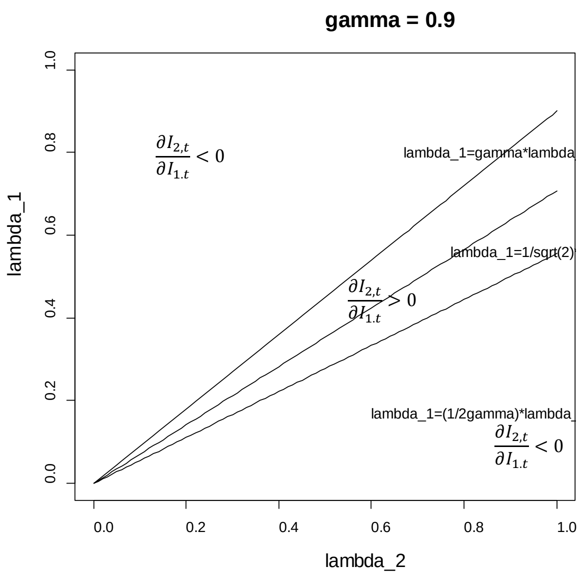


Figure 3: Two numerical examples concerning the impact of firm 1's investment on firm 2's incentive to invest in the same domain given that $\gamma > 1/\sqrt{2}$, i.e., $\gamma = 0.9$ and $\gamma = 1.5$.



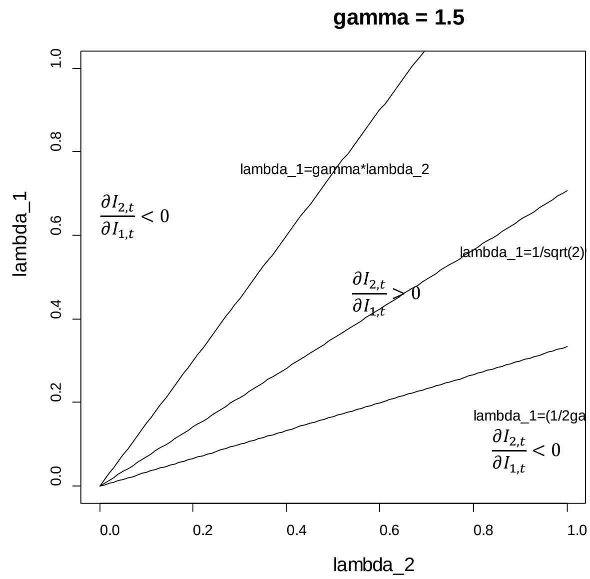


Figure 4: The impact of firm 1's investment on firm 2's incentive to invest in the same domain given that $\lambda_1 = 0.4$. and $\lambda_2 = 0.2$.

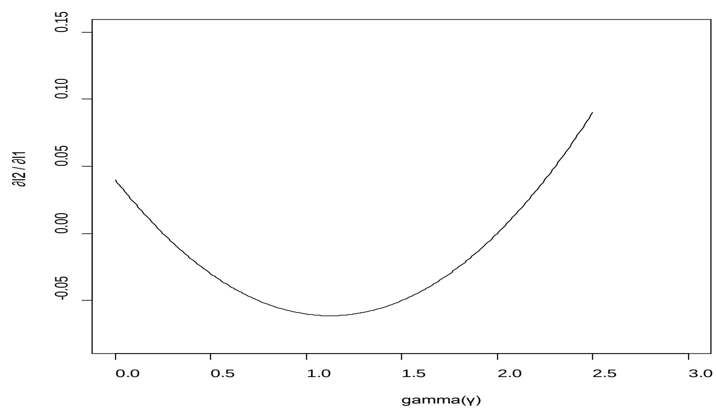


Figure 5: The U-shaped relationship between competitors' presence and the focal firm's investment

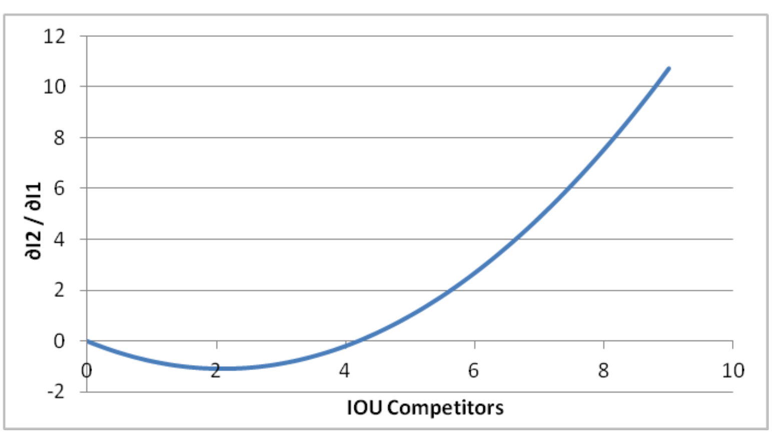


Figure 6: The impact of IPPs' newly added solar capacity

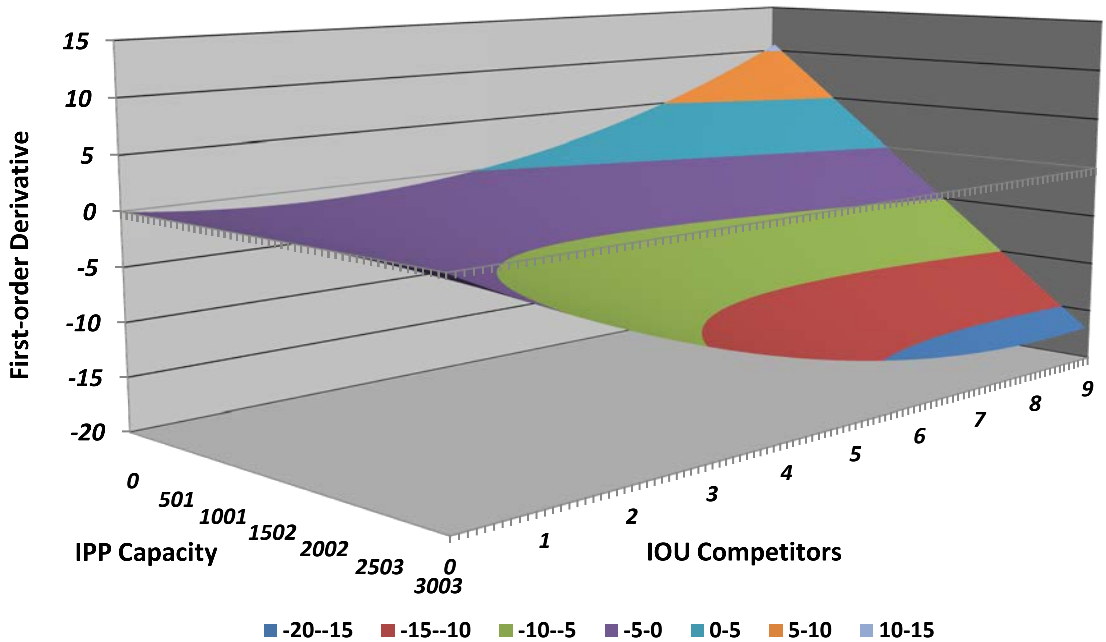


Figure 7: Hazard functions for utility companies that developed nuclear plants in 1960s and the counterpart group

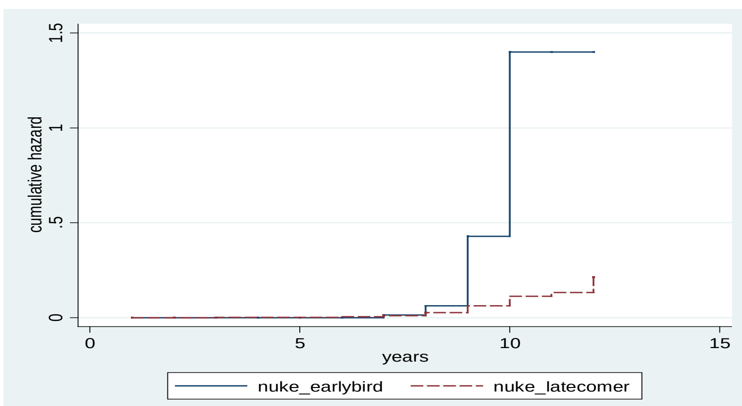
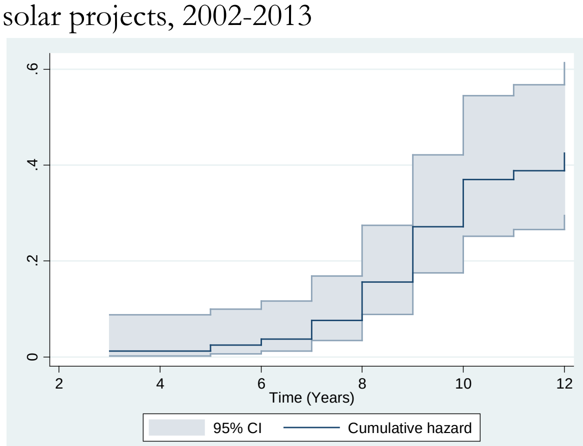
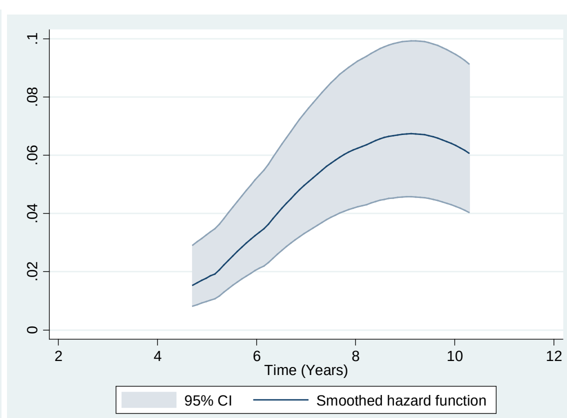


Figure 8: Cumulative hazard (8a) and smoothed hazard estimate (8b) of IOU investing in utility-scale solar projects, 2002-2013



(Figure 8a)



(Figure 8b)

Appendix A:

Consider a duopoly product market competition in which firms face a downward demand curve. Without competitive interaction, firm i's inverse demand function is given by

$$p_i = a - bd_i$$

where d_i is the demanded quantity of firm i's product, and p_i is the highest price that firm i can charge and still generate demanded quantity d_i. Nevertheless, if one firm's product has impact on demands for another firm's product, the demand function is specified as,

$$p_i = a - bd_i + dd_j,$$

where d_j is the demanded quantity of firm j's product. Assume a monotonically increasing production function of investment (cost) represented by,

$$d_i = f(I_i).$$

where I_i stands for the minimum investment required for producing quantity d_i. Then, we can specify the profit function, earnings gross of production cost, as the following expression:

$$\pi_i = (a-1)I_i - b{I_i}^2 + dI_iI_j.$$

The profit function can be generalized as

$$\pi_i = \mu I_i - \frac{1}{2}{I_i}^2 + \gamma I_i I_j,$$

where $\mu = a - 1, \gamma = d$, and to reduce complexity in calculation of the optimal investment choice, $b = \frac{1}{2}$.

□

Appendix B:

Since firm 1's investment choice is specified as,

$$I_{1,t} = (1-\lambda_1)\hat{\mu}_{1,t-1} + \lambda_1 z_{1,t} - \gamma I_{2,t} - \gamma I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} \tag{1}$$

it follows that

$$z_{1,t} = \frac{1}{\lambda_1}I_{1,t} + \frac{\gamma}{\lambda_1}I_{2,t} + \frac{\gamma}{\lambda_1}I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} - (\frac{1}{\lambda_1} - 1)\hat{\mu}_{1,t-1} \tag{2}$$

Firm 2, on the other hand, would choose the investment decision that maximizes its profits. The first order condition yields

$$\frac{\partial \pi_{2,t}}{\partial I_{2,t}} = (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{1}{2}\lambda_2 z_{1,t} - I_{2,t} - \gamma I_{1,t} = 0 \tag{3}$$

Substituting the expression for $z_{1,t}$ into (3) we have:

$$\begin{aligned}\frac{\partial \pi_{2,t}}{\partial I_{2,t}} &= (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{1}{2}\lambda_2\left[\frac{1}{\lambda_1}I_{1,t} + \frac{\gamma}{\lambda_1}I_{2,t} + \frac{\gamma}{\lambda_1}I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} - \frac{(1-\lambda_1)}{\lambda_1}\hat{\mu}_{1,t-1}\right] - I_{2,t} - \gamma I_{1,t} \\ &= (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{\lambda_2}{2\lambda_1}I_{1,t} + \frac{\lambda_2\gamma}{2\lambda_1}I_{2,t} + \frac{\lambda_2\gamma}{2\lambda_1}I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} - \frac{\lambda_2(1-\lambda_1)}{2\lambda_1}\hat{\mu}_{1,t-1} - I_{2,t} - \gamma I_{1,t} \\ &= (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{\lambda_2}{2\lambda_1}I_{1,t} + \left(\frac{\lambda_2\gamma}{2\lambda_1} - 1\right)I_{2,t} + \frac{\lambda_2\gamma}{2\lambda_1}I_{1,t}\frac{\partial I_{2,t}}{\partial I_{1,t}} - \frac{\lambda_2(1-\lambda_1)}{2\lambda_1}\hat{\mu}_{1,t-1} - \gamma I_{1,t}\end{aligned}$$

Solving for $\frac{\partial \pi_{2,t}}{\partial I_{2,t}} = 0$, we have

$$\omega I_{2,t} = (1-\lambda_2)\hat{\mu}_{2,t-1} + \frac{1}{2}\lambda_2 z_{2,t} + \frac{\lambda_2}{2\lambda_1}I_{1,t} + \frac{\lambda_2\gamma}{2\lambda_1}\frac{\partial I_{2,t}}{\partial I_{1,t}}I_{1,t} - \gamma I_{1,t} - \frac{\lambda_2(1-\lambda_1)}{2\lambda_1}\hat{\mu}_{1,t-1} \tag{4}$$

where $\omega = 1 - \frac{\lambda_2\gamma}{2\lambda_1}$.

We assume the second-order partial derivative of firm 2's investment with respect to firm 1's investment is zero. Differentiating Equation (4) with respect to firm 1's investment yields,

$$\frac{\partial I_{2,t}}{\partial I_{1,t}} = \frac{1}{\omega}(\frac{\lambda_2}{2\lambda_1} - \gamma) + \frac{1}{\omega}\frac{\lambda_2\gamma}{2\lambda_1}\frac{\partial I_{2,t}}{\partial I_{1,t}}$$

Substituting $\omega = 1 - \frac{\lambda_2\gamma}{2\lambda_1}$ into (4) yields,

$$\frac{\partial I_{2,t}}{\partial I_{1,t}} = \frac{\frac{1}{\omega}(\frac{\lambda_2}{2\lambda_1} - \gamma)}{1 - \frac{1}{\omega}\frac{\lambda_2\gamma}{2\lambda_1}} = \frac{\frac{\lambda_2}{2\lambda_1} - \gamma}{\omega - \frac{\lambda_2\gamma}{2\lambda_1}} = \frac{\frac{\lambda_2}{2\lambda_1} - \gamma}{1 - \frac{\lambda_2\gamma}{\lambda_1}} = \frac{1}{2}\frac{\lambda_2 - 2\gamma\lambda_1}{\lambda_1 - \gamma\lambda_2} \tag{5}$$

□