Preemptive Learning, Competency Traps, and Information Technology Adoption: A Real Options Analysis

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***Abstract*—Many previous real options studies suggest that increase in investment uncertainties makes deferral options more valuable. We propose a new real options model where both organizational capabilities and technological learning are emphasized. Our model demonstrates that when a company is capable of reaping sufficient benefits from preemptive learning of a new information technology, it will expedite its adoption of the technology under greater uncertainty. When exogenous gains created by technology advance are independent of technological learning, they tend to have minimal impact on the company's optimal adoption strategy. The results of our analysis also support the view that existing technology capabilities may lead to competency traps hindering a company's technological adaptation.**

***Index Terms*—Absorptive capacity, capital budgeting, competency traps, information technology (IT) adoption, organizational capabilities, preemptive learning, real options, stochastic optimization.**

I. Introduction

A FUNDAMENTAL challenge faced by modern corporations is how to create and sustain competitive advantages in an uncertain world where the business landscape could be suddenly reshaped by major technology breakthroughs. While a few companies have successfully maintained their dominance in certain industries, numerous others, including many established and reputable ones, have become victims of their own inability to quickly adapt to technology advance. Such a deficiency of adaptability is very harmful in today's digital economy characterized by the ubiquity of information technology (IT) and Schumpeterian rivalries.

Organizational learning has been well studied in the extant literature as an important channel through which companies adapt to changes in key technology domains. Specifically, some recent studies have pointed out that, through learning and experimentation of new technologies, firms can obtain strategic advantages and capitalize on opportunities generated by favorable technology development [12], [29], [36]. By conceptualizing these potential opportunities as strategic options associated with technology adoption, these papers advocate incorporating real options reasoning into technology investment decision-making. Some other researchers, based upon their observations of strong path dependencies in technology investment, have also made similar managerial recommendations, e.g., [19], [20], [41], and [42].

Researchers in both organizational theory and finance have recognized the importance of incorporating organizational learning into real options analyses [6], [22], [23]. For example, Kogut and Kulatilaka [22] point out that strategic investment in emerging technologies could facilitate organizational learning to explore "combinative potential" of existing organizational elements and new technologies, and, as a result, generate option-like capabilities that may be very valuable when new business opportunities arrive.

It is well known that technology assimilation can be viewed as an organizational learning process [4]. Previous studies have examined various characteristics and capabilities that make companies more proactive in technology adoption, and more effective in technology assimilation, e.g., [13] and [39]. In an insightful paper, Fichman [12] conceptually demonstrates the interactions among organizational learning, technology adaptation, and the real options associated with IT platform adoption. The primary objective of our paper is to present a continuous-time stochastic model where the interplay between these factors can be formally analyzed.

The main benefit of developing quantitative real options models is that these analytical models can be rigorously applied by various types of firms in different IT investment situations. It is worth noting that different types of firms have different attitudes toward emerging technologies. For many regular IT purchasing firms, their investment decisions are often driven by cost control and risk reduction. For example, enterprise resource planning (ERP) systems, which have been available in the market since mid 1980s, have not been widely adopted for about a decade. Most companies had adopted a wait-and-see strategy until they faced the Y2K problem in their legacy systems in mid 1990s [1], [34]. Compared to regular technology purchasing firms, technology vendors tend to make their technology investment decisions much more aggressively. In a recent case, SUN Microsystems paid $1 billion for MySQL, a software company whose open source database management system is a key technology of the popular open source Linux, Apache, MySQL, PHP/Perl/Python (LAMP) stack. SUN's investment decision is considered by many industry experts as very aggressive because MySQL, as an open source technology, currently generates very limited revenue despite the staggering $1 billion price tag paid by SUN [40]. In the conclusion section of this paper, we will discuss why our models can help managers better understand

Manuscript received January 1, 2008; revised July 1, 2008. First published March 27, 2009; current version published October 21, 2009. Review of this manuscript was arranged by Department Editor J. Sarkis.

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Digital Object Identifier 10.1109/TEM.2009.2016065

the two drastically different investment strategies used in the two cases.

We believe that, to analyze several delicate tradeoffs in IT adoption and investment timing, a customized real options model is warranted. Our model, in particular, recognizes the importance for companies to balance the tradeoff between exploiting current technologies and exploring new technologies. While a company can increase its profitability by refining its current technologies and capabilities, this type of success may paradoxically lead to *competence trap* as it usually reduces incentives for the company to explore new technologies [24], [25]. Very often the resultant competence trap is self-reinforcing because the company's incentive to sustain its current focus strengthens as its expertise and capabilities on current technologies increase [8], [9]. Furthermore, this self-reinforcing problem is exacerbated by the fact that the immediate returns from exploring new technologies are usually minimal if not negative. For example, Levinthal and March [24, p.106] state: "*the return from any particular innovation, technology, or reform is partly a function of an organization's experience with the new idea. Even successful innovations, when introduced, are likely to perform poorly until experience has been accumulated in using them.*"

Our model also emphasizes the economic tradeoff between preemptive learning of emerging technologies and prudent control of technology investment risk. We use "preemptive learning of emerging technologies" broadly to encompass technology experimentation, learning of technology related organizational resources and capabilities [6], and learning of the adaptive coupling of organizations and new technologies [22]. A typical technology investment project requires a significant initial outlay of capital, and is very often either partially or wholly irreversible. In addition, technology investment projects usually bear significant business and technological uncertainties, of which many will be resolved as time passes. Therefore, decision-makers often have incentives to defer their investment to let more uncertainties be resolved. By striking a balance between preemptive learning of emerging technologies and prudent deferral of risky investments, our analysis reinforces McGrath's [30] argument that real options reasoning can help decision-makers better manage investment risk while pursuing high-variance opportunities.

Furthermore, our analysis demonstrates the usefulness of supplementing real options heuristics with formal option pricing models. In the business strategy literature, real options thinking is often used as heuristics for strategic investment decision-making, allowing companies to better manage path dependencies, e.g., [31]. While this literature demonstrates that real options heuristics encourage experimentation and proactive exploration of uncertainties, it highlights the challenges faced by researchers and practitioners to rigorously apply real options theories in strategic decision-making [2], [7]. For example, a well-known technical difficulty with pricing real options is that, without finding a traded portfolio that can completely duplicate the risk characteristics of the underlying nontraded asset, standard option pricing models may be inappropriate tools to value a real option [21], [37], [38]. Despite these difficulties and challenges, formal real option pricing models are dearly needed to supplement and calibrate the business insights yielded by real options reasoning mainly based on heuristics or intuition (Benaroch *et al.* [5] provide some compelling empirical evidence that supports this argument). Using qualitative insights from extant real options literature to guide our model building, we develop a continuous-time option pricing model to formalize these business insights and to inspect their logical soundness. Instead of focusing on real options' valuation, our analysis emphasizes the adoption timing strategies of a firm facing new investment opportunities in an emerging technology domain. It quantitatively demonstrates how the firm's investment timing is affected by important factors like technological learning and adaptation, existing technology capabilities, and investment uncertainties.

The rest of this paper is structured as follows. In Section II, we begin with a formal presentation of two benchmark models, and show how we obtain the closed-form analytical solutions. Section III generalizes our benchmark models by considering the strategic benefits of preemptive learning of an emerging technology. Our model demonstrates that, depending on the magnitude of a company's absorptive capacity, it has different attitudes toward the uncertainties associated with an emerging technology. We give the conditions under which preemptive learning of new technologies may alter the standard implications of previous real options studies focusing on investment deferral under uncertainties. In Section IV, we present the results of our numerical analyses and intensive simulations to demonstrate the robustness of our main results. These simulation results are also used to graphically demonstrate the main insights from our comparative statics analysis. Section V concludes the paper.

II. Benchmark Models

We consider the investment timing decisions of a company facing the investment opportunities associated with the evolution of an emerging IT. While the emerging technology looks promising, the company is conservative about the associated investment opportunities. In our model, there are primarily two reasons that may lead to the company's cautiousness. First, it is often costly and risky to invest in an emerging technology, which gives the company an incentive to adopt a wait-and-see strategy, e.g., [21] and [32]. Second, the company has over the time developed strong capabilities in using its current technologies or technology platform. In cases where the interactions between these existing capabilities and the emerging technology are not complementary, it will be difficult for the company to economically justify its adoption of the emerging technology. Especially, when the new technology and the current technology are substitutable, existing capabilities applicable to the current technology are likely to become IT competence traps, preventing or delaying new technology adoption.

Similar to the model in Grenadier and Weiss [16], our model assumes that the emerging IT is evolving according to the following geometric Brownian process $dw/w = \alpha dt +$

TABLE I
MODELING NOTATION AND CONSTRUCT DEFINITIONS

MODEL NOTATION	DEFINITION	COMMENT
V_t	Expected technology adoption payoffs	Expected payoffs at the time of adoption *t*
w(t)	Geometric Brownian motion stochastic process used to model technology evolution process	Models the speed and the volatility of technology advance
C	Technology adoption cost	In terms of its present value, the adoption cost decreases over time due to the discounting effect
σ	Variance parameter affecting volatility of *w(t)*	Affects the volatility of the technology evolution process
dz	Wiener increment to characterize instantaneous changes in *w(t)*	Defines standard Brownian motion
r	Cost of capital for the risk-neutral firm	Affects the costs of waiting
w^*	Optimal investment point for *w(t)* in benchmark model	The firm should adopt the technology when *w(t)* hits w^*
$F(w^*)$	$F(w^*)=k(w^*-w_0)+V_0-C$	Value of the investment opportunity in benchmark model
R(w)	Gains from preemptive learning of the adopted technology	Proportionate to the firm's technology experience
G(w)	Growth option derived from *R(w)*	*G(w)* is not considered in the benchmark model
w_s^*	Optimal investment point for *w(t)* in general model	The firm should adopt the technology when *w(t)* hits w_s^* in general model
$F_s(w_s^*)$	$F_s(w_s^*)=G(w_s^*)+F(w_s^*)$	Value of the investment opportunity in general model
Z	A positive scalar variable used in the definition of *R(w)*	Affected by the firm's absorption capacity λ

$\sigma dz, \quad \alpha > 0, \quad \sigma \geq 0, \quad w = w_0$ when $t = 0$. The drift of the geometric Brownian motion α measures the growth rate of the technology evolution process (i.e., it describes how fast the technology advances). Note that σ is the variance parameter that affects the volatility of *w(t)* and *dz* is a Wiener increment that has the following two properties: 1) $dz = \varepsilon\sqrt{dt}$, with ε_t drawn from the normal distribution $N(0,1)$ and 2) $E(\varepsilon_t, \varepsilon_s) = 0$ for all $t \neq s$. If the company chooses to adopt the technology at time t, it expects the gross investment payoff of the adoption to be V_t, where $V_t = k(w_t - w_0) + V_0, k > 0$. Note that $V_t = V_0$ when $t = 0$, and V_t increases stochastically as the technology advances over time. The technology adoption cost C is constant over time. So, the net payoff of immediate investment is V_0–C. To link investment decision-making to the company's existing capabilities on current technologies, we let V_0 be dependent on b, an exogenous variable representing some existing technological capability. We let $\partial V_0/\partial b > 0$ if b measures some capability on an existing technology that the new technology complements[1], and we let $\partial V_0/\partial b < 0$ if b measures some capability on an existing technology that the new technology substitutes. For ease of reading our modeling development, the modeling notation and construct definitions are included in Table I.

[1]Sometimes increased capabilities on an existing technology may make it unnecessary for a firm to adopt a new complementing technology. This inequality does not hold in those situations.

To avoid the trivial case of immediate technology adoption, we let the net payoff of immediate investment V_0–$C < 0$. Therefore, without considering the strategic benefits of early investment, the company will wait for V_t to increase rather than adopting the emerging technology right now. We begin our analysis with two benchmark models. In the first benchmark model, we let $\sigma = 0$. As a result, both V and w are deterministic. Their values at time t are $w_t = w_0 e^{\alpha t}$, $V_t = k(w_0 e^{\alpha t} - w_0) + V_0$. Let the discount rate (the firm's cost of capital) be r, so the net present value of the technology investment payoff is $F(T) = [k(w_0 e^{\alpha T} - w_0) + V_0 - C]e^{-rT}$ (assuming today is $t = 0$ and the company invests at time *T*). To find the optimal investment time for the company, we need to maximize *F(T)*. Like most other real option models, our model assumes that $r > \alpha$. Otherwise, waiting indefinitely will obviously be the best choice. In addition, *F(T)* must be positive at the optimal investment time. Otherwise, the investment opportunity is valueless. For function $F(T)$, the first order condition is

$$\frac{dF}{dT} = (\alpha - r)kw_0 e^{(\alpha - r)T^*} - r(V_0 - C - kw_0)e^{-rT^*} = 0$$

which implies

$$T^* = \frac{1}{\alpha}\ln\left[\frac{r(V_0 - C - kw_0)}{(\alpha - r)kw_0}\right] = \frac{1}{\alpha}\ln\left[\frac{r(kw_0 + C - V_0)}{(r - \alpha)kw_0}\right].$$

To verify that the payoff function is maximized at time T^*, we need to check the second order condition as

$$\begin{aligned}\frac{d^2F(T^*)}{dT^2}&\\ &= (\alpha - r)^2 kw_0 e^{(\alpha-r)T^*} + r^2(V_0 - C - kw_0)e^{-rT^*}\\ &= [(\alpha-r)^2 + r(\alpha-r)]kw_0\left[\frac{r(V_0-C-kw_0)}{(\alpha-r)kw_0}\right]^{\alpha-r/\alpha}\\ &= \alpha(\alpha-r)kw_0\left[\frac{r(V_0-C-kw_0)}{(\alpha-r)kw_0}\right]^{\alpha-r/\alpha} < 0.\end{aligned}$$

Thus, we have proved that T^* is the optimal point. Based upon the assumptions of the model, we can further prove that T^* is positive. More importantly, we have the following proposition.

Proposition 1: In the deterministic benchmark model, the company's optimal decision is to adopt the emerging technology at $T^* > 0$, or equivalently at $w_D* > w_0$. At time T^*, the net present value of the investment payoff is greater than the investment cost C. The company adopts the technology earlier as discount rate increases. When the company has strong capabilities on an existing technology that the new technology complements, the company, ceteris paribus, has incentive to expedite its adoption of the new technology. When the company has strong capabilities on an existing technology that the new technology substitutes, the company, ceteris paribus, has incentive to delay its adoption of the new technology (IT competency trap in this case).

Proof: we know that $r(C + kw_0 - V_0) > (r-\alpha)kw_0 > 0$, so $T^* > 0$ and $w_D^* = w_0 e^{\alpha T^*} = (rw_0/(r-\alpha)) + (r(C-V_0)/k(r-\alpha)) > w_0$. We can also derive V^* from w_D^* as $V^* = k(w_D^* - w_0) + V_0 = C + (\alpha(C - V_0 + kw_0)/r-\alpha) > C$. The rest part of the proposition follows from the fact that $\partial w_D^*/\partial r < 0$, $\partial T^*/\partial r < 0$, and $\partial T^*/\partial V_0 < 0$. □

Because there are no uncertainties in the first benchmark model, the optimal investment time T^* is deterministic, and it is straightforward to perform comparative statics analysis.

Next, we generalize the deterministic benchmark model by modeling the uncertainties in the evolution of the emerging IT, i.e., $\sigma > 0$. As both V and w become stochastic in this case, maximizing the payoff function based on first and second order conditions does not work anymore. So we solve the problem by dynamic optimization, a technique used to solve similar real option problems in the literature, e.g., [10] and [16]. Denote the value of the company's option to adopt the emerging technology as *F(w)*. Bellman's principle suggests that the normal return required to hold this option should equal its expected capital gain provided that no immediate dividend is generated, i.e., $rFdt = E(dF)$. Expanding *dF* using Ito's Lemma[2], we have $dF = F'(w)dw + (1/2)\,F''(w)(dw)^2$. Plugging *dw* into the aforementioned equation yields $(1/2)\,\sigma^2 w^2 F''(w) + \alpha w F'(w) - rF = 0$. In addition, *F(w)* must satisfy three boundary conditions

$$F(0) = \max[0, V_0 - C - kw_0] = 0$$
(absorbing boundary)
$$F(w^*) = (V^* - C = k(w^* - w_0) + V_0 - C$$
(value matching condition)
$$F'(w^*) = k \qquad \text{(smooth pasting condition)}.$$

As w^* is the free boundary of the continuation region, the value matching condition says that the company gets a net payoff $V^* - C$ if it invests at $w = w^*$. The smooth pasting condition guarantees that $F(w)$ is continuous and smooth at w^*. Dixit and Pindyck [10] show that a better investment point exists if the smooth pasting condition is not satisfied at w^*. It is worth noting that we need three boundary conditions to solve the second-order differential equation because w^* is an unknown variable in our model.

For this second-order homogenous differential equation with boundary condition $F(0) = 0$, its solution must take the form $F(w) = Aw^{\beta_1}$, where β_1 is the positive root of the quadratic equation $Q(\beta) = (1/2)\,\sigma^2\beta(\beta-1) + \alpha\beta - r = 0$ with the following two roots

$$\beta_1 = (1/2) - \left(\alpha/\sigma^2\right) + \sqrt{\left(\left(\alpha/\sigma^2\right) - (1/2)\right)^2 + \left(2r/\sigma^2\right)} > 0$$

and

$$\beta_2 = (1/2) - \left(\alpha/\sigma^2\right) - \sqrt{\left(\left(\alpha/\sigma^2\right) - (1/2)\right)^2 + \left(2/\sigma^2\right)} < 0.$$

Because $Q(1) < 0$, we can further show that $\beta_1 > 1$. The value matching and smooth pasting conditions can be used to derive the two unknown variables—parameter A and w^* at which it is optimal to invest. The equation system for the two unknown variables is

$$\begin{aligned} A(w^*)^{\beta_1} &= k(w^* - w_0) + V_0 - C\\ A\beta_1(w^*)^{\beta_1 - 1} &= k.\end{aligned}$$

Through some rearrangement and manipulation, we get the following solution

$$\begin{aligned} w^* &= \frac{(C + kw_0 - V_0)\beta_1}{k(\beta_1 - 1)}\\ A &= \left(\frac{k}{\beta_1}\right)^{\beta_1}\left(\frac{\beta_1 - 1}{C + kw_0 - V_0}\right)^{\beta_1 - 1}.\end{aligned}$$

It is easy to prove that the deterministic case is a special case of the aforementioned solution with $\sigma = 0$. When $\sigma = 0$, we know from function $Q(.)$ that β equals r/α. Pluging it into the aforementioned general solution, we have $w_D^* = w^*$. As a matter of fact, we can further show that $1 < \beta_1 \le (r/\alpha)$, and $(\partial\beta_1/\partial\sigma) < 0$. Based on these results, we have the following proposition.

Proposition 2: The option to defer technology adoption is more valuable in the stochastic case than in the deterministic case. The company requires higher payoff to adopt the emerging technology as uncertainty increases. Higher discount rate or

[2]Ito's Lemma is a well known theorem in stochastic calculus that is used to take derivatives of a stochastic process. Its primary result is that the second order differential terms of a Wiener process become deterministic when they are integrated over time. Please see Merton [33] for further details.

lower expected growth rate of technology payoff reduces the company's investment payoff threshold for adopting the new technology.

Proof: The value of the option to defer the technology investment is $V^*–C$. Because V^* increases in w^*, we need to prove that $w^* > w^*_D$. Differentiating the quadratic equation Q totally, we have $(\partial Q/\partial \beta_1)(\partial \beta_1/\partial \sigma) + (\partial Q/\partial \sigma) = 0 \Rightarrow (\partial \beta_1/\partial \sigma) = -((\partial Q/\partial \sigma)/(\partial Q/\partial \beta_1)) < 0$. In addition, we have $((\beta_1/\beta_1 - 1))' < 0 \Rightarrow ((\beta_1/\beta_1 - 1)) > (r/r - \alpha)$, which implies $w^* > w^*_D$, $\partial w^*/\partial \sigma > 0$ and $\partial V^*/\partial \sigma > 0$. To find the effects of exogenous change in r or α on w^*, we rewrite the quadratic equation as $(1/2)\,\sigma^2 \beta(\beta - 1) = -\alpha\beta + r$. Since the left-hand side is monotonically increasing in β ($\beta > 1$) and the right-hand side is a straight line with negative slope, it is easy to show $(\partial \beta_1/\partial \alpha) < 0$ and $(\partial \beta_1/\partial r) > 0$. Since $dw^*/d\beta_1$ is negative, the aforementioned results imply $(\partial w^*/\partial \alpha) > 0$ and $(\partial w^*/\partial r) < 0$. Thus, higher discount rate or lower expected payoff growth rate reduces the company's investment payoff threshold for adopting the new technology. □

The major insight from our stochastic benchmark model, consistent with the results of many other real option models, is that increase in uncertainty leads to higher threshold payoff for the company to adopt the emerging technology (see [3] or [43] for a review of the deferral option models). The impact of the company's existing capabilities on technology adoption decision making in the stochastic benchmark model also depends on the interplay between the existing capabilities and the new technology. When the company has strong capabilities on an existing technology that the new technology complements, the company, ceteris paribus, has incentive to expedite its adoption of the new technology. When the company has strong capabilities on an existing technology that the new technology substitutes, the company, ceteris paribus, has incentive to delay its adoption of the new technology (competency trap in this case).

III. Preemptive Learning and Absorptive Capacity

While our two benchmark models demonstrate the impacts of uncertainties and existing capabilities on the company's decision making, they do not consider the strategic benefits of early technology adoption. There are at least two important reasons why the company may reap strategic benefits by adopting the emerging technology earlier. First, a company operating in a competitive industry has some incentive to act quickly in order to gain strategic advantages over its competitors. Based on a duopolistic real options game, several studies demonstrate how competitive dynamics affect the timing of new technology adoption [19], [20]. Second, it is often of strategic importance for a company to be well prepared for an emerging technology domain before it prevails in the market. Companies that adopt an emerging technology earlier have more time to experience the technology. Very often preemptive learning and experimentation of a new technology generate capabilities that are essential for a company to capitalize on the business opportunities created by the technology in the future.

To capture the significance of preemptive learning, we present a more general model where payoffs from technology adoption include some strategic benefits that materialize only after the technology advances to a given level. In this model, we are particularly interested in the following question: how preemptive learning and technological uncertainties interact in influencing the company's optimal investment decision? We extend our stochastic benchmark model by adding a threshold w^u in the technology evolution process.[3] The emerging technology has advanced enough to enable some major business opportunities when w *first* passes the threshold w^u. If the company has adopted the new technology prior to this point, it will obtain a business growth option whose value depends on the company's prior experience with the new technology, and its capabilities of assimilating and applying the new technology (its absorptive capacity).

In our model, we assume that the business growth option is so valuable that the company could not afford to lose it, which implies that the company must adopt the technology at some point prior to w^u. To quantify the strategic benefit of preemptive learning, we let the company's financial gains from the new opportunities enabled by technology advance be proportionate to its experience with the emerging technology. If the company adopts the new technology at w, it can gain $R(w) = [(w^u - w)/(w^u - w_0)]\,Z$, $w < w^u$, where $[(w^u - w)/(w^u - w_0)]$ is a measure of the company's technology experience and Z is a positive scalar variable whose value depends on the company's absorptive capacity λ (a company with high absorptive capacity enjoys greater gains, i.e., $(\partial Z/\partial \lambda) > 0$).[4] For example, the company can gain Z from the new opportunities if it invests at $w = w_0$. To characterize the optimal adoption timing strategy in this situation, we first need to calculate the value of the business growth option.

Denote *G(w)* as the value of the growth option at w. According to Bellman's principle of optimality and Ito's lemma, *G(w)* must satisfy the following equilibrium differential equation:

$$\frac{1}{2}\sigma^2 w^2 G''(w) + \alpha w G'(w) - rG = 0$$

subject to $G(0) = 0$ and $G(w^u) = [(w^u - w^*_s)/(w^u - w_0)]\,Z$, where w^*_s is the optimal adoption time to be derived later. Note that here we only need two boundary conditions because w^u is a known variable instead of a free bound. The solution to the second-order homogenous differential equation is given as $G(w) = [(w^u - w^*_s)/(w^u - w_0)]\,Z\,(w/w^u)^{\beta_1}$, where β_1 is the

[3] By adding the threshold in the technology evolution process, we can use the first passage time of the stochastic process to characterize a random time in the future. The first passage time is a technical term frequently used in stochastic analysis. It is the first time for a stochastic process to reach a predetermined threshold (See [11] and [35] for its statistical properties). Grenadier and Weiss [16] use the first passage time of a geometric Brownian motion to characterize the random arrival time of a future innovation. Our paper uses the first passage time to characterize the random time at which some major business opportunities arise due to technology advance.

[4] For mathematical tractability, we assume that *R(w)* is linear in w and Z. A nonlinear relationship may be more appropriate in some real world situations. For example, a company with very significant absorptive capacity may fully reap the strategic benefits of learning in a relatively short time period, thereby making very early adoption unnecessary.

positive root of the quadratic equation $Q(.) = 0$ (see our second benchmark model for details).

Having the solution of $G(w)$, we are able to derive the company's optimal adoption time w_s^*. Denoting $F_s(w)$ as the value of the technology investment opportunity in our general model, we have the following equilibrium equation:

$$\frac{1}{2}\sigma^2 w^2 F_s''(w) + \alpha w F_s'(w) - rF_s = 0$$

Subject to

$$F_s(0) = F(0) + G(0) = 0$$
$$F_s'(w_s^*) = G'(w_s^*) + k \text{ and}$$
$$F_s(w_s^*) = G(w_s^*) + k(w_s^* - w_0) + V_0 - C.$$

Similar to the equilibrium equation in the benchmark model, the dynamic equilibrium equation needs three boundary conditions to be solvable. The first condition says that zero is still an absorbing bound. The other two equations are value matching condition and smooth pasting condition, respectively. For the second-order homogenous differential equation, the first boundary condition suggests that the solution of the differential equation must take the form $F_s(w) = Yw^{\beta_1}$, where Y is an unknown variable and β_1 is the positive root of the quadratic equation $Q(\beta) = (1/2)\,\sigma^2\beta(\beta - 1) + \alpha\beta - r = 0$. Using the other two boundary conditions, we get the following system of equations:

$$Y\beta_1(w_s^*)^{\beta_1 - 1} = k + \frac{w^u Z\beta_1(w_s^*)^{\beta_1 - 1}}{(w^u - w_0)(w^u)^{\beta_1}} - \frac{(\beta_1 + 1)Z}{(w^u - w_0)}\left(\frac{w_s^*}{w^u}\right)^{\beta_1}$$

$$Y(w_s^*)^{\beta_1} = \frac{(w^u - w_s^*)}{(w^u - w_0)}Z\left(\frac{w_s^*}{w^u}\right)^{\beta_1} + k(w_s^* - w_0) + V_0 - C.$$

After combination and manipulation, we find that w_s^* must satisfy the following equation $-k(\beta_1 - 1)w_s^* + \beta_1(kw_0 + C - V_0) = \left[(w_s^*)^{\beta_1 + 1}Z\big/(w^u - w_0)(w^u)^{\beta_1}\right]$. It is worth noting that the equation degenerates to the equilibrium equation in the stochastic benchmark model if we set the extra gains from new business opportunities, Z, to be zero. In this sense, our stochastic benchmark model is a special case of our general model with preemptive learning. Since the aforementioned equation is very nonlinear, finding a closed-form analytical solution is difficult. However, we prove that a solution does exist, is unique and economically plausible in the following proposition.

Proposition 3: There is a unique nonnegative w_s^* at which it is optimal for the company to adopt the emerging technology. Moreover, the company will adopt the technology earlier than the case in which the strategic benefits of preemptive learning are not considered, i.e., $w_s^* < w^*$, where w^* is the optimal investment point in our stochastic benchmark model.

Proof: We first prove the uniqueness of the nonnegative solution w_s^*. For the equilibrium equation, we define $\text{LHS}(w) = -k(\beta_1 - 1)w + \beta_1(kw_0 + C - V_0)$ and $\text{RHS}(w) = \left[(w)^{\beta_1 + 1}Z\big/(w^u - w_0)(w^u)^{\beta_1}\right]$.

We know from the equilibrium equation that the optimal point w_s^* should satisfy $\text{LHS}(w_s^*) = \text{RHS}(w_s^*)$. It is easy to find that $\text{LHS}(0) > 0, \quad \text{LHS}(w^*) = 0, \quad \text{RHS}(0) = 0, \quad \text{RHS}(w^*) > 0$.

In addition, we have $d\text{LHS}(w)/dw = -k(\beta_1 - 1) < 0$ and $(d\text{RHS}(w)/dw) = \left(Z(\beta + 1)_1(w)^{\beta_1}\big/(w^u - w_0)(w^u)^{\beta_1}\right) > 0$. Thus, there is a unique nonnegative point w_s^* that satisfies $\text{LHS}(w_s^*) = \text{RHS}(w_s^*), \quad 0 < w_s^* < w^*$. □

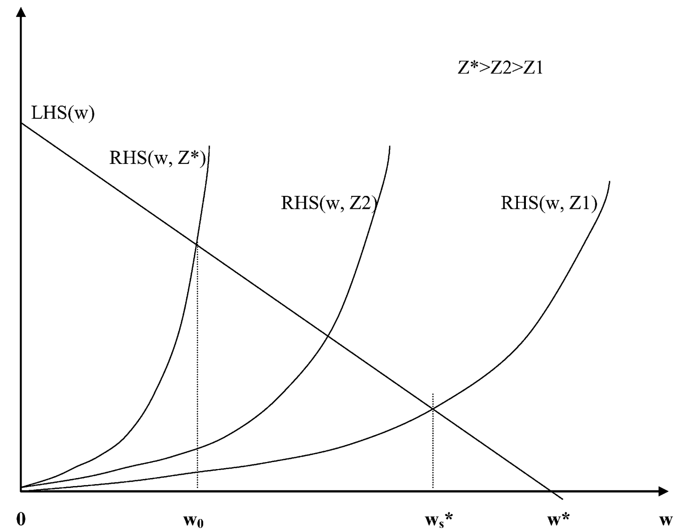


Fig. 1. Existence and uniqueness of w_s^*.

We depict LHS(.) and RHS(.) in Fig. 1 to demonstrate the main result of Proposition 3. The figure also shows that w_s^* decreases as Z increases. It is worth noting that w_s^* may be less than w_0 if Z is sufficiently large. In this case, the strategic gains of early adoption dominate the benefits of waiting for uncertainty resolution. Consequently, the optimal timing strategy is to adopt the new technology immediately when $w_s^* < w_0$. Proposition 4 gives the threshold value of Z at which immediate adoption is the optimal strategy.

Proposition 4: The company will invest earlier as Z increases. It will invest immediately if $Z > Z^*$, where the value of Z^* can be derived from the equilibrium equation. If the company expects that the new business opportunities will arise earlier (i.e., a lower w^u), it will adopt the new technology immediately at a lower threshold of Z.

Proof: To find the effect of Z on w_s^*, we define the following function:

$$\phi(w_s^*, Z) = \frac{(w_s^*)^{\beta_1 + 1}Z}{(w^u - w_0)(w^u)^{\beta_1}} - k(\beta_1 - 1)w_s^*.$$

The equilibrium equation suggests $\phi(w_s^*, Z) = \beta_1(kw_0 + C - V_0)$. Differentiating the equation totally, we get $(\partial\phi/\partial w_s^*)(\partial w_s^*/\partial Z) + (\partial\phi/\partial Z) = 0$. In addition, we have $(\partial\phi/\partial Z) = ((w_s^*)^{\beta_1 + 1}/(w^u - w_0)(w^u)^{\beta_1}) > 0$ and $(\partial\phi/\partial w_s^*) = ((1 + \beta_1)(w_s^*)^{\beta_1}Z/(w^u - w_0)(w^u)^{\beta_1}) > 0$. Thus, we know $(\partial w_s^*/dZ) = -(\partial\phi/\partial Z)/(\partial\phi/\partial w_s^*) < 0$. Next plug $w_s^* = w_0$ into the equilibrium equation to derive $Z^* - k(\beta_1 - 1)w_0 + \beta_1(kw_0 + C - V_0) = ((w_0)^{\beta_1 + 1}Z^*/(w^u - w_0)(w^u)^{\beta_1}) \Rightarrow Z^* = ((w^u - w_0)(w^u)^{\beta_1}[kw_0 + \beta_1(C - V_0)]/(w_0)^{\beta_1 + 1})$, which obviously implies $(\partial Z^*/\partial w^u) > 0$. □

Our model emphasizes that earlier adoption provides the company with more time for technology experimentation and learning. To highlight the role played by learning in affecting adoption timing, we study an alternative model setup where the company's financial gains from the new opportunities enabled by technology advance are fixed. Specifically, we consider the situation where $R(w)$ is a positive constant for any $w \leq w^u$ and $R(w) = 0$ otherwise. This setup implies that the company will gain some fixed payoffs from new business opportunities as long as it adopts the technology before $w(t)$ passes w^u, which is different form our original model setup where the gains are proportionate to the company's experience with the technology. Proposition 5 examines the company's technology adoption strategy under this scenario.

Proposition 5: When the company's gains from new business opportunities are fixed and not proportionate to its prior technological experience, the company will make its optimal adoption timing decision as if there are no strategic benefits from new business opportunities enabled by the advance of the new technology. Consequently, the optimal adoption time w_s^* is equal to w^*, the optimal adoption time derived in our stochastic benchmark model.

Proof: Under this alternative model setup, the value of the strategic growth option $G(w)$ does not depend on w_s^* anymore. Similar to the equilibrium equation in the generalized stochastic model, this model setup results in the following differential equation:

$$\frac{1}{2}\sigma^2 w^2 F_s''(w) + \alpha w F_s'(w) - rF_s = 0.$$

Subject to

$$F_s(0) = F(0) + G(0) = 0$$
$$F_s(w_s^*) = G(w_s^*) + k(w_s^* - w_0) + V_0 - C$$
$$F_s'(w_s^*) = G'(w_s^*) + k.$$

Because in this case $G(w) = Z\,(w/w^u)^{\beta_1}$, we need to solve the following system of equations:

$$Y(w_s^*)^{\beta_1} = Z\left(\frac{w_s^*}{w^u}\right)^{\beta_1} + k(w_s^* - w_0) + V_0 - C$$
$$Y\beta_1(w_s^*)^{\beta_1 - 1} = k + \frac{Z\beta_1(w_s^*)^{\beta_1 - 1}}{(w^u)^{\beta_1}}.$$

Its closed-form solution is $w_s^* = [(C + kw_0 - V_0)\beta_1/k(\beta_1 - 1)] = w^*$. So it is easy to show that the company should invest at $\min(w_s^*, w^u)$. □

Proposition 5 demonstrates that the benefits from new opportunities enabled by technology advance, if not dependent on the company's prior technological experience, have no impact on the optimal timing of new technology adoption. This is because the company can reap all the benefits of the growth option as long as it invests before $w(t)$ reaches w^u. Consequently, when $w^u > w^*$, the company can disregard the influence of preemptive learning on its technological capabilities, and adopt the optimal solution derived in our stochastic benchmark model. This result is important because it demonstrates that the strategic benefits of preemptive learning, coupled with the expected gains from new business opportunities, are the major drivers behind the company's earlier adoption decision.

Returning to our original model setup where the company's financial gains from new opportunities are dependent on technological experience gained through learning and experimentation, we believe that it is very important to understand how preemptive learning interacts with uncertainties and discount rate in affecting technology adoption timing. In our stochastic benchmark model, we have proved that $(\partial w^*/\partial\sigma) > 0$ and $(\partial w^*/\partial r) < 0$. The following proposition demonstrates that these interactive effects somewhat complicate our comparative statics results, and, as a consequence, considerably enrich our model.

Proposition 6: When the expected gains from new opportunities enabled by technological advance are significant enough, small changes in discount rate or uncertainty have no effect on adoption timing. Otherwise, there are two scenarios as described next.

1) When the expected gains are less than a threshold, the company adopts the new technology at a later stage of its evolution process as uncertainty increases. As discount rate increases, the company invests earlier or equivalently, adopts the new technology at an earlier stage of its evolution process.
2) When the expected gains are greater than a threshold, all the aforementioned effects are converse.

Proof: Proposition 4 has shown that the company will invest immediately if $Z \geq Z^*$, where $Z^* = \left[(w^u - w_0)(w^u)^{\beta_1}[kw_0 + \beta_1(C - V_0)]/(w_0)^{\beta_1+1}\right]$. In this case, we have $(\partial w_s^*/\partial\sigma) = 0$ and $(\partial w_s^*/\partial r) = 0$.

When $Z < Z^*$, rewrite the equilibrium equation as

$$\delta(\beta_1, w_s^*) = \frac{(w_s^*)^{\beta_1+1}Z}{(w^u - w_0)(w^u)^{\beta_1}} + k(\beta_1 - 1)w_s^* - \beta_1(kw_0 + C - V_0) = 0.$$

Differentiating the equation totally yields $(\partial\delta/\partial w_s^*)(\partial w_s^*/\partial\beta_1) + (\partial\delta/\partial\beta_1) = 0 \Rightarrow (\partial w_s^*/d\beta_1) = [-(\partial\delta/\partial\beta_1)/(\partial\delta/\partial w_s^*)]$.

In addition, we have $\partial\delta/\partial w_s^* = [Z(\beta_1+1)(w_s^*)^{\beta_1}/(w^u - w_0)(w^u)^{\beta_1}] + k(\beta_1 - 1) > 0$ and $\partial\delta/\partial\beta_1 = [(w_s^*)^{\beta_1+1}Z/(w^u - w_0)(w^u)^{\beta_1}]\ln(w_s^*/w^u) + k(w_s^* - w_0) + V_0 - C$. Define the following threshold function:

$$\bar{Z}(w_s^*) = \frac{[k(w_s^* - w_0) + V_0 - C](w^u - w_0)(w^u)^{\beta_1}}{(\ln w^u - \ln w_s^*)(w_s^*)^{\beta_1+1}}.$$

From the equilibrium equation, we can derive

$$Z(w_s^*) = \frac{[-k(\beta_1-1)w_s^* + \beta_1(kw_0 - V_0 + C)](w^u - w_0)(w^u)^{\beta_1}}{(w_s^*)^{\beta_1+1}}.$$

It is easily to prove $\bar{Z}(w_0 + (C - V_0/k)) = 0$, $Z(w_0 + (C - V_0/k)) > 0$ and $\bar{Z}(w^*) > 0, Z(w^*) = 0$, where w^* is the solution in the stochastic benchmark model. Moreover, notice that

$$Z(w_s^*) - \bar{Z}(w_s^*) = P(w_s^*)\frac{(w^u - w_0)(w^u)^{\beta_1}}{(w_s^*)^{\beta_1+1}}$$

where

$$P(w_s^*) = -k(\beta_1 - 1)w_s^* + \beta_1(kw_0 + C - V_0) - \frac{k(w_s^* - w_0) + V_0 - C}{\ln w^u - \ln w_s^*}$$

$$\frac{\partial P(w_s^*)}{\partial w_s^*} < 0 \,\forall\, w_s^* > \left(w_0 + \frac{C - V_0}{k}\right)$$

$$\lim_{Z \to \bar{Z}} \frac{\partial[Z(w_s^*) - \bar{Z}(w_s^*)]}{\partial w_s^*} = P'(w_s^*)\frac{(w^u - w_0)(w^u)^{\beta_1}}{(w_s^*)^{\beta_1+1}} < -k(\beta_1 - 1)\frac{(w^u - w_0)(w^u)^{\beta_1}}{(w_s^*)^{\beta_1+1}} < 0.$$

Therefore, we can find an unique positive threshold $\hat{Z}$ such that

$$\frac{\partial \delta}{\partial \beta_1} > 0 \quad \text{and} \quad \frac{\partial w_s^*}{\partial \beta_1} < 0, \quad \text{if } Z < \hat{Z}$$
$$\frac{\partial \delta}{\partial \beta_1} = 0 \quad \text{and} \quad \frac{\partial w_s^*}{\partial \beta_1} = 0, \quad \text{if } Z = \hat{Z}$$
$$\frac{\partial \delta}{\partial \beta_1} < 0 \quad \text{and} \quad \frac{\partial w_s^*}{\partial \beta_1} > 0, \quad \text{if } Z > \hat{Z}.$$

Because $(\partial\beta_1/\partial\sigma) < 0$ and $(\partial\beta_1/\partial r) > 0$, we know that there is a threshold $\hat{Z} \in (0, Z^*)$ that satisfies

$$\frac{\partial w_s^*}{\partial \sigma} > 0 \quad \text{and} \quad \frac{\partial w_s^*}{\partial r} < 0, \quad \text{when } Z < \hat{Z}$$
$$\frac{\partial w_s^*}{\partial \sigma} < 0 \quad \text{and} \quad \frac{\partial w_s^*}{\partial r} > 0, \quad \text{when } Z > \hat{Z}.$$

□

Proposition 6 suggests that the standard implications offered by previous real options research should be scrutinized when the role of preemptive learning is emphasized in technology adoption. When the potential benefits from learning and experimentation are below a certain threshold, the major implications from previous real options studies hold. For example, increase in uncertainties gives the company more incentives to defer technology adoption. Higher discount rate reduces the value of the company's deferral option, and thus, encourages earlier adoption. However, when the potential benefits from learning and experimentation are significant (above a certain threshold), applying results from previous real options studies may lead to erroneous conclusions. Under this scenario, the company, when facing more uncertainties associated with the new technology, is better off by expediting rather than delaying its adoption. Moreover, while higher discount rate certainly increases the cost of waiting, it reduces the company's potential gains from preemptive learning (in terms of their present values). So even under a higher discount rate, the company will not adopt the new technology earlier, contrary to suggestions made by most extant real options models.

An immediate corollary of this proposition is that the impacts of uncertainties and discount rate on adoption timing depend on the company's absorptive capacity λ. Since $(\partial Z/\partial\lambda) > 0$, the company will be more preemptive in adopting the new technology under uncertainties when its absorptive capacity is above a certain threshold. This result is consistent with Cohen and Levinthal's [9] argument that it is essential for firms to develop absorptive capacity to better exploit business opportunities provided by new technology advance, and it also reinforces McGrath's [30] point that real options thinking encourages companies to develop capabilities facilitating exploration instead of uncertainty avoidance.

IV. Simulation and Numerical Experiments

Having derived the optimal solutions under different scenarios, we can use numerical analysis and computer simulation to demonstrate how various factors influence the company's optimal adoption timing. We focus on the most general scenario where strategic benefits of learning and experimentation exist. In our numerical analysis, we normalize k, w_0, and C to be 1. We let $V_0 = 0.9 < C$. So without the strategic benefits of early investment, the payoff of immediate investment is negative. The scalar variable Z that affects the strategic benefits of early investment is also set at 1. The discount rate r is initially set at 30%. The standard deviation σ is initially set at 0.2. The drift of the geometric Brownian motion α that describes how fast the new technology advances is set at 0.15. Note that α must be smaller than r, otherwise waiting indefinitely is the best strategy [10]. The threshold w^u that determines when new business opportunities arise is set at 2.6. Based on the assigned values of the aforementioned parameters, it on average takes about seven years for $w(t)$ to hit w^u. In other words, it on average takes about seven years for the advance of the new technology to trigger the emergence of some major business opportunities.

Given all these parameter values, the numeric solution of the optimal adoption point is $w_s^* = 1.7745$, which implies that the company should adopt the new technology once $w(t)$ hits 1.7745. Without considering the strategic benefits of preemptive learning, our numerical analysis shows that the company should invest when $w(t)$ hits $w^* = 2.4649$. In addition, our analysis suggests that the company should adopt the new technology immediately if Z is greater than $Z^* = 10.608$.

To test the robustness of our analytical results, we compare the average payoff of the optimal timing solution implied by our model with those of three other competing timing strategies under the circumstances where some parameter values are randomly drawn from some prespecified distributions. The four competing strategies compared in our simulation are listed as follows.

1) *Strategy A*: The optimal strategy implied by our model considering the strategic benefits of preemptive learning. The company adopts the new technology once $w(t)$ hits $w_s^* = 1.7745$.
2) *Strategy B:* The optimal strategy implied by our second benchmark model. The company adopts the new technology once $w(t)$ hits $w^* = 2.4649$.
3) *Strategy C:* The traditional discounted cash flow approach. The company adopts the new technology once the expected net present value (NPV) becomes positive. Since

TABLE II
AVERAGE PAYOFFS OF FOUR COMPETING STRATEGIES (NO NOISE IN PARAMETER SPACE)

	Strategy A	Strategy B	Strategy C	Strategy D	Number	Percent
1	0.328346	0.280567	0.076657	0.291766	24884	49.77%
2	0.329501	0.281747	0.077483	0.292768	24940	49.88%
3	0.327305	0.279516	0.075803	0.290725	24886	49.77%
4	0.32981	0.282272	0.077884	0.293176	24875	49.75%
5	0.327681	0.279842	0.076115	0.291162	24900	49.80%
6	0.329536	0.281927	0.077498	0.292589	24892	49.78%
7	0.327499	0.27951	0.075961	0.291225	24892	49.78%
8	0.32851	0.28102	0.076836	0.291812	24842	49.68%
9	0.328644	0.2807	0.076893	0.292227	25012	50.02%
10	0.327833	0.280219	0.076234	0.291055	24815	49.63%

Parameters values: $w_0 = 1$, $w^u = 2.6$, $Z = 1$, $\sigma = 0.2$, $w_s^* = 1.7745$, $r = 30\%$, $k = 1$, $\alpha = 0.15$, $w^* = 2.4649$, $w' = (w_0 + w_s^*)/2 = 1.38725$, $C = 1$, and $V_0 = 0.9$.

the expected NPV (including the strategic benefits of early adoption) is positive at $t = 0$, the company will adopt the new technology at $t = 0$, or equivalently at $w = w_0$.

4) *Strategy D:* The company adopts the new technology once $w(t)$ hits w', where w' is an arbitrarily chosen threshold between w_0 and w^u. In our simulation, we let $w' = (w_0 + w_s^*)/2 = 1.38725$.

We run our simulation program ten times to ensure that the results converge very well. Each time our program generates 50 000 sample paths, and the average strategy payoffs are calculated as the estimates of the expected payoffs. Our simulation program also counts the number of sample paths for which Strategy A generates the highest payoffs. Table II lists the average payoffs of the four timing strategies in ten rounds of simulation. It is easy to see that Strategy A strictly doxminates other three strategies in terms of average strategy payoffs. In addition, it generates the highest payoff for nearly 50% of the sample paths. This result is not surprising at all because we do not introduce any noise into the parameter space. In fact, we are more interested in the simulation results when some parameter values are randomly drawn from some prespecified distributions. Table III lists the average strategy payoffs of the four timing strategies when Z is uniformly distributed between 0.5 and 1.5. Of course, variation in Z will generate more uncertainty about the magnitude of the strategy benefits of preemptive learning. Nevertheless, our simulation results show that the average strategy payoffs are quite stable with the presence of randomness in Z. Again, Strategy A generates the highest payoff for nearly 50% of the sample paths. In Table IV, we compare the average investment payoffs when Z and σ are both uniformly distributed. We move a step further to let w^u be uniformly distributed between 2.5 and 2.7 in Table V. Like Table III, both tables suggest that Strategy A, the optimal strategy given in our analysis is very robust to random noise in parameter space.

Because w' is arbitrarily chosen to be compared with w_s^*, the simulation results in Tables II–V may not convince some readers that our optimal strategy is very robust, especially within the near optimum region. Therefore, we depict the expected strategy payoff function through intensive simulation. Such computer simulation is time consuming, but it is very helpful for us to further validate the optimal strategy and to demonstrate its robustness. We use *ANSI C* to code our simulation programs. Using 0.03 as an increment in w, we draw the expected investment payoffs as a function of w in Fig. 2. Fig. 2(a) shows that the average payoff function achieve its maximum at $w = 1.79$. As our model yields the optimal numeric solution at $w_s^* = 1.7745$, we believe the two results are quite close given that the increment in w is 0.03 in our simulation. Because the magnitude of Z plays a very important role in our model, we change Z from

TABLE III
AVERAGE PAYOFFS OF FOUR COMPETING STRATEGIES (Z IS UNIFORMLY DISTRIBUTED)

	Strategy A	Strategy B	Strategy C	Strategy D	Number	Percent
1	0.331463	0.282462	0.078154	0.293821	25043	50.09%
2	0.329572	0.281458	0.077235	0.292714	24766	49.53%
3	0.330487	0.281874	0.077527	0.293231	24929	49.86%
4	0.329853	0.281191	0.077179	0.292489	24897	49.79%
5	0.330422	0.282234	0.077923	0.293487	24865	49.73%
6	0.331695	0.282398	0.077908	0.293672	25044	50.09%
7	0.328629	0.28098	0.076821	0.29206	24704	49.41%
8	0.33145	0.282351	0.077962	0.293587	25059	50.12%
9	0.329429	0.281381	0.077023	0.292628	24707	49.41%
10	0.3313	0.282402	0.078202	0.29383	25040	50.08%

Parameters values: $w_0 = 1$, $w^u = 2.6$, Z is uniformly distributed between 0.5 and 1.5, $\sigma = 0.2$, $w_s^* = 1.7745$, $r = 30\%$, $k = 1$, $\alpha = 0.15$, $w^* = 2.4649$, $C = 1$, $V_0 = 0.9$, and $w' = w_0 + w_s^*)/2 = 1.38725$.

TABLE IV
AVERAGE PAYOFFS OF FOUR COMPETING STRATEGIES (Z AND σ ARE BOTH UNIFORMLY DISTRIBUTED)

	Strategy A	Strategy B	Strategy C	Strategy D	Number	Percent
1	0.329287	0.281634	0.077254	0.292343	25504	51.01%
2	0.329806	0.282117	0.077596	0.292607	25510	51.02%
3	0.330171	0.282897	0.078132	0.293192	25328	50.66%
4	0.328711	0.281273	0.077008	0.291862	25523	51.05%
5	0.331051	0.283899	0.07875	0.29384	25363	50.73%
6	0.328496	0.28052	0.076732	0.291704	25556	51.11%
7	0.330973	0.283765	0.078533	0.293533	25397	50.79%
8	0.32938	0.281581	0.077127	0.292345	25535	51.07%
9	0.330582	0.28335	0.078648	0.293498	25397	50.79%
10	0.328999	0.281356	0.076851	0.292051	25473	50.95%

Parameters values: $w_0 = 1$, $w^u = 2.6$, Z is uniformly distrituted between 0.5 and 1.5 standard deviation σ is uniformly distributed between 0.1 and 0.3, $w_s^* = 1.7745$, $r = 30\%$, $k = 1$, $\alpha = 0.15$, $w^* = 2.4649$, $C = 1$, and $V_0 = 0.9$, $w' = (w_0 + w_s^*)/2 = 1.38725$.

TABLE V
AVERAGE PAYOFFS OF FOUR COMPETING STRATEGIES (Z, σ, AND w^u ARE UNIFORMLY DISTRIBUTED)

	Strategy A	Strategy B	Strategy C	Strategy D	Number	Percent
1	0.330833	0.282307	0.078806	0.293937	25512	51.02%
2	0.33055	0.281447	0.077971	0.293201	25614	51.23%
3	0.330353	0.281804	0.078375	0.293518	25486	50.97%
4	0.330707	0.281757	0.078333	0.293596	25558	51.12%
5	0.330153	0.281324	0.078114	0.293126	25571	51.14%
6	0.33015	0.281495	0.078191	0.293313	25565	51.13%
7	0.330892	0.281713	0.078443	0.293705	25588	51.18%
8	0.330376	0.281741	0.0785	0.293642	25495	50.99%
9	0.330716	0.281438	0.077952	0.293346	25636	51.27%
10	0.330858	0.282327	0.078714	0.293931	25522	51.04%

Parameters values: $w_0 = 1$, w^u is uniformly distrituted between 2.5 and 2.7, Z is uniformly distributed between 0.5 and 1.5, standard deviation σ is uniformly distributed between 0.1 and 0.3, $w_s^* = 1.7745$, $r = 30\%$, $k = 1$, $\alpha = 0.15$, $w^* = 2.4649$, $C = 1$, $V_0 = 0.9$ and $w' = (w_0 + w_s^*)/2 = 1.38725$.

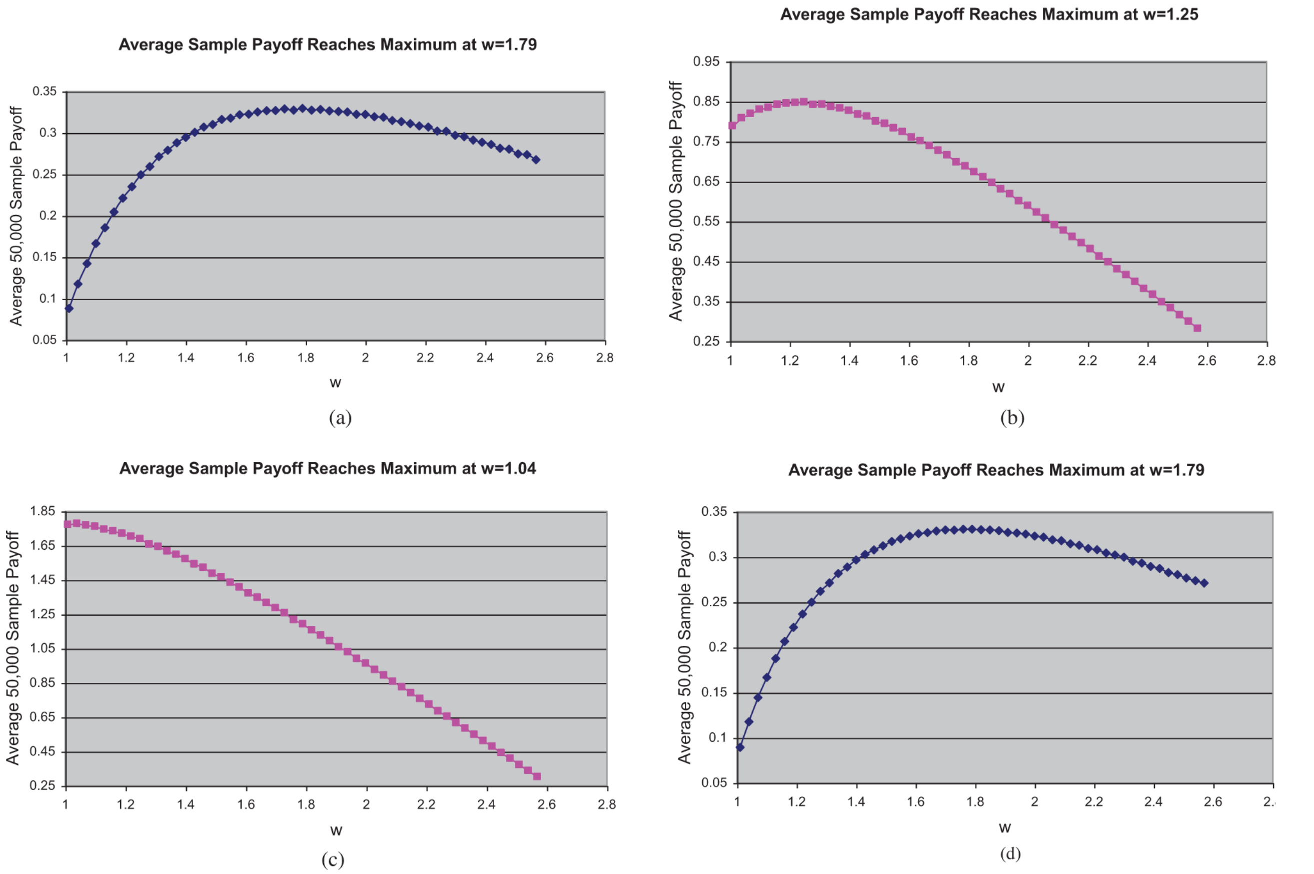


Fig. 2. (a) and (b) 50 000 sample path average payoff as a function of w. (a) $Z = 1$, $\sigma = 0.2$, and $w^u = 2.6$. (b) $Z = 5$, $\sigma = 0.2$, and $w^u = 2.6$. (c) $Z = 10.60807$, $\sigma = 0.2$, and $w^u = 2.6$. (d) Z is uniformly distributed between 0.5 and 1.5, σ is uniformly distributed between 0.1 and 0.3, and w^u is uniformly distributed between 2.4 and 2.6.

1 to 5 and draw the average sample payoff as a function of w in Fig. 2(b). The graph shows that the average payoff function achieves its maximum at $w = 1.25$ that is also very close to the optimal point $w_s^* = 1.23$ derived from our model. In Proposition 4, we prove that the company will invest immediately if $Z > Z^*$, and derive the mathematical expression of Z^*. Given the parameter values used in our simulation, our calculation indicates that Z^* is approximately 10.60807. We draw the average sample payoff as a function of w in Fig. 2(c) where $Z = Z^*$. The graph shows that the function is maximized at $w = 1.04$ that is also very close to our optimal solution $w_s^* = 1.0$.

We also address the issue of robustness through intensive simulation. We let Z, σ, and w^u be all uniformly distributed, and draw the average sample payoff function in Fig. 2(d). Even with so much noise added into the system, the function depicted in Fig. 2(d) looks almost identical to the function showed in Fig. 2(a). The average sample payoff function also achieves its maximum at $w = 1.79$. Therefore, we believe that our model is very robust to random fluctuation of model parameter values. Moreover, we find that the average payoff functions are very flat within the near-maximum region, as shown in Fig. 2, which implies that the penalty for minor deviation from the optimal strategy is relatively light.

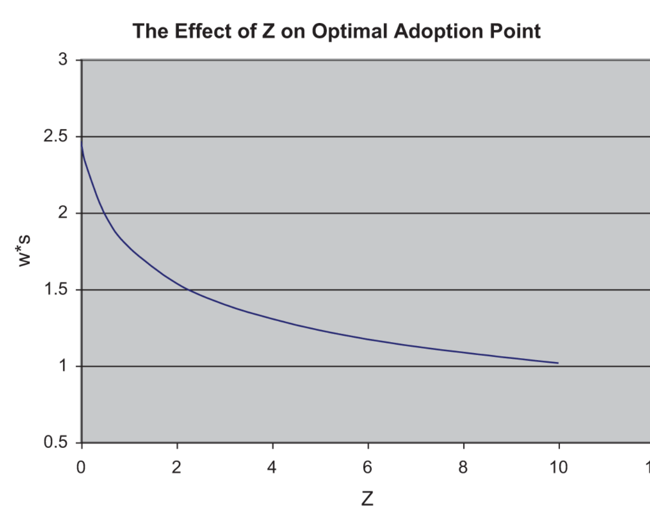
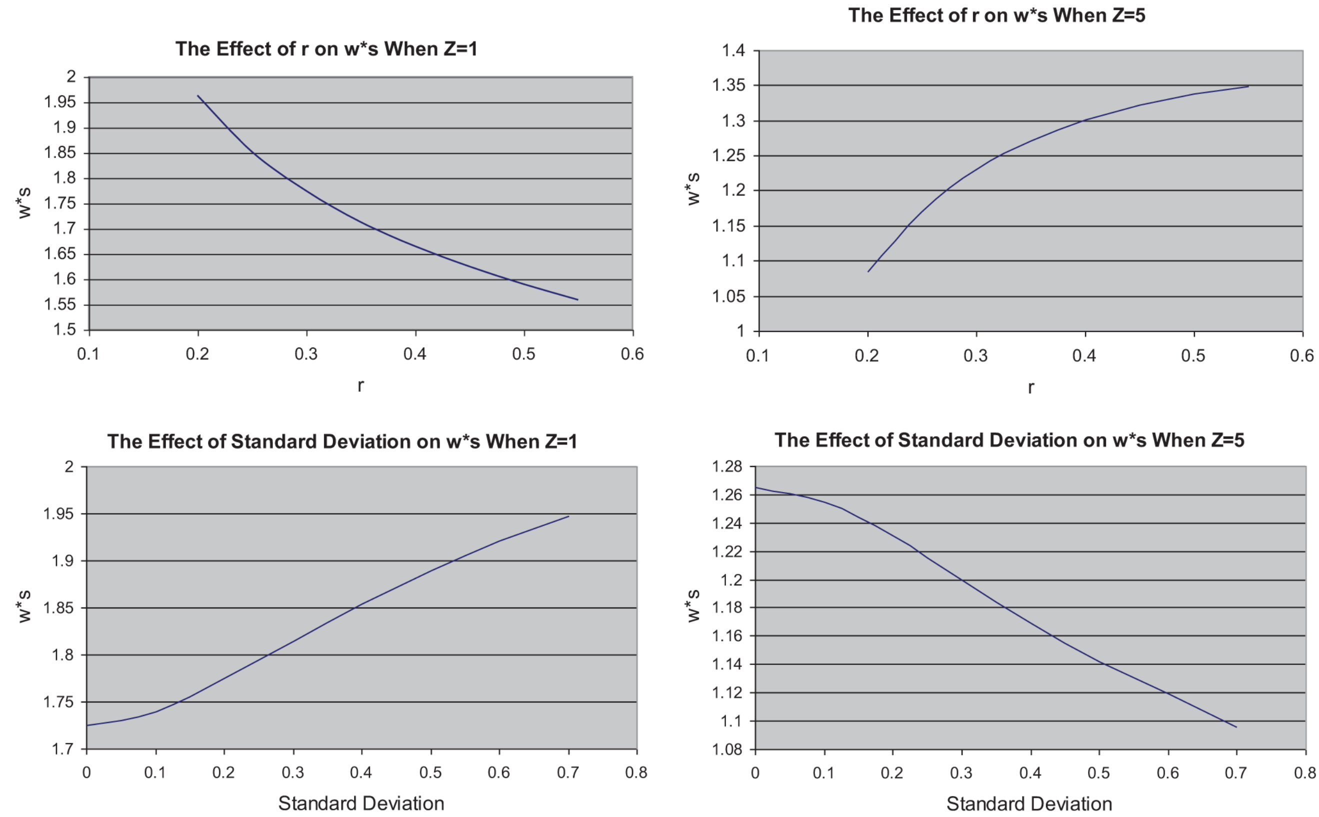


Fig. 3. Optimal adoption point w_s^* as a function of Z.

Based on our simulation results, Fig. 3 demonstrates the main results of comparative static analysis. It is easy to see that w_s^* decreases as Z increases in Fig. 3. As proved in Proposition 6, the effects of r and σ on w_s^* depend on the magnitude of Z.



(a) (b)

Fig. 4. (a) Optimal adoption point w_s^* as a function of r and σ when $Z = 1$. (b) Optimal adoption point w_s^* as a function of r and $\underline{\sigma}$ when $Z = 5$.

So we set Z at 1 and 5 in Fig. 4(a) and (b), respectively. They clearly demonstrate what we have proved in Proposition 6.

V. Discussions and Conclusion

Path dependencies matter when companies evaluate investment opportunities in emerging ITs. By linking a company's IT adoption decisions with its capabilities to gain from learning and experimentation, our paper highlights the important role played by preemptive learning in influencing a company's attitude toward uncertainties associated with a new technology. Most previous real options studies focusing on investment deferral under uncertainties suggest that increase in uncertainty gives a company more incentives to adopt a wait-and-see strategy. Our analysis demonstrates that, with the benefits of preemptive learning considered, higher uncertainty sometimes encourages earlier adoption of a new technology. This is because higher uncertainty not only increases payoff variation, but also heightens the expectations that new business opportunities enabled by technology advance may arrive earlier. When a company's gains from these new opportunities, as our model describes, depend on its preemptive learning of an emerging technology, learning benefits from expedited adoption could dominate risk reduction benefits from delayed adoption. This effect is especially noticeable when the company's absorptive capacity is sufficiently large so that it can gain significantly from preemptive learning.

While organizational theorists have long pointed out that the values of real options are dependent on organizational capabilities and decision heuristics [22], [23], formal real options models focusing on their relationships are very rare in the extant literature. By modeling learning, real options, and competency traps in the context of IT adoption, our study represents an early attempt to formally analyze their interactive dynamics. For example, our analysis supports the notion that companies are often slow to adapt because of competency traps created by their existing capabilities. Our paper further shows that existing capabilities may not necessarily lead to competency traps, and that only strong capabilities on an existing technology that the new technology substitutes lead to higher adoption thresholds (consequently delaying new technology adoption).

It is time for us to revisit the two cases discussed at the beginning of this paper. In the ERP case, our stochastic benchmark model provides an appropriate justification for most companies' wait-and-see strategies. Based on our stochastic benchmark model, there are at least two reasons why it took more than a decade for many firms to adopt ERP systems. First, most companies did not see significant benefits of preemptive adoption, so they waited for uncertainties to be resolved. Second, in 1980s and early 1990s, most firms viewed ERP systems as a substitute technology for their legacy systems. Over years they have developed strong capabilities in using and managing their legacy systems, which, as our benchmark model suggests, gives them less incentive to adopt ERP systems (i.e., competency traps). The situation changed in late 1990s when most firms found out that it was too costly to make their legacy systems Y2K compliant. So the Y2K problem inadvertently diminished the competency traps sustained by the legacy systems, and triggered widespread adoption of ERP systems in a relatively short period. While some industry experts questioned whether SUN should pay $1 billion for MySQL, an open source technology that currently generates very limited revenue, many others including SUN's top management believe that this move will position SUN as a major player in the future business related to the open source LAMP stack, thereby enabling it to capture potential opportunities in the Web 2.0, Enterprise 2.0, and software as a service (SaaS) spaces [40]. In this case, the insights from our general model can be used to justify SUN's investment decision. When SUN made the decision, it clearly expected that major business opportunities could arise as the open source LAMP stack becomes a key technology enabler in the next generations of Web and enterprise computing. As a major player in the Web and enterprise computing industry, SUN has the capacity to gain significantly through preemptive learning. In addition, MySQL complements many of SUN's existing technologies like JAVA, Solaris operating system (OS), and SUN's enterprise server hardware. All these factors, as implied in our model, will give SUN strong incentives to make very aggressive investment decisions. Of course, SUN's move is very risky. For instance, competing open-source database management systems may emerge in the future, or LAMP stack may not become as successful as SUN expected. However, as our analytical results suggest, more uncertainties should not defer SUN's investment as long as the strategic benefits of early investment are expected to be significant.

As most companies operate in some competitive industry, their IT adoption strategies are usually influenced by their competitors' strategies. Our study, based upon partial equilibrium analyses, is incapable of addressing issues related to competitive interactions among multiple parties. For example, both interfirm coordination and social learning have been proposed as important drivers behind companies' IT adoption strategies [26], [27]. In addition, with many companies trying to adapt to the same new technology, a company's incentives of exploring the new technology may be reduced because it is often better to exploit the "successful explorations of others" [24]. This type of incentive problems caused by the public goods nature of learning cannot be analyzed in a single firm learning model like ours. Extending our model to multiple decision-maker settings would presumably require some game theoretic real options approach, e.g., [17], [18], and [20]. Our model can also be extended to study how real options valuation is affected by managerial rent seeking and entrenchment, another type of incentive problems frequently influencing technology adoption decisions, e.g., [28]. As an early work that aims to incorporate insights from organizational theories into stochastic real options modeling, our study reinforces Gibbon's [14], [15] view that many promising research topics may emerge as the economics and noneconomics literature on organizational decision-making continue to converge.

ACKNOWLEDGMENT

The author would like to thank J. Conlon, J. Johnson, R. Kauffman, and K. Womer for their helpful suggestions and comments. This paper greatly benefits from the valuable input of the department editor, J. Sarkis, and three anonymous reviewers.

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