Clean Energy Investment and Government Policies under Technology Risk

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Abstract: This paper investigates a clean energy firm's optimal investment timing and scale under technological change. We show that the firm will not follow a consistent investment pattern when new technologies and learning-by-doing, two different types of technological change, are both accounted for. The firm will invest earlier and on a smaller scale when the learning effect is strong but the next new technology takes a long time to arrive, otherwise it will invest later but on a larger scale. This is in contrast to the common finding in real-options literature that technological change delays investment. The policy implication of this result is discussed and compared with observed firm behavior in the clean energy market.

Keywords: Clean energy investment; Technological change; Innovations; Technological learning; Real options;

1. Introduction

When firms contemplate irreversible investments in a market, their investment strategies are heavily influenced by the technological progress they could exploit. In the electricity market, for example, the current solar photovoltaics (PV) based on silicon cells still generates more expensive electricity than the conventional fossil-based system. In such a circumstance, firms planning investments in the solar PV would compare two choices: i) waiting for the next generation PV based on organic cells, which directly reduces the cost below the fossil-based system (Baker et al.,2009); ii) investing in the existing silicon PV and in the hope of gradually reducing the cost below the fossil-based system via exhibited steep learning curve (Bollinger & Gillingham, 2014).

The reason driving such a comparison is that firms face different paths of technology progress before and after investments. Before investments, firms still keep opportunities of adopting more efficient technologies developed in the future, thus getting a lower production cost at the moment of investments. On the other hand, after investments, firms could use existing technologies more proficiently over time, thereby quickly moving down the future production cost along the learning curve. Thus, a trade-off emerges: by investing late, firms have the potential to use a more superior technology; at the same time, this waiting is at the cost of exploiting learning economies for existing technologies by investing early.

The purpose of this paper is to study a firm' investment strategy under such a tradeoff. Specifically, we analyze the firm's optimal investment timing and scale under a technological environment where it faces a flow of new technologies arriving sequentially over time and each technology is characterized by learning curve in the production process. Such a technological environment is common at early stages of many industries, especially when the current available technology is still not profitable. However, firms follow different strategies across industries. For instance, in the industries of solar and wind energy, most firms choose to invest quickly and on a large scale in the existing technologies. As a result, the two industries contribute more than 67%

of U.S. electric generation capacity addition in 2015, with more than $33 billion invested (Wiser & Bolinger, 2016; SEIA, 2016). In contrast, the industry of cellulosic ethanol, another hopeful source of clean energy produced from grasses, crop residual, and wood, is still lacking investments. The U.S. produced volume of cellulosic ethanol was less than 4 million gallons in 2015, far behind the initial target of 3 billion gallons imposed by the Clean Air Act (EPA, 2015).

Our model could identify the characteristics of technological environments that drive the differences in such behavior. Moreover, our combined considerations of timing and capacity could reveal the net impact of technological environment on investment outcome. Even if the investment is deferred, the accumulated output over a certain period may still increase as long as the late entry is compensated by a larger productive capacity (Huberts et al., 2015). This capacity-timing tradeoff is particularly important in issues involving long-term investment plan, such as investments in the clean energy, or in the adaptations to climate change. Finally, our model also has important implications for designing government policies regarding investment promotion. If firms have different strategies under different technological environments, policymakers should be aware of how their policies would change technological environments faced to firms (e.g., government R&D expenditure may accelerate the arrival of new technologies while production subsidy may encourage learning-by-doing), which in turn cause firms to adjust their investment behaviors.

In order to decide whether to invest, a firm would compare profits under taking more efficient technologies arriving in the future and under employing existing technologies for the learning-by-doing. For the former question, Farzin et al. (1998) investigate optimal investment timing when a firm faces a sequence of innovations arriving stochastically over time. Based on Farzin et al.'s model, Doraszelski (2004) extends that when each innovation arrives, it will trigger a stochastic process of engineering refinements that improve the basic innovation. Because the choices of innovations and refinements are both irreversible, a firm can only adopt them before investments, lacking the path to enhance the productivity after investment. As a result, both models predict that the firm will delay its investment to reduce the risk of missing new innovations or refinements. For the latter question, Majd & Pindyck (1989) and Della Seta et al. (2012) study a firm's optimal investment (production) strategy under the learning curve. Because learning curve is the only source of technological progress and could only be triggered after production, both paper conclude that the firm will invest (produce) earlier to exploit the process of learning-by-doing.

Unlike these studies, our model considers a firm's investment strategies when it has channels to enhance the technology efficiency both before and after investments. Before investment, a firm holds the option to invest while facing a flow of technologies arriving sequentially over time. The technology choice is irreversible, meaning that firms already adopting the old technology cannot adopt the new one. We interpret these technologies as "innovations". In each period, the firm can invest in the current cutting-edge innovation, or it can await the arrival of more efficient innovations on the horizon. When each innovation becomes commercial available, a sequence of engineering refinements ("refinements") that complements this innovation is spurred. Thus, the firm does not have to invest immediately after a new innovation arrives. Instead, it can wait for this innovation developed efficient enough by the spurred refinements and invest then. When deciding to invest, the firm has to determine the capacity level for the planned producing facility. After investment, the firm is locked in the adopted innovation, but triggers the process of learning-by-doing ("learning") that gradually improves the efficiency of adopted innovation over the accumulated output. Different technological environments differ in the pace and value of innovations and refinement, as well as the steepness of learning curve.

We show that the firm will not follow a consistent investment pattern in this setting. Instead, its investment timing heavily depends on the competition between two components. The first component, which we call the "prospect effect", represents the increasing project value mainly contributed by exploiting learning economies after investment. The other component, which we call the "lag effect", reflects that the investing option is more expensive to exercise due to the risk of stuck in an obsolete technology shortly. The competition between the two effects only arises when the technological path faced to the firm is differentiated before and after investment. Hence, this prospect-vs.–lag situation is a distinct feature of our model, and plays a key role in explaining firms' diverse investment behavior.

We say that the firm follows "prospector strategy" if it invests earlier and on a larger scale. In this case, the firm will respond quickly to existing innovations, in anticipation of prospecting learning economies earlier and at a larger rate after the plant is in place. This strategy is optimal if the prospect effect dominates the lag effect. Thus, it prevails when the learning curve is steep and the next revolutionary innovation takes a long time to arrive. Such a technological environment currently fits for the industries of solar and wind energy, where the technological progress is mainly driven by the learning economies of large-scale deployment of existing technologies (Nemet, 2009) and the next generation technology is still under the long-term R&D phase in the scope of several decades (Baker et al.,2009; Wiser, et al., 2016).

In contrast, we say that the firm follows "laggard strategy" if it invests later and also on a larger scale. In this case, the firm has enough patience to wait for the sufficiently advanced technology available, and will build a plant with larger capacity since the advanced technology considerably raises the capital payoff at the moment of investment. This strategy is adopted when the lag effect outweighs the prospect effect, which suggests a technological environment where breakthrough innovations are likely to arrive in the near feature and existing innovations are quickly directed towards maturity by strong refinements. Such a technological environment is exhibited in the cellulosic ethanol industry, where two new breakthrough refinery technologies are anticipated to arrive very soon and the cost of existing enzymatic hydrolysis technology also drops fast (e.g., Laser et al., 2009; NREL, 2010; Bloomberg, 2013). Thus, despite the fact that learning economies are also strong in this industry, most firms choose to wait and see.

2. Model

We consider a risk-neutral firm that contemplates a one-time investment in a technology environment that embraces three different patterns of technological change.[1] Before investing, the firm faces a sequence of innovations arriving sequentially over time. When a new innovation becomes commercial available, a sequence of engineering refinements that complements this innovation is spurred. The firm could invest in the current innovation, or it can wait for the future innovations to invest. Moreover, the firm does not have to invest immediately after a new innovation arrives. Instead, it can wait for this innovation developed efficient enough by the spurred refinements and invest then. If the firm decides to invest, the technology efficiency will continue to be improved via both the learning economies and the refinements pertained to the adopted innovation.

To produce, the firm has to pay an irreversible investment cost I. The unit capital cost is B, so the total investment expense to build a plant with the capacity of K units is $I = KB$. In addition to the physical establishment cost, B and I could also contain the cost of getting the employed technology such as the R&D spending or the royalty payment. After producing, the total operating cost C in period t is expressed as a quadratic cost function

$$C_t(q_t) = aq_t^2 + s\theta_t q_t \quad (1)$$

where q_t is the output quantity in period t; s is a positive parameter reflecting the benchmarking cost to produce unit output such as the input cost at the beginning; θ_t measures the decrease of s in period t due to the technological change with $\theta_0 = 1$. The non-negative parameter a represents reduced cost efficiency and decreasing return to marginal inputs as the producing scale expands, like the abundant produced electricity that are not purchased by the utility company or the increasing management cost.[2] Because allowing a to change does not provide any new insight into our results, we assume that this part of cost cannot be reduced by the technological progress.[3] Here we refer to the technological change as the process development that reduces the operating cost, but all results derived in our model have the potential to apply in cases where technological change occurs in product development that raises the output price. The investment problem encountered by a firm is when and how much to invest under the technology evolution of θ_t.

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[1] To focus on our central point and make our analysis concise, we only consider a one-time investment problem. As shown in Grenadier & Weiss (1997), the investment strategy based on multi-investment problem is considerably similar as the strategy derived by one-time investment problem, with merely the difference of magnitude (p. 408, Fig.1; p. 410, Fig. 2). In addition, Doraszelski (2001) proves that the multi-investment problem holds the same basic form as the one-time investment problem.

[2] The cost inefficiency due to increasing scale is documented widely in empirical studies, especially in the renewable energy sector. For example, Chen and Khanna (2012) find significant decreasing return to scale in the corn ethanol production. If there is no such the cost inefficiency that $a = 0$, the optimal capacity choice is a corner solution that the firm will always choose the capacity up to the physical capacity limitation or its financial constraint. But in this case all results about the investment timing do not change compared to the non-zero case.

[3] The effect for the decrease of a could be captured by the change of θ via learning economies in our model.

2.1 The technological change

A distinct feature in our model is that θ does not evolve the same way before and after investment because different patterns of technological change are triggered. We use number "0" ("1") to denote the state of θ before (after) investment. Before investment, there exist three possibilities of technology progress occurring during a small time interval *dt*:

$$\frac{d\theta^0}{\theta^0} = \begin{cases} -U & \text{with probability } \lambda dt \\ -W & \text{with probability } \mu dt \\ 0 & \text{else} \end{cases} \qquad (2)$$

The first possibility is that a new innovation arrives with probability λdt. Moreover, the extent of efficiency gain from the innovation is also uncertain, governed by a stochastic variable U with the expected value u. The second possibility is that the refinements advance the current best innovation by the extent of variable W with the expected value *w*, which occurs at the probability μdt. To prevent technology regress, we assume $U > 0$ and $W > 0$. Finally, it is also possible that no technological progress achieved in such a small interval. To keep our focus on the differentiation of technological path before and after investment, we assume that both λ and μ are time-invariant, i.e., the arrival rates of innovations and refinements do not change over time.[4]

In this setting, technological progress before investment is exogenous to firms and uncertainties are embedded in both the pace and rate of innovations and refinements due to the uncertain R&D outcome. Firms do not know exactly when and by how much the technology will advance due to its limited knowledge (Foster, 1986), but they still have the ability to control or forecast the average arrival time and the extent of efficiency improvement. This setting is similar as Farzin et.al (1998) and Doraszelski (2004). However, a key difference is that in their models both innovations and refinements cannot be adopted after investment, resulting in a stagnant technology efficiency once investing. In our model, even though investing firms are also stuck into their adopted innovation once investing, they could still update the technology through refinements and learning.

The path of θ is thus different from equation (2) after investment. First, the firm has lost the option of adopting innovations in the future due to incompatibilities between old and new innovations. Second, learning economies will be triggered. Following Spence (1981), Majd & Pindyck (1989), and Della Seta et.al (2012), we use $c_t(Q) = ce^{-\Gamma Q_t}$ to measure this effect. c_t is the unit production cost in period *t* and Q_t is the cumulative output in period *t*. Γ is the non-

4 An alternative assumption is that the arrival rates for innovations or refinements are diminishing or hump-shaped, which are discussed in Doraszelski (2004). Because our focus is on the comprehensive technological environment rather than a specific pattern of technological change, we use the time-invariant assumption to simplify our analysis. Many industries still follow a certain pace to upgrade the technology. In the microprocessor industry, the number of transistors in an integrated circuit doubles approximately every two years, which is well known as "Moore's law". In the lighting-emitting diodes (LED) industry, Haitz's law states that every decade the amount of light generated by an LED increases by a factor of 20.

negative learning parameter with the expected value γ. The extent of efficiency gains from learning depends critically on firm's output q and the expected learning speed γ . To simplify our analysis, we consider a case that the firm always produces at the full capacity after investment, i.e., the quantity of produced output q is equal to the plant capacity K in each period.[5] Under this constant production rate, the per-period percentage reduction of production cost due to learning economies could be expressed as $e^{-\Gamma q}-1$. Then the path of θ over dt after investment can be summarized as:

$$\frac{d\theta^1}{\theta^1} = (e^{-\Gamma q}-1)dt + \begin{cases} W & \text{with probability } \mu dt \\ 0 & \text{else} \end{cases} \qquad (3)$$

Comparing equation (3) with (2), we see clearly that after investments, firms trigger the stable incremental learning economies by the extent of $e^{-\Gamma q}-1$ but sacrifice the opportunity of adopting future innovations represented by U and λ. In the meanwhile, the refinements are still open to investing firms. In this way, we capture the idea that technological path is associated with investment decisions by distinguishing the path before and after investment. The investment strategy therefore relies on a comparison of technological benefits under waiting and producing.

2.2 The project value after investment

We first analyze firms' profits after investment. In order to keep our focus on the technology part, we consider a competitive market with the given price P such as the renewable energy market.[6] The profit of a producing firm with the capacity q in period t can be written as:

$$\pi_t = (P - aq - s\theta_t^1)q \qquad (4)$$

Here technology efficiency θ_t^1 evolves according to equation (3) rather than equation (2) because profit could be yielded only after production. Given the discount rate ρ, the firm's total expected payoff upon investing is

[5] Producing up to capacity may not be always optimal. However, established firms often try to maintain at the full capacity level for two reasons. First, producing at a high rate could deter other firms' entry even though it is not profitable to do so (reviwed by Spulber, 1981). Second, even when the market condition is not favored, many firms may find it difficult to produce considerably below the capacity level because of the fixed and suspension cost involved labor and machine as well as the financial pressure from their suppliers and loan banks. The learning economies itself also enhances this assumption. For more discussions regarding the full-capacity assumption, see Goyal & Netessine(2007), Della Seta et al.(2012) and Huisman & Kort (2015). For studies on firm's flexibility to adjust their output after investment, see Chicu (2013) and Wen, Kort, & Talman (2015).

[6] Investment decisions are also heavily influenced by uncertainties surrounding the market price and the market structure. For question of this type, see Murto (2007), Guthrie (2012), Della Seta et.al (2012), and Huisman & Kort (2015).

$$V(\theta_1, q) = E\left[\int_0^{+\infty} e^{-\rho t}\,(P - aq - s\theta_t^1)qdt\right] = \left(\frac{P - aq}{\rho} - \frac{s\theta_1}{\rho + 1 - e^{-\gamma q} + w\mu}\right)q \quad (5)$$

On the right-hand side of equation (5), the first term in the bracket represents unit capacity revenue net of the increasing cost inefficiency aq over the plant life and the second term is the lifetime production cost. Due to the refinements and learning economies, we see that the cost part is discounted more quickly than the net revenue by the rate of $1 - e^{-\gamma q} + w\mu$. This rate essentially illustrates how the technological progress after investment raises project payoff, providing primary incentives to early investment.

2.3 The option value before investment

We now analyze the option value before investment. At this time, the firm still keeps the option to adopt future innovations, which means θ^0 evolves according to equation (2). The value of investing option $F\,(\theta^0)$ arises from uncertainties embedded in innovations and refinements, expressed as the following Bellman equation:

$$F\,(\theta^0) = \frac{1}{1 + \rho dt} E[F(\theta^0 + d\theta^0)] \quad (6)$$

Expanding equation (6) by Ito's lemma, the standard real options model (Dixit & Pindyck, 1994) gives the ordinary differential equation:

$$(\lambda + \mu)F\left[\left(1 - \frac{\lambda}{\lambda + \mu}u - \frac{u}{\lambda + \mu}w\right)\theta^0\right] - (\rho + \lambda + \mu)F(\theta^0) = 0 \quad (7)$$

The general solution of the investing option is in the form of $F\,(\theta^0) = D(\theta^0)^\beta$ where β is the negative root of

$$(\lambda + \mu)\left(1 - \frac{\lambda}{\lambda + \mu}u - \frac{u}{\lambda + \mu}w\right)^\beta - (\rho + \lambda + \mu) = 0 \quad (8)$$

using the condition that $F\,(\theta_0 \to \infty) = 0$.[7] Technological risk is reflected by β, a risk parameter determined by $\lambda, \mu, u,$ and w. As β increases, the investing option is more expensive to exercise, making the waiting option more attractive.

2.4 The optimal investment strategy

Finally, we analyze how firms compare the benefit-cost before and after investment to make the final investment decision. Standard real options model often suggests a more stringent entry condition when technological uncertainties are involved in the investment decisions. In our framework, however, this is not necessarily the case because technological path is differentiated

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[7] $F\,(\theta^0 \to \infty) = 0$ means that as the production cost approaches to infinity, investing cannot be profitable and therefore, the option of investing does not have any value.

before and after investment. The trade-off between innovations, refinements, and learning leads to a more complicated investment strategy. To show this, we first derive the investment threshold and optimal capacity level using the value-matching and smooth-pasting conditions. Although the path of θ are differing before and after production, they are crossed with each other at the point of investment trigger. Accordingly, the investment threshold is simplified to $\theta^* = \theta_0^* = \theta_1^*$.

$$F(\theta^*, q^*) = V(\theta^*, q^*) - Bq^* \quad (9)$$

$$F_{\theta^0}(\theta^*, q^*) = V_{\theta^1}(\theta^*, q^*) \quad (10)$$

$$V_q(\theta^*, q^*) - B = 0 \quad (11)$$

Equation (9) and (10) say that at the investment threshold θ^*, the total (marginal) value of the investing option should be equal to the total (marginal) payoff yielded by the project. Equation (11) is the first order condition of the optimal capacity level. It means that firms choose the capacity level at which the marginal capacity payoff equals the capital cost at the moment of investing. Solving the system of equation (9), (10), and (11) by the substitution of equation (5) and (8) yields

$$\frac{P}{\rho} - \frac{\left(\frac{P - aq^*}{\rho} - B\right)\beta q^* \gamma e^{-\gamma q^*}}{\rho - e^{-\gamma q^*} + 1 + w\mu} = B + \frac{aq^*(2-\beta)}{\rho} \quad (12)$$

$$\kappa^* = 1 - \theta^* = 1 - \underbrace{\left(\rho + 1 - e^{-\gamma q^*} + w\mu\right)}_{\text{prospect effect}} \underbrace{\frac{\beta}{\beta - 1}}_{\text{lag effect}} \underbrace{\frac{1}{s}\left(\frac{P - aq^*}{\rho} - B\right)}_{\text{scale effect}} \quad (13)$$

Equation (12) states that the marginal capacity benefit should equal the marginal capacity cost at the optimal capacity level. The left-hand side shows the marginal capacity benefit composed of two parts. Besides the market revenue P/ρ, the second term demonstrates that increasing one capacity unit also contributes to the faster decline of future production cost because of learning economies (recall that β <0 so the second term is positive). The marginal capacity cost is described by the right-hand side. For each incremental size, the firm incurs an increasing organization cost $aq^*(2-\beta)/\rho$ in addition to the establishment cost B. Technological environment has two channels to affect the capacity choice. First, the firm will choose how much to invest to exploit future learning economies, which depends on the learning speed γ. Second, the capacity choice is also based on the technology efficiency level at the moment of investing, which is impacted by the technology risk parameter β.

Equation (13) demonstrates factors determining the optimal investment timing. To interpret our results more intuitively, in the rest of this article we use the proportion of cost reduction $\kappa^* = 1 - \theta^*$ as the indicator of investment trigger. In this way, the greater κ^* is, the higher the investment trigger is. The term denoted by the “prospect effect” illustrates how the technological progress shortens the investment timing by raising the project value $V(\theta_1, q\ )$ after investment, which makes investing early as a possible optimal strategy that are not allowed in Farzin, et al.'s (1998) and Doraszelski (2004)'s models. This effect could be decomposed into two parts. First, $1 - e^{-\gamma q^*}$ represents the value of triggered learning economies after investment. Second, $w\mu$ describes the expected efficiency gain from refinements that the producing firm could still employ to update the adopted innovation. Innovations do not involve in the prospect effect because the producing firm loses the option to adopt them after investment.

The "lag effect" shows how the technological environment delays firms' entry before investment. As innovations and refinements arrive stochastically over time, the firm has to bear two types of risks in its faced technology environment, which raise the option value $F\ (\theta^0)$. First, investing early exposes the firm to the risk of missing future innovations. If a revolutionary innovation is expected to arrive very soon, the cost of missing such an innovation is too huge to be afforded by the firm. Second, even if future innovations will not be achieved in the short run, the firm still has the incentive to wait for the improvement of existing innovations by refinements. If investing early, the firm has to produce at a much higher cost level before the adopted innovation is further refined, which may not be economical compared with investing until the innovation becomes sufficiently advanced.

The final term "scale effect" describes how the capacity choice affects the investment timing. As the producing capacity increases, the increasing cost inefficiency aq^* will diminish the economic attractiveness of the project. Under such a condition, the firm will require a more efficient technology to invest, thereby leading to an investment delay. The optimal investment timing depends on competition between prospect, lag, and scale effects.

3. Choice of investment strategy

3.1. Benchmark: myopic case

We use the myopic case where firms base their investment strategies only on the technology efficiency level in the current period as our benchmark. Here, myopic firms do not anticipate any pattern of technological change beforehand (Feichtingera et al., 2006a), solving the problem of equation (12) and (13) with all technology parameters $\{\lambda, u, \mu, w, \gamma\}$ equal to zero. This problem is equivalent to firms first choosing the optimal investment scale under the criteria of profit maximization and then calculating the investment trigger using the net present value method. We denote the derived investment strategy as $\{\bar{q}, \bar{\kappa}\}$. The difference between the myopic and the forward-looking firm is that while the myopic firm will invest as long as the project value based on the current technology efficiency reaches the investment cost, the forward-looking firm additionally internalizes the future technological change into its investment decision, which changes the project value and gives rise to the value of waiting option, thereby shifting the investment trigger from $\bar{\kappa}$ to κ^*. Thus, even though the accelerated technological progress (e.g., increase in λ) may reduce the mean time to invest for both myopic and forward-looking firms by making current κ approach $\bar{\kappa}$ and κ^* more quickly, the forwarding-looking firm will still invest relatively later (earlier) than the myopic firm as long as κ^* is greater (smaller) than $\bar{\kappa}$.

3.2. Comparative analysis

In order to illustrate the comprehensive effect of technological environment on investment strategies, we first separately analyze how the emergence of innovations, refinements, or learning affects firms' investment behaviors starting from the myopic case. All mathematical proof of following propositions is given in Appendix A. In the next section, we turn to a comprehensive technological environment where innovations, refinements, and learning compete with each other.

Proposition 1. Both the optimal capacity q^* and the investment trigger κ^* are increasing in λ and u, i.e., $\frac{dq^*}{d\lambda} > 0$, $\frac{dq^*}{du} > 0$, $\frac{d\kappa^*}{d\lambda} > 0$, and $\frac{d\kappa^*}{du} > 0$.

Proposition 1 formalizes the main conclusion by Farzin et al. (1998) and additionally explores the capacity impact of innovations under a convex cost function. It reveals that the firm has incentive to defer its investment but will choose a larger productive capacity when innovations arrive more frequently or become more valuable. The effect of increasing capacity can be explained by the fact that, given the accelerated process of innovations, the firm will face a more advanced innovation at the time of investment, which increases the capacity profitability and thus results in a larger capacity q^*.

The investment-delay effect can be demonstrated by equation (13). Because innovations are not open to producing firms, λ and u are not involved in the prospect effect that reduces the investment timing. But in the meanwhile, their increase enhances the lag effect by sharply raising the risk parameter β, leading the firm to require a higher investment trigger to reduce the risk of missing revolutionary innovations in the near future. Besides the lag effect, the increasing scale effect of innovations also makes investing early less attractive. As a result, the existence of only the lag and the scale effect offers the firm strong incentive to await technology pushed sufficiently efficient by innovations.

Proposition 2. The optimal capacity q^* is increasing in both μ and w, i.e., $\frac{dq^*}{d\mu} > 0$ and $\frac{dq^*}{dw} > 0$. The investment trigger κ^* is a non-monotonic function of both μ and w. There exist a unique $\bar{\bar{\mu}}$ and a unique $\bar{\bar{w}}$ respectively, i.e., $\frac{d\kappa^*}{d\mu} < 0$ for $\mu < \bar{\bar{\mu}}$ and $\frac{d\kappa^*}{d\mu} > 0$ for $\mu > \bar{\bar{\mu}}$, and $\frac{d\kappa^*}{dw} < 0$ for $w < \bar{\bar{w}}$ and $\frac{d\kappa^*}{dw} > 0$ for $w > \bar{\bar{w}}$.

Proposition 2 states that while the refinements always raise the productive capacity, the investment is first accelerated and then delayed with the pace and magnitude of refinements. The refinements increase the capacity q^* via two channels. First, similar as the innovation effect, the firm faces a more refined available innovation at the moment of investment and thus decides to invest more; Additionally, because the refinements are still open to producing firms, the forward-looking firm also recognizes that the capacity payoff will be further raised by arrival of new refinements after investment, thus internalizing this future benefit into its current capacity decision.

Unlike the innovation, the timing effect of refinement follows a U-shape pattern since it is involved in both the prospect and the lag effect. When the refinement is characterized by rare occurrence ($\mu < \bar{\bar{\mu}}$) or small improvement ($w < \bar{\bar{w}}$), the firm tends to invest early because the waiting benefits brought by the arrival of weak refinements are not big enough to compensate the opportunity costs of waiting. Referring to equation (13), this implies that the prospect effect dominates the lag and scale effect and the firm therefore will take the advantage of refinements by adopting them after investment rather than delay investment to await them. This effect differs from Doraszelski's (2004) results that any refinement provides incentive to delay because refinement is not open to investing firms in his model.

On the contrary, if the valuable refinements are expected to arrive shortly, the firm most likely postpone its investment until the technology is refined efficient enough, because the foregone profits during the waiting period is smaller compared to the benefit of employing a more refined innovation at the time of investment. This suggests that the lag and scale effects outweigh the prospect effect when μ and w become large. To distinguish investment timing impacts imposed by different types of refinements, we define the refinements with $\mu > \bar{\bar{\mu}}$ or $w > \bar{\bar{w}}$ as "major refinements" that result in investment delay and the refinements with $\mu < \bar{\bar{\mu}}$ or $w < \bar{\bar{w}}$ as "minor refinements" that cause investment acceleration.

Proposition 3. The optimal capacity q^* is increasing in γ, i.e., $\frac{dq^*}{d\gamma} > 0$. The investment trigger κ^* is decreasing in γ, i.e., $\frac{d\kappa^*}{d\gamma} < 0$.

Proposition 3 says that the firm will take the advantage of learning economies in a manner of investing early and on a larger scale. Because of the learning curve, now each incremental capacity size also contributes to a faster decline of the future production cost in addition to the normal producing profits, which raises the payoff of the capacity investment. In this way, the stronger the learning economies is, the larger investment scale is triggered. [8] For the timing strategy, equation (13) shows that learning parameter γ is only involved in the prospect effect since learning economies could only be exploited after investment. As a consequence, waiting

[8] Our results about $dq^*/d\gamma$ differs from the findings by Della Seta et al. (2012) due to the presence of different uncertainties. Proposition 3 in their article concludes that the optimal capacity q^* is first increasing and then decreasing in learning speed γ in the presence of demand uncertainty. Because all uncertainties in our model steam from innovations and refinements, our results about $dq^*/d\gamma$ when $u = 0$ and $w = 0$ actually describe how the firm's capacity choice responds to the increasing learning economies in the absence of any uncertainties, which is similar as the result of Proposition 1 in Della Seta et al.'s paper.

option becomes more expensive to exercise at the cost of learning, making investing early more attractive.

3.3 General case

We now generalize the choice of investment strategy under the comprehensive technological environment. Because the analytical solution for q^* is not available, the following assumptions will much simplify our general analysis. Keep in mind that as q^* is a pure function of all technology and other parameters, it can be directly numerically solved using only equation (12). Then the value of q^* is combined with other parameters to determine the investment trigger κ^* using equation (13).

Assumption 1. $q \leq 1/\gamma$.

Assumption 1 imposes an upper bound for the capacity choice. This assumption is appealing because it rules out the case that the firm chooses an unreasonable large capacity to exploit learning economies[9], and is supported by the fact the capacity level is often limited by the maximum physical capacity or firms' financial constraints. A relaxed assumption $q \leq d/\gamma$ for any $d > 0$ would also apply in our model. In the following, we use $d = 1$ as a special case to illustrate our analysis.

In order to guarantee that equation (12) gives a meaningful solution of q^*, we need $V_{qq}(\theta^*, q^*) < 0$, i.e., the second order condition of equation (11) to be negative. Under assumption 1, this requires

Assumption 2. $a - \frac{\rho\gamma - a - B\gamma\rho}{\rho + 1 - e^{-1} + w\mu} e^{-1} > 0$.

This assumption says that the increasing marginal cost a should be greater than the marginal value of learning when q is approaching $1/\gamma$. Violating this assumption leads the firm always choosing the corner solution at the upper limit to exploit learning economies, making the capacity choice meaningless.

Under assumption 1 and 2, the next two propositions show how the technological environment reshapes the forward-looking firm's investment strategy$\{q^*, \kappa^*\}$ compared to the myopic case $\{\bar{q}, \bar{\kappa}\}$.

Proposition 4. $q^* > \bar{q}$.

Proposition 4 implies that when the technological environment is considered, the forward-looking firm always chooses a larger investment scale than the myopic firm. This choice is intuitive because from proposition 1 to 3, we see that technological change, no matter in which

[9] This assumption performs the similar function as assumption 1 in Della Seta et al. (2012) in order to avoid the situation in which firms indefinitely defer their investments.

pattern, always spurs a larger scale of investment by either providing a more efficient technology at the moment of investment or raising the future capacity payoff in the production process after investment. As a consequence of this result, we use $b = q^*/\bar{q} > 1$ to measure the increase of investment scale due to the technological change. In contrast to the unambiguous scale effect, the next proposition shows that timing effect for different technological environments is differing.

Proposition 5. (a) if $1 - e^{-\gamma q^*} + w\mu > \rho(\frac{\beta}{\beta-1}b - 1)$, then $\kappa^* < \bar{\kappa}$.

(b) if $1 - e^{-\gamma q^*} + w\mu < \rho(\frac{\beta}{\beta-1}b - 1)$, then $\kappa^* > \bar{\kappa}$.

$1 - e^{-\gamma q^*} + w\mu$ represents the incentive of investing earlier to exploit learning and refinements in the current technological environment, which corresponds to the prospect effect in equation (13). Similarly, $\beta/(\beta - 1)$ measures the incentive of waiting for a sufficiently advanced technology to reduce the technology risk under such an environment, which indicates the lag effect in equation (13). Finally, b represents the increasing scale effect in equation (13). Thus, proposition 5a says that when the firm is faced to the technological environment where the prospect effect dominates the lag and scale effect, it chooses to accelerate its investment plan, and vice versa in proposition 5b. According to proposition 4 and 5, we can formally distinguish two investment strategies for different technological environments as below.

Definition 1. We define the investment strategy $\{q^*, \kappa^*\}$ as prospector strategy if

$$\kappa^* < \bar{\kappa} \text{ and } q^* > \bar{q}$$

and as laggard strategy if

$$\kappa^* > \bar{\kappa} \text{ and } q^* > \bar{q}.$$

Definition 1 describes two alternative investment strategies when the firm takes the technological environment into account. As said by proposition 5, the prospector strategy focuses on raising the future productivity in the production process, thus involving investing earlier and on a larger scale to take advantage of stronger learning economies. In contrast, the laggard strategy emphasizes the risk of missing a more advanced technology by investing too soon, thus entailing investing later to wait for a more advanced technology and increasing the investment scale when this advanced technology is delivered.

4. Optimal investment strategies in different technological environments

In this section, we discuss how different strategies are applied in differing technological environments based on our model results. As argued by the main body of theoretical literature that considers technology adoption as an embedded option, the laggard strategy appears to have played an essential role in investment policies in agriculture and manufacturing (Farzin et al., 1998; Doraszelski, 2004). This model result is consistent with the empirical observation by

Weiss (1994) that investments in new technology are considerably slow in the printed-circuit assembly equipment market. This lag, however, is at the considerable cost of learning economies in many industries (Majd & Pindyck, 1989; Della Seta et al., 2012), making the prospector strategy more compelling for many firms. For instance, Rosenthal's (1984) empirical results on investments in computer-aided manufacturing processes (CAMP) show that "leading-edge users of CAMP believe in learning by doing. Most have proceeded in an incremental fashion to develop an internal base of experience with factory automation technologies……They generally feel they cannot afford to postpone decisions until improved technologies become available".

4.1. A numerical example of cellulosic ethanol

We examine the effect of characteristics of the technological environment on firms' investment strategies using a numerical example from the renewable energy industry. In particular, we simulate a technological environment encountered by the potential entrant of the cellulosic ethanol market. We choose this market because cellulosic refineries are currently undergoing rapid but different patterns of technological progress. Specifically, gasification and fermentation (GF) and enzymatic hydrolysis (EH) are two refinery technologies that are currently commercial viable in the market (Dwivedia et al., 2009). However, ethanol produced from these technologies is still far away from becoming cost competitive to replace either the gasoline or the corn ethanol. As expected by numerous technology reports (e.g., Laser et al., 2009; NREL, 2010), two innovative technologies, simultaneous saccharification and fermentation (SSF) and dilute acid hydrolysis (DCH), are on the horizon in the next three to five years and they are estimated to reduce the operation cost of cellulosic ethanol by about 35% to 65%. In addition to these new technologies, the existing technologies also undergo a series of refinements. For example, the enzyme cost, accounting for 30% of the total production cost in the EH, decreased by 72% between 2008 and 2012 (Bloomberg, 2013). Because all these technological progresses are mainly driven by the government R&D spending (Babcock et al., 2011), they could be treated as exogenous technology shocks to firms. Finally, empirical studies (Hettinga, et al., 2009; van den Wall Bake et al., 2009; Chen & Khanna, 2012) also show that learning economies in the bioethanol sector is particularly strong, which is anticipated to reduce the operation cost of cellulosic ethanol by about 30% to 70% as long as the commercial production is initiated (Chen et al., 2012).

Based on these technology information, the benchmark parameters depicting the technological environment of cellulosic refineries are given in Table 1. The value of reduced efficiency parameter a is used from the empirical study by Chen & Khanna (2012) in the corn ethanol. All other parameters are cited from Yang et al.(2015) and updated by the latest avaliable data. By defitnion 1, the myopic case is used as our benchmark scenario, denoted by "myopic" in terms of the solid line in the following figures. The investment trigger κ^* above (below) the "myopic" line reflects the technology environments where the laggard (prospector) strategy is optimal. We use $b = q^*/\bar{q}$ to show the effect of increasing productive capacity.

Table 1: Parameter Values for the Cellulosic Refineries

Parameters	P	B	s	a	ϒ	u	λ	w	μ	ρ
Value	3.23	11.35	3.59	0.000037	6%	45%	25%	11%	35%	8%

Fig.1 illustrates how firm's investment strategy depends on the extent of efficiency improvement u and the arrival speed λ of emerging innovative technologies in the cellulosic technological environment. In line with Proposition 5, the cellulosic firm switches from the prospector strategy of investing earlier to the laggard strategy of waiting as κ^* increases sharply with λ and u in the left panel. The reason is that as the valuable innovation is likely to be delivered in the near future, the risk of missing such a milestone breakthrough is too huge to be afforded by the firm, which creates adequate incentives for the firm to postpone its investment. As a result, the firm chooses to exploit the technological benefits by waiting for the arrival of the new innovative technologies, requiring a higher efficiency level to trigger its investment. For example, the investment trigger κ^* rises to 80% when the cellulosic firm projects that the new technology, either SSF or DCH, will bring about 80% efficiency improvement in the next three years. In such an environment, the firm will only invest after the new refinery technology is delivered, regardless of how strong the learning economies is.

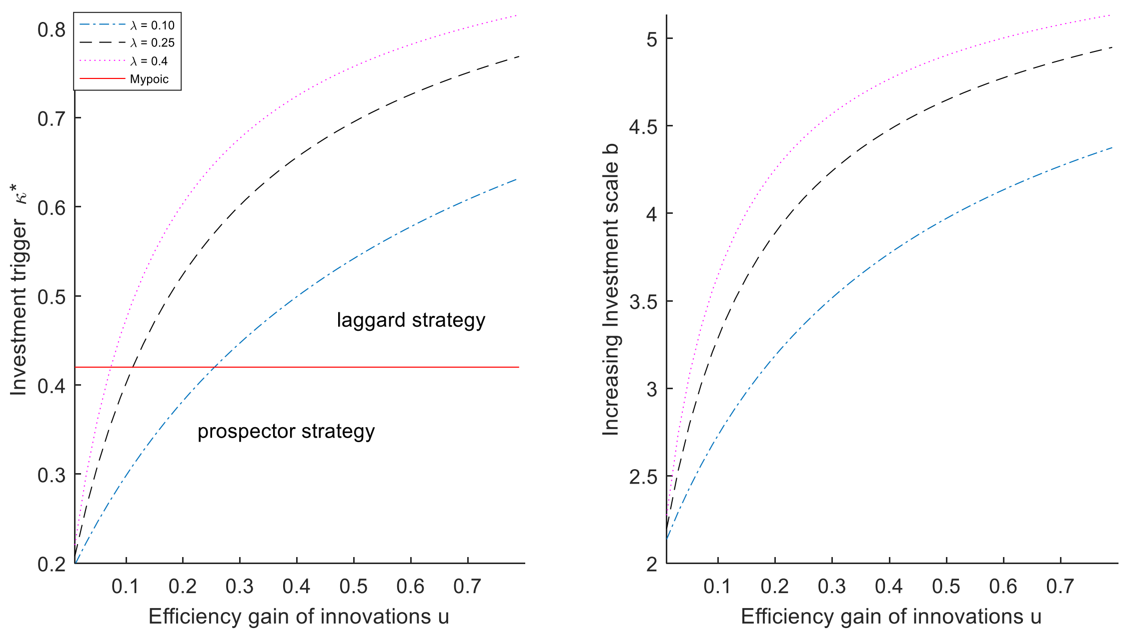


Figure 1: Investment trigger κ^* and optimal scale q^* for different values of u and λ

Fig.2 shows how the trigger value κ^* and optimal capacity level q^* response with the change of μ and w of refinements in the cellulosic technological environment. In accordance with Proposition 2 and 5, the left panel presents a U-shape pattern that minor refinements encourage prospector strategy and major refinements promote laggard strategy. When $\mu = 0.05$, κ^* is first decreasing with small values of w because it is not economical to wait for the minor refinements at the potential cost of foregone profits during the waiting period. Instead, a better way to exploit the benefits of refinements is triggering the production earlier to earn more profits, in the hope that the project profitability is further improved by the arrival of refinements after investment. Because these coming refinements are weak, the added project payoff is limited, resulting in only a slight investment acceleration. The timing effect has changed for large values of w. In this case, the cost saving from new refinements is greater than the opportunity cost of waiting, thereby making it worthwhile to wait.

But when μ increases from 0.05 to 0.35, this U-shape pattern becomes less obvious as the inflection point $\overline{\overline{w}}$ (see Proposition 2) turns smaller. The reason is that while each refinement is weak, they add up quickly to a considerable efficiency improvement as the arrival rate μ increases, thereby leading firms more likely to wait for the refined technology.

Unlike the divergent timing effect, the right panel of Fig.2 depicts that refinements always raise the productive capacity for the planned refinery facility. Even if the firm invests before the refinements occur, it is aware of that the project profitability will be enhanced by future refinements, thus increasing its investment scale to capture this benefit. It is also important to note that firm's investment strategy is more sensitive to the change of innovations than refinements in the technological environment. This is because firm's choice of innovations is irreversible, therefore requiring a higher investment trigger to guarantee that it does not miss any breakthrough innovation. In contrast, the refinements such as cheaper enzyme or feedstocks for existing EH technology are still open to investing firms. Therefore, even though the firm misses the important refinements by investing too soon, it still has the chance to make up for this mistake by adopting them after investment.

The investment delay due to the anticipations of future significant technological innovations or refinements is studied extensively by existing theoretical literature (e.g., Farzin et al., 1998; Doraszelski, 2004) and documented by quite a few empirical studies (e.g., Antonelli, 1989; Weiss, 1994). The intuition of these models and empirical observations is straightforward: the potential technological breakthrough, either in the form of innovations that develop a new technology, or in the form of engineering refinements that improve the technological elements to deliver a more mature technology, considerably raises the value of waiting option, thereby leading to exercise the investing option quite expensive. In our model, however, this is the case only when the anticipated technological breakthrough is sufficiently strong or rapid enough, very likely rendering the current technology obsolete in the near future. Besides the timing impact, we also investigate the impacts of such breakthroughs on the investment scale at the moment of investing, which has been paid little attention by ROA literature in this field. We show that the investment delay is always accompanied with a larger investment scale when investing, as a result from increasing marginal capital payoff due to the arrival of technological breakthrough.

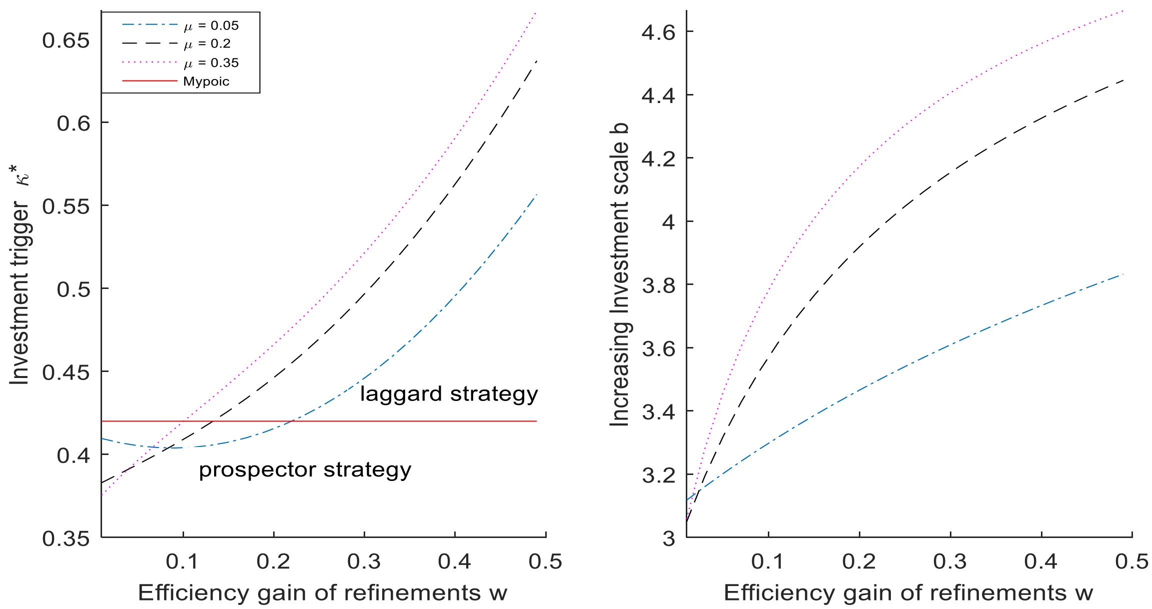
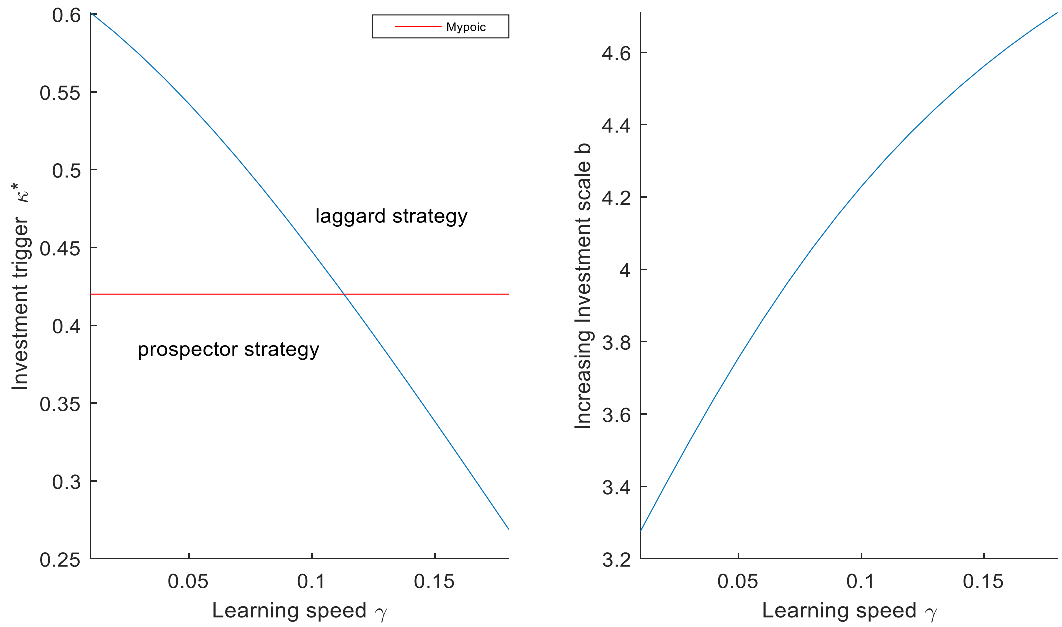


Fig.3 demonstrates the dependency of firm's investment strategy on the extent of learning economies in the cellulosic technological environment. Consistent with Proposition 3 and 5, the left panel shows that the stronger the learning economies is, the more likely the current refinery technology will be adopted. The reason is straightforward. When the learning economies are taken into account, waiting for the new and refined technology is not only at the cost of foregone profits during the waiting period. What is more important, the waiting firm also loses the opportunity to accumulate knowledge in the production process, which quickly moves down the production cost via the learning curve. As the learning economies turn stronger, the waiting option also becomes more expensive to exercise, leading many firms switching to investing in the current refinery technology to pursue the technological path of learning.

The right panel of Fig.3 shows that the stronger learning economies also stimulate a lager investment scale. Since a firm that produces more output today will have a lower production cost in the future, it tends to invest more to capture this learning benefit.



4.2. Optimal investment strategies

As clear seen from the above analysis, when technological environment is considered, firms will always pursue a larger investment scale; however, the investment could be either relatively accelerated or deferred, depending on how fast and by how much the firm could exploit the benefits of technological change before and after investment. When learning economies and minor refinements dominate the technological environment, firms adopt the "prospector strategy" to investing earlier and on a larger scale with the use of current technologies. In contrast, when the productivity is mainly pushed by innovations and major refinements, firms rely on the "laggard strategy" to entering the market later and investing on a larger productive capacity, with the use of sufficiently advanced technologies.

In practice, the prospector strategy is more popular in the market starting with a relatively established technology, where the acquisition of production knowledge and experience is placed in the first priority and cannot be replaced by R&D investments (reflected by a higher learning rate). For instance, in the wind turbines case of renewable energy, Nemet (2009, p.702) notes that "the location-specific turbulence that turbines cast on downwind turbines, as well as the longer-term effects of the ambient environment on component materials, have been important for improving the technology and yet have proven extremely difficult to replicate in a laboratory setting". Largely due to the learning feature of cost reduction in wind technological environment, investments are increasing quickly and substantially in this sector, contributing 41% of total U.S. generation capacity addition in 2015 with $14.5 billion invested, even though the power purchasing agreement price declines from $55/MWh in 2009 to $20/MWh today (Wiser & Bolinger, 2016).

In contrast, the laggard strategy is more prevalent in the market staring with a totally new technology, where mature theoretical/ practical knowledge is not developed yet, and technology breakthrough is likely to be achieved in the near future, yielding numerous benefits. Our numerical example of cellulosic ethanol, another hopeful source of renewable energy, provides us a good example to explain technological environment fitting for the laggard strategy. As the breakthrough refinery technologies SSF and DCH are on the horizon coming very soon, many firms in this environment try to avoid the risk of missing the milestone technologies by investing too early. Even for firms that consider investing in the current technology EH, the fast decline in the cost of enzyme and feedstock provides strong incentives for these firms to wait for the current technology more refined. Thus, despite the fact that learning economies is also strong in this industry, most firms choose the laggard strategy in this industry. As a result, even with the strong government subsidy and mandate, the actual produced volume of cellulosic ethanol was less than 4 million gallons in 2015, far behind the initial target of 3 billion gallons imposed by the Clean Air Act. Moreover, even for already-built refinery plants, EPA observes that all of them produce significantly below their nameplate capacities (often no production), implying that they are facing the technological challenge and waiting for the more refined technology (EPA, 2015, p.168-177). Thus, we see that even within the clean energy sector, firms present divergent investment behaviors due to different technological environments.

5. Extension to the model

By far our model has considered the technological change involved in the process development that reduces the operation cost in the production process. However, the technological change could also occur in the investment cost part or in the product development that enhances the product quality. In the former case, the unit capital cost B is expected to decline over time following a jump process. Since the capital cost is one-time irreversible expenditure, the technological progress occurring in capital cost has similar timing and scale effects as innovations in Proposition 1. First, because firms do not incur any further capital cost after investments in our model, the progress of capital cost only yields the lag effect, leading firms to wait for the capital cost decreasing to a profitable level. Second, due to the lower investment expenditure, firms will face a larger value of capital payoff at the time of investment, thereby deciding to invest more.

Our model also has the potential to apply in cases where technological change occurs in product development that enhances the product quality. Standard economic theory suggest that a higher quality product will sell at a higher price (Stiglitz, 1987). Thus, if the product development causes the firm receiving a higher price for its output, this increasing price impact could be easily transformed to the impact of decreasing cost. Consider the equation $\pi = p(1+\theta_p) - \mathrm{c} = p - c(1 - p\theta_p/c)$. This equation implies that if the product development raises the firm's output price by θ_p, this effect is equal to reducing the production cost by $p\theta_p/c$. In words, we can say that the firm could produce a higher quality product at equal cost, or equivalent, we can say that the firm could produce the equal higher quality product at a lower cost. Using the lower cost as a proxy of higher price or greater performance is widely adopted by the literature in energy and environment economics (discussed by Jaffe et al., 2002 and Kahouli-Brahmi, 2008). In order to further check the robustness of this intuition, we still develop a model in which θ refers to the product development that raises the output price P. It follows immediately that all our results derived from the cost reduction model remain valid, so that our model could generalize to the product development that increases the output price.

The extension to the product development substantially enriches the explanatory power of our model, especially combined with extending the concept of learning economies. In recent years, there is a growing trend towards investing earlier and on a larger scale even with the initial profit loss in modern high-tech industries like electronics, software, and telecom. Although the market competition is an important factor to explain this behavior, still the early and large investment policies are heavily influenced by the technological environments in these industries where cost and quality of the products could be substantially improved after entry, otherwise the late entrants with more superior products will always win the final competition (Lilien & Yoon, 1990). In the view of technological environment, the key attribute characterizing these industries is strong learning economies. Since labors' manufacturing skill is almost gained through repetitive tasks in these industries, the cost and quality of products are very sensitive to the output volume. For instance, as the accumulated output doubles, the decline in production costs could be as high as 27.1% in the semiconductor industry (Irwin & Klenow, 1994) and 14.1% in the LCD industry (Park et al., 2003).

Besides the learning-by-doing at the manufacturing stage, another critical source of learning economies for these industries is learning from customers as a result of use of products (Rosenberg, 1986). Due to the customer-driven market characters, integrating users' evolving needs and solutions of unanticipated problems into products plays a distinct role in these industries. However, the inability to identify existing and potential customers' needs and problems before "doing" makes the early entrance as necessary (von Hippel & Tyre, 1995). In these market, many technical issues are found by customers in their use and then reported to the producing firm. Furthermore, users' innovations also promote the development of the new product, thereby benefiting producing firms. As shown by von Hippel (1988) and von Hippel & Katz (2002), products in the scientific instruments and the software are developed much more quickly by users' innovative activities, often beyond the initial products design. Finally, as the development of information technology, particularly the social media, today the customers' needs, problems, and innovations derived from their use experiences are more quickly and deeply responded to the firm with a much lower cost compared to the traditional costly market research methods that only skim the face. The improved communications between firms and customers make learning from customers more efficiently, leading to a substantially enhanced learning economies (Venturini, 2007). Therefore, combined with the labors' steep learning curve, learning economies dominate the technological environment of these industries, leading prospector strategy to be optimal.

Following Farzin et.al (1998) and Doraszelski (2004), we model innovations and refinements as exogenous technological shocks to firms' investment projects. This assumption is valid in our primary examples of clean energy sector, where R&D activities are mainly driven by the government expenditure and most innovations and refinements are thus public to private investors (Pizer & Popp, 2008). In general, this exogenous technological shock also makes much more sense over the past two decades. As both the patent system and the capital market become more complete, nowadays it is common that get a new technology through ways of royalty payment or directly acquiring the technology provider. For example, Google has acquired more than 190 start-up companies since 2005 for technology accumulation. Even within a firm's own R&D department, "the 'do-it yourself' mentality in technology and R&D management is outdated" as noted by Gassmann (2006). Industries such as software, electronics, telecom, pharma and biotech devote to build a "technology platform", where the new technology could be shared between multiple products or between companies. All these phenomena are documented by a numerous body of studies in the field of technology management, summarized as "open innovation" by Gassmann (2006) and Gassmann et al. (2010) that emphasizes the share and cooperation on R&D activities between firms, research institutions, and products.

In our model, innovations, refinements, and learning economies are three independent patterns of technological change parallel with each other. In reality, it is also possible that they are linked with each other. The first possible case is that the pace and magnitude of refinements show a diminishing pattern over time as the efficiency potential of its pertained innovation reaches its limit. Our model can be extended to this case by

5. Conclusions

In this article, we extend the literature on optimal investment policies under technological change by distinguishing between innovations, refinements, and technological learning. As a result of this distinction, the path of technological change encountered by a firm is differentiated according to its decision on investment timing and scale. Before entering the new product market, the firm relies on the technological breakthrough based on innovations and major refinements to exploit benefits of technological change while seeking to take advantage of technological learning and minor refinements after entry. To capture this idea, we use different stochastic processes to distinguish between technological evolvements before and after investments. In this manner, the choice of different technological paths is taken into account in the investment decisions and value of options for the standard ROA model. In contrast to the main body of literature in this field that only focuses on either the innovation (refinement) or the technological learning, our model allows us to explore optimal investment strategies in a more complicated technological environment where innovations, refinements, and technological learning exist simultaneously. We summarize the major assumptions and findings of our model in Table 2.

Table 2: The effects of different patterns of technological change on investments

Pattern	Source	Form	Timing	Scale	Strategy	Example
Innovations	R&D Activities	Large Sudden Jump Before Entry	Delay	Increase	Laggard	Biomedicine
Major Refinements	R&D Activities	Medium Sudden Jump Before and After Entry	Delay	Increase	Laggard	Nuclear Power
Minor Refinements	R&D Activities	Small Sudden Jump Before and After Entry	Accelerate	Increase	Prospector	Smartphone
Learning Effects	Labor/User Learning	Incremental Improvement After Entry	Accelerate	Increase	Prospector	Software

Besides the theoretical contributions, we further apply our developed model to analyze the investment behaviors in the markets of cellulosic ethanol. Our model predictions are empirically supported by firms' investment behaviors in this market. We also provide potential explanations for differing investment strategies in different technological environments. The prospector strategy is most likely adopted by firms in markets or industries characterized by fast learning and minor engineering refinements, which are in the form of labors' learning-by-doing, learning from customers, and solutions to undetected technical problems before production. In contrast, the laggard strategy has a greater chance to prevail in markets or industries where mature theoretical/ practical knowledge is not established yet and the revolutionary technological breakthrough is thus anticipated in the future.

Our idea that the stochastic process of studied variables is differentiated before and after investments could be applied to other problems investigated in ROA literature, especially for variables influenced by investment decisions. For instance, firms may also face different government policy variables if policies are made on the basis of firms' entrance decisions like the mandate of cellulosic biofuel. Further studies motivated by our model could investigate the role played by government policies aimed at promoting investments in pollution-abatement industries (e.g., clean energy), where technological change is recognized as a vital force for the industry development but often simplified to a known progress in each period (e.g., Fischer et al., 2003; Fischer & Newell, 2008). In our model, the policy effects on technological change could be further decomposed through different patterns of technological change, which provides a more complete picture to understand the policy effectiveness in terms of private investment decisions on timing and scale. As an example, technology subsidy is often considered as necessary to encourages transition to clean technology (e.g., Acemoglu et al., 2012), but if this subsidy (often in the form of government direct R&D spending through research institutions or universities) makes firms anticipate that a significant technological breakthrough will be delivered in the near future from public sectors, it may delay the industry development for a little while but stimulates a much stronger industry growth once the advanced technology arrives.

An important extension of our model is to consider strategic interactions between firms. This is critical if the technology itself is the basis of market power. If the firm has a more advanced technology than all other firms, it may enter the market earlier with a larger productive capacity to take advantage of the monopoly price and deter other potential entrants. This behavior is in part described by our model where early and large scale investments are preferred as the firm observes a higher market price $\bar{P}$. This technological monopoly makes the prospector strategy more appealing because the monopoly firm often faces less technological breakthrough than other firms, so it may seek to apply its technology in the production process to enhance the technological efficiency. Another extension of our model is to relax the pace and value of refinements being constant. It seems plausible that refinements will be accelerated or enhanced after production because many of them are developed based on customers' use experience.

Appendix A. Mathematical Proofs

A1. Proof of Proposition 1

Because both λ and u are independent of the learning parameter γ and the efficiency gain of refinement w, without loss of generality we assume $\gamma = 0$ and $w = 0$ to simplify our proof. Then the solutions of equations (14) and (15) are:

$$q^* = \left(\frac{p}{\rho} - B\right)\frac{\rho}{a(2-\beta)} \quad (A1)$$

$$\kappa^* = 1 - \left(\frac{\bar{P}}{\rho} - B\right)\frac{\rho - \bar{\alpha}_\theta}{C}\frac{\beta}{\beta - 2} \quad (A2)$$

To evaluate the impact of λ and u on the timing and scale of investment, the first step is to know how they affect the risk parameter β. We denote equation (10) as $G(\beta, \lambda, \mu, u, w, \sigma_\theta^2) = 0$. Using implicit function theorem, we differentiate equation (10) with respect to λ and u, repspectiely. Because $\beta < 0$, the differentiations yield

$$\frac{d\beta}{d\lambda} = -\frac{\partial G/\partial\lambda}{\partial G/\partial\beta} = -\frac{(1-u)^\beta - 1}{\sigma_\theta^2\left(\beta - \frac{1}{2}\right) + \lambda(1-u)^\beta \ln(1-u)} > 0 \quad (A3)$$

$$\frac{d\beta}{du} = -\frac{\partial G/\partial u}{\partial G/\partial\beta} = -\frac{-\lambda\beta(1-u)^{\beta-1}}{\sigma_\theta^2\left(\beta - \frac{1}{2}\right) + \lambda(1-u)^\beta \ln(1-u)} > 0 \quad (A4)$$

Then we have

$$\frac{dq^*}{d\lambda} = \frac{\partial q^*}{\partial\beta}\frac{\partial\beta}{\partial\lambda} = \left(\frac{\bar{P}}{\rho} - B\right)\frac{\rho - \bar{\alpha}_\theta}{\psi(2-\beta)^2}\frac{\partial\beta}{\partial\lambda} > 0 \quad (A5)$$

$$\frac{d\kappa^*}{d\lambda} = \frac{\partial\kappa^*}{\partial\beta}\frac{\partial\beta}{\partial\lambda} = \left(\frac{\bar{P}}{\rho} - B\right)\frac{2(\rho - \bar{\alpha}_\theta)}{C(2-\beta)^2}\frac{\partial\beta}{\partial\lambda} > 0 \qquad (A6)$$

By similar arguments, we can prove $\frac{dq^*}{du} > 0$ and $\frac{d\kappa^*}{du} > 0$.

A2. Proof of Proposition 2

Because both μ and w are independent of the learning parameter γ and the efficiency gain of innovations u, without loss of generality we assume $\gamma = 0$ and $u = 0$ to simplify our proof. By solving the equation system of (14) and (15), the optimal capacity q^* is the same as q^* in equation (A1). The solution for the technological threshold κ^* is different, shown as

$$\kappa^* = 1 - \left(\frac{\bar{P}}{\rho} - B\right)\frac{(\rho - \bar{\alpha}_\theta + w\mu)}{C}\frac{\beta}{\beta - 2} \qquad (A7)$$

Differentiating equation (10) with respect to μ and w yields

$$\frac{\partial\beta}{\partial\mu} = -\frac{(1-w)^\beta - 1}{\sigma_\theta^2\left(\beta - \frac{1}{2}\right) + \mu(1-w)^\beta \ln(1-w)} > 0 \qquad (A8)$$

$$\frac{\partial\beta}{\partial w} = -\frac{-\mu\beta(1-w)^{\beta-1}}{\sigma_\theta^2\left(\beta - \frac{1}{2}\right) + \mu(1-w)^\beta \ln(1-w)} > 0 \qquad (A9)$$

Because q^* here holds the same form as in the proposition (1), we can prove $\frac{dq^*}{d\mu} > 0$ and $\frac{dq^*}{dw} > 0$ by similar arguments in Proposition 1. For the effect of μ on investment timing, by equation (A7) and (A8) we obtain that

$$\frac{d\kappa^*}{d\mu} = \overbrace{\frac{\partial\kappa^*}{\partial\mu}}^{propsect\ effect} + \overbrace{\frac{\partial\kappa^*}{\partial\beta}\frac{\partial\beta}{\partial\mu}}^{lag\ effect}$$
$$= -\left(\frac{\bar{P}}{\rho} - B\right)\frac{1}{C}\frac{1}{\beta - 2}\left[w\beta + (\rho - \bar{\alpha}_\theta + w\mu)\frac{2}{\beta - 2}\frac{L(\mu)}{H(\mu)}\right] \quad (A10)$$

where $L(\mu) = (1-w)^\beta - 1 > 0$ and $H(\mu) = \sigma_\theta^2\left(\beta - \frac{1}{2}\right) + \mu(1-w)^\beta \ln(1-w) < 0$.Define $Z(\mu) = w\beta + (\rho - \bar{\alpha}_\theta + w\mu)\frac{2}{\beta-2}\frac{L(\mu)}{H(\mu)}$. When μ is small, given that $\lim_{\mu\to 0}\beta$ is negative bounded, we can always find a $\underline{\mu}$ such that $Z\left(\underline{\mu}\right) < 0$. When μ is large, given that $\lim_{\mu\to+\infty}\beta \to 0$, we can always find a $\bar{\mu}$ such that $Z(\bar{\mu}) > 0$. Because

$$\frac{dZ}{d\mu} = w\frac{\partial\beta}{\partial\mu} + w\frac{2}{\beta-2}\frac{L(\mu)}{H(\mu)} - (\rho + w\mu)\frac{2}{(\beta-2)^2}\frac{L(\mu)}{H(\mu)} + (\rho + w\mu)\frac{2}{\beta-2}\left[\frac{(1-w)^{\beta}\ln(1-w)}{H(\mu)} - \frac{L(\mu)(\sigma_{\theta}^2 + \mu(1-w)^{\beta}(\ln(1-w))^2}{H(\mu)^2}\right] > 0 \quad (A11)$$

$Z(\mu)$ is a monotonically increasing function of μ. Hence, there exists a unique $\bar{\bar{\mu}}$ such that $Z(\bar{\bar{\mu}})$=0. $Z(\mu) < 0$ for $\mu < \bar{\bar{\mu}}$ and $Z(\mu) > 0$ for $\mu > \bar{\bar{\mu}}$. Similar arguments apply for $\frac{d\kappa^*}{dw} < 0$ for $w < \bar{\bar{w}}$ and $\frac{d\kappa^*}{dw} > 0$ for $w > \bar{\bar{w}}$.

A3. Proof of Proposition 3 and the Market Price $\bar{P}$

Because the learning parameter γ is independent of u and w, without loss of generality we assume $u = 0$ and $w = 0$ to simplify our proof. Because γ is involved in the exponential functions, the analytical solutions for q^* and κ^* are not available in this case. However, we can still conduct the comparative analysis using the implicit function theorem. We first rearrange equation (14) and denote $Y(\gamma)$ as

$$Y(\gamma) = \frac{\bar{P}}{\rho} - \frac{\Lambda\beta q^*\gamma e^{-\gamma q^*}}{\Omega} - \frac{\psi q^*(2-\beta)}{\rho} - B \quad (A12)$$

where $\Lambda = \left(\frac{\bar{P}-\psi q^*}{\rho} - B\right) > 0$ and $\Omega = \rho - \overline{\alpha}_{\theta} - e^{-\gamma q^*} + 1 > 0$ The impact of γ on q^* is given as $\frac{dq^*}{d\gamma} = -\frac{\partial Y/\partial\gamma}{\partial Y/\partial q^*}$. To guarantee that the optimal q^* exists, the second order condition of equation (13) requires that $\partial Y/\partial q < 0$, which is equivalent to require

$$1 - e^{-\gamma q^*}\frac{\rho + 1 - e^{-\gamma q^*}(\beta\gamma - 1)}{\Omega} < 0 \quad (A13)$$

by expanding $\partial Y/\partial q$. To determine the sign of $\partial Y/\partial\gamma$, we have

$$\frac{\partial Y}{\partial\gamma} = \Lambda\beta q^*\left(1 - e^{-\gamma q^*}\frac{\rho+1}{\Omega}\right) > 0 \quad (A14)$$

because $\beta < 0$ and $(A13) < 0$. Hence, we obtain $\frac{dq^*}{d\gamma} > 0$. By similar arguments, it is easy to prove $\frac{dq^*}{d\bar{P}} > 0$. The effect of γ on κ^* is given as

$$\frac{d\kappa^*}{d\gamma} = \frac{\partial\kappa^*}{\partial\gamma} + \frac{\partial\kappa^*}{\partial q^*}\frac{\partial q^*}{\partial\gamma} = -\frac{1}{C}\frac{\beta}{\beta-1}\left[\Lambda q^* e^{-\gamma q^*} - \left(\frac{\psi}{\rho}\Omega - \Lambda\gamma e^{-\gamma q^*}\right)\frac{\partial q^*}{\partial\gamma}\right] \quad (A15)$$

Because equation (14) requires $-\left(\frac{\psi}{\rho}\Omega - \Lambda\gamma e^{-\gamma q^*}\right) > 0$ and we have already proved $\frac{dq^*}{d\gamma} > 0$, we derive $\frac{d\kappa^*}{d\gamma} < 0$. By similar arguments, we have $\frac{d\kappa^*}{d\bar{P}} < 0$.

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