Journal of Economics and Finance ! Volume 18, Number 1 ! Spring 1994 ! Pages 101–123

Adoption, Diffusion, and Public R&D

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ABSTRACT

This paper studies the impact of public RD&D (Research, Development, and Demonstrations) on the market penetration of a new government-sponsored technology. First, the technology adoption behavior of a firm under uncertainty is reviewed. Secondly, the diffusion of the new technology in a competitive industry that benefits from learning-by-doing is analyzed. Numerical simulations are conducted to determine the effect that variations in government R&D policies have on the rate and level of market penetration. Productive R&D investments affect the *level* of diffusion and R&D demonstrations the *rate* of diffusion.

Introduction

This paper is a theoretical analysis of the adoption and diffusion of a new government-sponsored technology. The paper analyzes in particular the impact of government research, development, and demonstrations (RD&D) on the market penetration of a new government-sponsored (or publicly-funded) innovation. The purpose is to fill the following gaps in the literature on RD&D and productivity growth.

First, technology diffusion plays a vital role in linking R&D activities to productivity growth. Productivity growth will typically not occur, or be measurable in the data, unless the new technologies resulting from R&D activities penetrate the marketplace. Several empirical studies (see Griliches 1991) have focused on finding the effects of R&D on productivity growth, or on linking patenting activities to productivity growth, while ignoring the intermediary role of 'technology adoption' in translating the benefits of R&D to measured productivity growth. The limited market penetration of new technologies may explain why several advanced nations, including the U.S., have achieved enormous accumulations of R&D and human capital, yet have been experiencing a slowdown in productivity growth. The problem may not be the lack of R&D, or its quality, but the fact

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that potentially productive new technologies seem to "sit on the shelf." Greater attention is needed on examining the appropriate incentives that motivate economic agents to adopt new technologies.

Second, while the literature on R&D abstracts from technology adoption, the current literature on technology adoption behavior typically abstracts from R&D activities.[1] The existence of a new technology is given exogenously, and the focus of debate is on how market characteristics, industrial organization, and firm attitudes toward risk and uncertainty, determine technology adoption behavior. This paper introduces an R&D sector to show how R&D interacts with technology diffusion. At one level, increased R&D can improve the efficiency of a new innovation and make it more attractive to potential adopters. At another level, an improved market for new technology raises the return to R&D and thereby stimulates R&D investment.

Third, the current literature on technology adoption focuses on private sector innovations. This study focuses on a government-sponsored innovation and on government R&D activities. This focus helps to address issues relevant to the ongoing debate on "technology transfer," for which there are few, if any, theoretical economic analyses (see Brown et al. 1991). The argument is that government R&D laboratories have been largely unsuccessful at transferring knowledge to the private sector. Coupled with the perception that government R&D is less efficient than private, or that governments sponsor projects that are privately unproductive (see Cohen and Noll 1991), several have called for reducing government research (to allow scarce resources such as human capital to shift to private laboratories) or for limiting government's role to improving licensing and patent laws. However, one point often missed is that public R&D exists in many instances to sponsor technologies that generate social (rather than private) benefits, such as those which improve the nation's environment, health, and defense, among other things. While the purpose of this paper is not to explore what the government's optimal technology policy should be, it provides a positive analysis of how government RD&D can stimulate the transfer of the government-sponsored technology to the marketplace. The existing literature lacks a conceptual framework for investigating how government RD&D contributes to "technology transfer" (from the public sector to the private).

The analysis here builds upon the previous literature on technology adoption to study the relationship between government RD&D and the diffusion of a government-sponsored new technology in an industry-wide setting. A study of the determinants of technology adoption must deal with at least two stylized facts.[2] First, there is often a *delay* between the invention of a new technology and its market penetration. Second, new technologies are not adopted simultaneously but *sequentially* by adopters. To explain these facts, it is necessary to account for factors such as imperfect information, sunk costs, irreversibility, and market structure.

The paper is organized as follows: section II discusses adoption. It briefly reviews the framework, method of analysis, and some findings in the previous literature. Section III analyzes diffusion. While "adoption" refers to the action taken by a single firm, "diffusion" refers to the adoption of a technology by several firms. Thus, diffusion is studied at an industry-level. After a simple two-sector dynamic model is developed, some numerical simulation results are presented. The experiments illustrate how various policy shocks affect the level and rate of market penetration. Section IV contains concluding remarks. The analysis finds that public RD&D has the potential to stimulate the adoption of new government-sponsored technologies by improving the productivity of government innovations and by providing information to help potential adopters better assess the market and the new technologies.

Adoption: Literature Review

In the existing literature on technology adoption (see for example, Jensen 1982, Balcer and Lippman 1984, McCardle 1985, Bhattarcharya et al. 1986, and Reinganum 1989), the concepts of search theory and optimal stopping are used to characterize the adoption decision. Potential adopters search for new technologies (products or processes) or information about new technologies, and must decide when to stop searching and to make a decision on whether to adopt or reject a new technology.

The unit of analysis is typically the firm. The firm initially produces output using a conventional technology (denoted by CT) and has the option to switch to a new technology (NT). Investing in the new technology entails a fixed (sunk) cost which represents the up-front cost of transforming the enterprise.[3] The firm can either adopt the new technology right away or wait to learn more about it. If it chooses to wait, the firm can search for information about NT and the new market. Search can be costless or costly. The information acquired can be used to resolve two kinds of uncertainty: (1) technical uncertainty (regarding the innovation itself), and (2) market uncertainty (regarding rival behavior and demand). Information can be obtained from the firm's own research activities, from other firm's search activities, or from government information sources. Government R&D demonstration projects, for example, can help reduce technical uncertainty or lower the search costs of firms.

The decision to search under uncertainty is viewed as an optimal stopping problem, the solution to which determines both the *decision* itself (reject or adopt) conditional on information received and the *timing* of the decision. The firm is assumed to be profit-maximizing and forward-looking. The firm compares whether adoption or non-adoption yields the greater present discounted value of profits. Adoption is typically "triggered" by the following condition: $V_{NT} - I \geq V_{CT}$, where V_{NT} represents the present discounted value of profits associated with the new technology NT, I the fixed costs of adoption (or installation costs), and V_{CT} the present discounted value of profits associated with the conventional technology CT. However the firm is uncertain whether $V_{NT} - I$ exceeds V_{CT} and thus attaches a probability assessment that this condition is fulfilled - namely:

$$Pr_{\{} V_{NT} - I \geq V_{CT} \mid \Omega_{\}} = \rho$$

where Pr {. | .} denotes conditional probability, $0 \leq \rho \leq 1$ the probability value of this condition, and Ω the information set. By searching for and acquiring information about the new technology or about the market, the firm expands its information set Ω and revises its estimate, ρ.

The firm typically has the following *decision rules*:

(I)	Adopt	if $\rho \geq \rho_{HIGH}$
(II)	Reject	if $\rho \leq \rho_{LOW}$
(III)	Search	otherwise

where ρ_{HIGH} is a sufficiently high assessment and ρ_{LOW} a sufficiently low assessment. The probability estimate, ρ, is revised in "Bayesian" fashion - that is, as information is received the firm updates its prior beliefs of ρ to obtain its posterior beliefs of ρ.[4]

Using these decision rules as a basis for discussion, the literature analyzes a number of determinants of technology adoption behavior at the *firm level* - for instance the role of search costs, imperfect information, uncertainty, sunk costs, and irreversible investment. The multi-firm model in the next section builds upon the existing literature by examining how government RD&D interacts with these 'determinants' of technology adoption behavior to stimulate firms to adopt a (government-sponsored) new technology.

A few comments about these 'determinants' would be useful. In Jensen (1982) search activity is costless, whereas in McCardle (1985) search activity is costly. The latter study introduces the idea that there are diminishing returns to search. The effect of this feature is to force the two thresholds given by decision rules (I) and (II) to converge at some finite time, leading the firm eventually to make a decision on adoption or rejection. In other words, search activity cannot go on indefinitely as it can when there are non-diminishing costs to searching. In this generic class of search models, there is nothing to rule out type I or type II errors - that is, the rejection of a profitable innovation or the acceptance of an unprofitable innovation, respectively. Better quality information reduces the likelihood of these kinds of errors. Thus one potential role for public R&D demonstrations is to provide information about the true profitability of the innovation. Demonstration projects can therefore help reduce search costs.[5]

The effect on the adoption decision of the arrival of future new technologies is analyzed in Balcer-Lippman (1984). The firm has an additional option to defer adoption (and avoid the associated fixed costs) in order to acquire some future new technology. If the rate of discovery of the future new technology is relatively slow, so that the firm's technology lag exceeds a certain threshold, the firm will adopt the existing best technology. One of the implications of this analysis is that the mere "announcement" of a forthcoming (but not certain) new technology can postpone the adoption decision of a firm. In this sense, R&D plays an important role since current research activities could signal the arrival of future new or improved technologies.

The literature also typically assumes "irreversibility" of the adoption decision. This is a strong assumption. If a firm realizes after adopting NT that its estimates were incorrect, the firm may want to consider the option of abandoning it (assuming that it is technically feasible to do so). However, just as there is a fixed cost to adopting, there is also likely to be a fixed cost to abandoning. Once the firm abandons, it has to incur a fixed cost again should it want to re-adopt the new technology if future external (market) or internal (managerial and technical) conditions improve favorably. Thus, under uncertainty, a firm may hesitate to abandon NT even if it seems profitable do so. Just as a firm waits before adopting a profitable innovation, it is likely to wait before abandoning an unprofitable one - hence the abandonment and adoption decisions can be rather symmetrical.

Thus far the focus has been on a single firm. The diffusion model in the next section allows for multiple firm interactions. Every firm that adopts a new technology has an effect on the profitability of existing and future adoptions of this technology. The diffusion model shares some of the features that determine the technology adoption behavior of the firm, as reviewed in this section. For instance, imperfect information serves to delay adoption until a firm acquires sufficiently good information to make a (profitable) decision. Furthermore, an R&D sector whose activities can improve the productivity of the new technology serves also to affect the timing and outcome of a firm's adoption decision.

Diffusion: A Small-Scale Simulation Model

In this section the optimal stopping condition (namely $V_{NT} - I \geq V_{CT}$) is used to derive an industry level diffusion, or market penetration, curve. The principle is essentially to aggregate across the stopping criteria of *individual* firms. This traces the time path of the adoption of the new technology by individual firms.

The model consists of two sectors: an Adoption sector and an R&D sector. Each of these sectors will be developed in turn. The Adoption sector represents the market served competitively by profit-maximizing firms that have adopted the new technology. The R&D sector refers to that sector which invests in R&D in order to create and improve the performance of a new technology funded by the public sector. The actual innovation can be the result of contract government R&D, government laboratory work, or a joint public-private venture. The two sectors are interdependent. In the adoption sector, the returns to adoption depend not only on market demand conditions but also on the technical efficiency gains from switching to the new technology, which in turn depend on the R&D invested in the new technology. In the R&D sector, the returns to R&D investment depend on the discounted benefits of increasing the stock of public R&D capital, which in turn depend upon the profitability of adoption.

After the two sectors are developed, the model is parameterized and numerical simulations are used to investigate the effects of exogenous policy shocks and to investigate the sensitivity of the results to alterations in parameter values. The focus throughout is on the crossing of the "upper" threshold - that is, on the decision to adopt (after some or no search). The decision to reject, upon reaching the "lower" threshold, can be modeled analogously, but is not considered here. Other simplifications are needed in order to keep the analysis tractable and focused on the main factors driving diffusion, without at the same time causing the results to be too sensitive to those simplifications. These additional simplifications will be mentioned at the appropriate juncture. Table 1 contains a list of the notation used and the key equations.

TABLE 1

NOTATION AND EQUATIONS

A. List of Key Notation

V_{NT}	present value of adopting the new technology (NT)
V_{CT}	present value of using the conventional technology (CT)
I	fixed costs of adoption
p	market price
c	constant marginal cost
p_i	instantaneous profits associated with technology i = NT, CT
A_i	index of technical efficiency, i = NT, CT
k	composite supply of factor inputs
r	real interest rate
δ	depreciation rate of R&D capital
n	cumulative level (measure) of adoptions
z	stock of public R&D capital
R	gross investment in public R&D capital
q	shadow price of a unit of additional R&D capital
θ	firm's assessment of A, the new technology's productivity
λ	speed of learning
γ	output elasticity of public R&D capital
α	coefficient of elasticity of I with respect to n
β	coefficient of elasticity of p with respect to n
R_1	sensitivity of R&D to q

B. System of Equations in the Simulation Model

(I) Adoption Sector:

$$(7)\quad \frac{dn}{dt} = \frac{\theta p(n) - rI(n)}{-I'(n)}$$

$$(12)\quad d\theta/dt = \lambda[A(z) - \theta]$$

(II) R&D Sector:

$$(10)\quad dq/dt = (r + \delta)q - pA'(z)$$

$$(9a)\quad dz/dt = R_0 + R_1 q - \delta z$$

Adoption Sector

Again consider two technologies, NT and CT, the new (government-sponsored) technology and the conventional technology, respectively. Assume that CT is used to serve a perfectly competitive market. Assume that NT is used to serve a market that allows free entry and exit. Because the NT serves a market that is new, the size of this new market will vary as firms enter (or exit). Firms enter this new market by adopting the NT.

Let the instantaneous operating profits associated with the new technology, NT, be

$$\pi_{NT} = (p - c)y \tag{1}$$

where y = A_{NT} k is the production function. y denotes output, k a composite factor input, p the market price (or the demand curve for output produced using NT), and c the constant marginal cost. In effect, the benefits of adopting NT are that it raises the technical efficiency of production. The marginal productivity of the composite input k can be enhanced. Let

$$A_{NT} = A(z) > 0 \tag{2}$$

measure the technology index of the production process, where z is the stock of public R&D capital embodied in the new technology. The technological performance of the new technology is assumed to be positively related to the amount of public R&D capital embodied. Given A' = dA/dz > 0, A'' < 0 implies diminishing returns to public R&D capital, A'' = 0 constant returns, and A'' > 0 increasing returns.

Let the instantaneous operating profits associated with the conventional technology be $\pi_{CT} = (p_0 - c_0)y$, where y = A_{CT} k. A_{CT} denotes the conventional technology's index of technical efficiency, p_0 the market price for the output produced using CT, and c_0 the constant marginal cost under the conventional technology process. Because of the assumption of perfect competition in the market served by CT, economic profits are zero - that is, $\pi_{CT} = 0$.

To simplify, the analysis abstracts from any interdependence between the demand for CT-produced output and the demand for NT-produced output. It also is assumed that the supply of other factors k is inelastic so that k can be normalized to one. Define the present discounted value of profits from adopting NT as:

$$V_{NT} = \int_t^{\infty} e^{-r(s-t)} \pi_{NT}(s)\, ds \tag{3}$$

where r is the constant real interest rate.

The adoption of NT requires incurring a fixed cost, I, at the time of adoption. This fixed cost represents the initial costs of installing the new technology and adapting it to the firm's production environment. A firm adopts at time t if: $V_{NT} - I \geq V_{CT} = 0$.

The pool of potential adopters is assumed to be homogeneous. However, because of the following assumptions, firms will not adopt simultaneously at once, but rather sequentially over time. First, following Jovanovic-Lach (1989), Quirmbach (1986) and Reinganum (1981), let the market demand be:

$$p = p(n), \qquad p' < 0 \tag{4}$$

where n is the cumulative measure of adoptions. As more firms adopt, the supply of output increases, and the market price decreases. The gains to a firm from adoption are less than what they would be if the firm adopts sooner, when there are fewer adopters (or entrants in the new market).

A second assumption, however, is that:

$$I = I(n), \qquad I' < 0 \tag{5}$$

that is, the fixed costs of adoption decline as the level of previous adoptions increases. The idea behind this assumption is that there exists "learning by doing." A new firm can observe the experience of previous adopters and thereby learn how to install and adapt to the new technology in a more cost effective way. As a consequence, one firm's fixed costs of adopting NT are lower than another firm's if it is the later adopter.

Each firm balances the merits of early adoption (to obtain a higher market price for its output) against the higher fixed costs of early adoption. Because of the initial imperfect information about NT (less learning early on), the early adopters and users of the new technology will incur higher fixed costs of installing NT and transforming their enterprises than will later adopters and users (who get to learn from previous adopters). In a sense, the early adopters are generating "spillover" (information) benefits to later adopters but are not compensated for these benefits by the later adopters.

Because there is free entry/exit in the market served by NT and zero economic profits in the market served by CT, the condition $V_{NT} = I$ will hold exactly in equilibrium (as each adopter takes the time path of future prices as given, earns zero discounted profits, and is indifferent as to the date of adoption). In equilibrium there will be a solution for n over time such that all firms are satisfied with the timing of their adoption decisions.

Note that there are other ways to generate diffusion. Other studies consider a heterogeneous pool of adopters - for example Ireland-Stoneman (1986) differentiate adopters by firm size, Jensen (1982) by prior initial beliefs about NT, and Bhattacharya et al. (1986) by the information sets available to firms. Heterogeneous modelling is useful but generates diffusion automatically by the assumption of heterogeneity. Firms adopt at different times because they are different. Some firms, based on their given characteristics, have a higher propensity to adopt than others have. Diffusion is therefore determined exogenously. In this model, in contrast, diffusion is derived endogenously. All firms are assumed to be identical and to follow the same optimal stopping rule ($V_{NT} = I$), while the structure of demand and the presence of learning-by-doing (given by Equations (4) and (5)) determine the timing of adoption, adoption rate, and level of adoptions, endogenously in an intertemporal, profit-maximizing equilibrium.

After incorporating all of the above assumptions and simplifications, the stopping condition becomes (using Equations (1), (2) and k = 1):

$$V_{NT} = \int_t^\infty e^{-r(s-t)} \pi_{NT}(n(s))\, ds = I(n(t)) \tag{6}$$

where $\pi_{NT}(n(s)) = p(n(s))\, A(z)$.

Note that the assumption of zero marginal cost is incorporated in (6) - that is, c = 0. As Jovanovic-Lach (1989) discuss, this amounts to precluding firms from "exiting," or reversing the adoption decision. "Exits" occur if revenues (pA) fall below variable costs.

Here, if variable costs are low (or zero), firms never abandon NT. The analysis is more complicated if $c > 0$ and exits are allowed. In this case firms may also need to incur fixed costs of exiting or abandoning NT. As discussed in Section II, under imperfect information and uncertainty firms may not exit even if operating profits are negative; just as a firm hesitates to adopt a profitable NT and enter a market, it will hesitate to abandon it and exit from the market if there are significant sunk costs of entering and exiting in a world of imperfect information and uncertainty. Thus, extending the model to allow for a reversal of the adoption decision is feasible but more complex. The interest here is to focus primarily on the factors that lead to first-time adoption of NT.

The diffusion curve is obtained by time-differentiating Equation (6), the intuition being that by observing changes in the optimal stopping rule over time one can trace the path of technology adoption:

$$\frac{dn}{dt} = \frac{\pi(n(t) - rI(n(t))}{-I'(n(t))}, \; n \in [0, \infty) \tag{7}$$

where dn/dt is the time-derivative of n.

Some properties of this equation should be noted. First, there are no discrete jumps in n. If for instance a mass of firms, m, adopted at time 0, each of these firms would incur a fixed cost of I(0). But by adopting an instant later, any one of these firms could take advantage of lower fixed costs of I(m). Thus if every firm but one waits at each instant, the diffusion process will be smooth (continuous) over time.

Secondly, an issue that has been raised in the literature is whether the time path of n, the cumulative diffusion of the new technology, is S-shaped - that is, convex initially $d^2n/dt^2 > 0$ and concave thereafter $d^2n/dt^2 < 0$. This issue has been of importance because it indicates whether adoptions of a new technology eventually reach a peak and settle down to a steady-state, which would not be the case if the path is forever convex. Intuition suggests that diffusion should reach a steady-state since new technologies continue to emerge over time that can replace or modify existing technologies. Diffusion should also reach a peak if the demand for NT is finite. Time-differentiating (7) shows that $d^2n/dt^2 <$ ($>$) 0 according to whether $[(\pi' - rI')(-I') - I''] > (<) 0$, indicating that the time path of n will be convex as long as I'' is sufficiently positive. $I'' > 0$ implies diminishing returns to learning-by-doing: that is, the fixed costs, I, decrease as n increases, but they decrease at a decreasing rate. Awareness of diminishing returns encourages firms to take advantage of the early gains to adoption, since the largest decreases in fixed costs occur earlier on. If I'' is negative, the diffusion curve will be concave throughout.

Another property is that as long as p' and I' are bounded, n reaches a steady-state limit (as time goes to infinity), thus ruling out convexity of the diffusion curve everywhere. The long run value of n, or the total cumulative measure of adoptions, is determined by setting the numerator of Equation (7) to zero (i.e. $\pi_{NT}(n^*) = rI(n^*)$, where beyond n*, potential adopters face negative discounted profits).

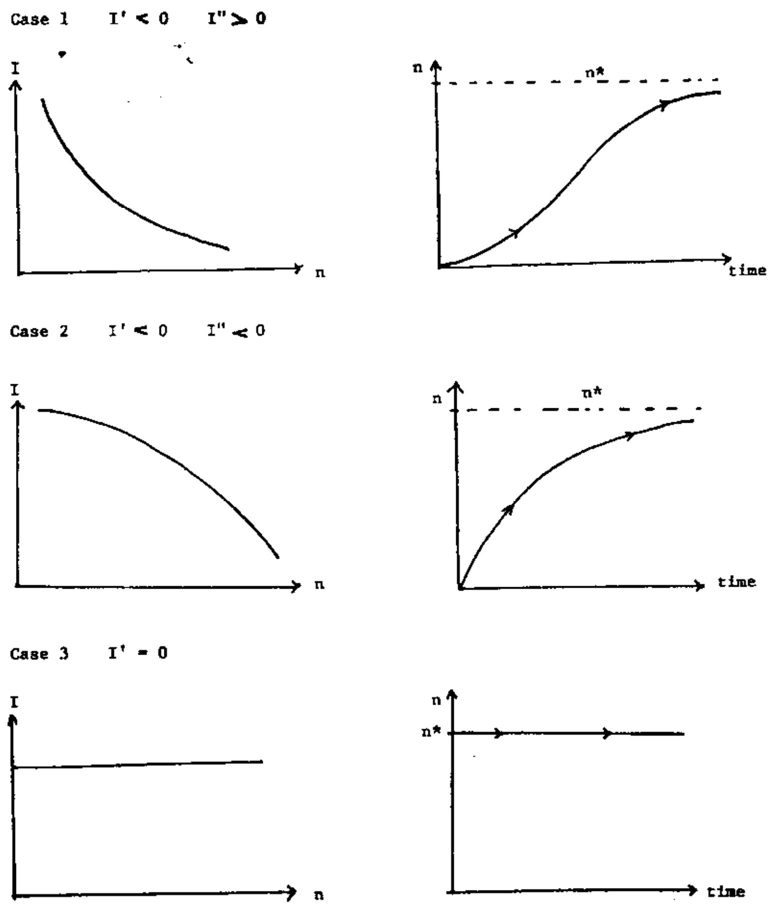
Finally if I is independent of n, then from (7), dn/dt tends to infinity, meaning that adoption takes place by all the potential adopters simultaneously at time 0 (provided the innovation is profitable, in the sense of $V_{NT} = I$). Figure 1 summarizes the properties of Equation (7).

R&D Sector

The R&D sector performs R&D to produce a technology sponsored by the public sector. This sector can refer to a government-industry R&D consortium, a government research lab, or a private lab under government contract. The dissemination of information about the new technology is (as is usually the case) undertaken by the government. Assume for simplicity that the new technology, NT, is the only innovation produced in this sector. The innovation's productivity level varies with the amount of government R&D invested in it. Assume that at time 0 there have not yet been any adoptions - i.e. n(0) = 0. What triggers the pool of potential adopters to begin adopting is an increase in government R&D investment in the new technology above a critical level - namely that level which makes the innovation profitable in the marketplace ($V_{NT} \geq I$). The government also provides "demonstrations" so that potential adopters can observe better the capability of the new technology.

R&D investment decisions are made *exogenously* through discretionary changes in R&D plans and *endogenously* through feedbacks received by the R&D sector from events in the Adoption sector. Endogenous R&D is driven by the returns to R&D investment. For example, increases in the expected present discounted value of the marginal products of the new technology will stimulate further R&D investments in NT. Later it will be seen that R&D investment declines endogenously as the diffusion process reaches its limit, since the returns to investment in NT decline when diffusion slows down.

Fig. 1. Diffusion and the role of diminishing returns to learning-by-doing.



The government's main goal is to see the diffusion of the publicly-sponsored new technology. To carry out this goal, the government is assumed to be guided by some underlying efficiency criterion. The criterion is that publicly-sponsored R&D maximize the discounted welfare of private firms. Thus the R&D sector chooses R&D investment to maximize the discounted stream of net profits owing to the new technology:

$$\max_{R} V = \int_t^{\infty} [e^{-r(s-t)} \pi_{NT}(s) - q(s) R(s)] \, ds \quad \textbf{(8)}$$

subject to:

$$dz/dt = R - \delta z \quad \textbf{(9a)}$$

$$\pi_{NT} = pA(z) \quad \textbf{(9b)}$$

$$A(z) = A_0 z^{\gamma} \quad \textbf{(9c)}$$

where R is gross public R&D investment, dz/dt net public R&D investment, z the stock of public R&D (or knowledge) capital, q the price of R&D investment, δ the rate of obsolescence of the stock of R&D capital, γ the output elasticity of public R&D capital, and A_0 an exogenous parameter reflecting omitted variables in A(z). Equation (8) is therefore the R&D sector's objective functional and Equation (9a) the net (of depreciation) R&D accumulation constraint.[6] Equation (9c) is the technology production function, where $\gamma < 1$ implies diminishing returns.

The Euler (necessary) condition for maximizing (8) subject to (9a-c) is:

$$\frac{dq}{dt} = (r + \delta) q(t) - \pi'_{NT}(t) \quad \textbf{(10)}$$

where π_{NT}' is the marginal *value* product of z. Solving (10) forward provides an economic interpretation of q:

$$q(t) = \int_t^{\infty} e^{-(r+\delta)(s-t)} \pi'_{NT}(s) \, ds \quad \textbf{(10a)}$$

namely, q is the present discounted value of the stream of future marginal value products of z, where the discount rate is the sum of the real interest rate plus the rate of obsolescence. Hence q can be interpreted as the "shadow" price of a unit of additional public R&D capital - that is, the discounted benefits associated with augmenting the stock of z by a unit. Note that q, in (8), is also the cost of R&D investment, which equals the returns to R&D investment, given by (10), under conditions of optimization by the R&D sector.[7]

The higher the q, the more attractive it is for the R&D sector to invest in public R&D capital. Hence it is postulated that the endogenous response of R&D investment is:

$$R = R(q), \qquad R' > 0 \quad \textbf{(11)}$$

A similar specification in which the marginal benefits of R&D drive R&D investments is developed in Stoneman (1987) using a different model. Equation (11) can be interpreted as the government's feedback rule, or investment function.

As R increases, the stock of public R&D capital, z, increases, so that the new technology, NT, embodies a greater amount of z through A(z) and becomes more productive. Of course, increased z could generate other new technologies - but for simplicity the attention is restricted to one particular (existing) innovation, whose productivity can be improved over time with increased R&D investments.

In summary the R&D sector can be modelled by Equations (10) and (9a) above. While the R&D sector determines (q, z), this sector is very much linked to the market penetration of the new technology. That is, there are "feedbacks" between the R&D and Adoption sectors. For instance, increases in z affect the diffusion of the new technology. Immediate improvements in the new technology from a higher z stimulate adoption, while expected future improvements arising from future increases in z delay adoption. The diffusion process in turn influences investments in z in the following way. As n increases, profits per firm decline. This causes q to fall, thereby lowering the returns to R&D. Hence R&D investment would endogenously decline and cause the accumulation of government R&D capital, z, to slow down. Then as z is affected, diffusion activity would be affected as each new vintage of the government's new technology incorporates smaller increments of z. However, it is rather cumbersome to take all of these feedback effects into account analytically. For this reason, numeral simulations are used to study the full general equilibrium dynamics.

Simulations

An additional dynamic equation needed in the simulation model is the information resolution process discussed in section II and the Appendix. In a Bayesian learning framework, adopters seek information in order to learn about the new technology. This search activity serves to delay the adoption decision - if not avert it altogether. The better the information received, the more likely will the firm adopt NT. To capture the friction caused by imperfect information and learning, assume that the true productivity of NT, given by A(z), is gradually discovered by the potential adopters. Thus let θ be the firms' estimate of A, and the revision of θ be given by:

$$\frac{d\theta}{dt} = \lambda[A(z(t)) - \theta(t)] \qquad \textbf{(12)}$$

where λ is the speed of adjustment. If λ = 0, no learning takes place and A(.) = θ only by coincidence; if λ is infinite, instantaneous learning takes place, and A(.) = θ always. In the model, it is assumed that government R&D demonstrations and information dissemination services affect the rate of learning, λ. The Appendix motivates the dynamic adjustment mechanism given by (12) by showing how (12) can be the outcome of a Bayesian learning process.

It is necessary to specify functional forms for R(q), p(n), and I(n), and values for A_0, γ, δ, λ, r, and for the parameters associated with the p, I, and R functions. The following functional forms have been chosen:

$$R = R_0 + R_1 q$$
$$I(n) = I_0 e^{-\alpha n}$$
$$p(n) = P_0 e^{-\beta n}$$

The R&D equation is assumed to be linear, where R_0 is the exogenous component and R_1q the endogenous component. The functional forms for p and I yield elasticities varying with n.

The *simulation model* can be summarized by Equations (7), (9a), (10), (12) reproduced in part B of Table 1. There, $A'(z) = \gamma A(z)/z$ is the marginal product of z, where $A(z) = A_0 z^{\gamma}$. In the equations, the time indexes are suppressed as these are implicit. In Equation (7), θ replaces A to indicate that adopting firms act on the basis of their *estimate* of A. Also, the equation $R = R_0 + R_1q$ is substituted into Equation (9a).

The model presented thus far is a continuous-time deterministic model. A stochastic version is a natural extension to develop whereby Equation (12), the learning equation, can either (1) be affected by shocks following a geometric Brownian process, or (2) be specified as part of a richer Bayesian learning environment (in which case the probability distributions of θ (the 'beliefs') and the signals (information received) must be specified). Both approaches are more complex (in a multi-firm setting), but the essential economic insights are contained in the simpler deterministic setting. The system of four Equations (7), (12), (10), and (9a) is *linearized* about an initial steady state (where n = 0) and solved using a dynamic simulation package, PSREM.[8] The system consists of four state variables (n, θ, q, and z) and one control variable, R_0.

Note that because p(n) and I(n) are *linearized*, the values of α, β need to be restricted. Unless $n < \min[1/\alpha, 1/\beta]$, either p or I, or both, will eventually be negative.

TABLE 2

SIMULATIONS - BENCHMARK SCENARIO AND POLICY CHANGES

Initial Parameters and Values:

r = 5%,	P_0 = 100,	I_0 = 1600,	δ = 10%,	A_0 = 0.2,
γ = 0.333,	λ = 0.1,	α = 0.00833,	β = 0.01	

	Initial Steady-State	Final Steady-State Policy A	Final Steady-State Policy B
R	6.4	7.04	7.68
n	0	18.78	37.55
A(z)	0.8	0.83	0.85
z	64	70	75.92
I	1600	1350	1100
p	100	81.2	62.4
Time to Reach Steady-State	--	440.4	440.4

Policy A: A Permanent, Unanticipated Increase in Gross R&D Investment (R) of 10% at time 0
Policy B: A Permanent, Unanticipated Increase in Gross R&D Investment (R) of 20% at time 0

The remainder of this section discusses both the simulation results and the results of tests of sensitivity against alternative parameterizations of the benchmark simulation model. The initial parameter values and initial steady-state values of the variables are given in Table 2.[9]

The initial steady-state is perturbed by increasing the exogenous component of R&D spending, R_0, by 10% (i.e. from its existing steady-state level of 6.274). The final steady-state results of this policy change are shown in the second column of Table 2. Figure 2 shows the transitional dynamics.

Note that n is initially convex and begins to turn concave around period 80. The level of adoptions in the long run is 18.78 units. By period 80, 8.6376 units of adoption occur. That is, 46% of the total adoptions take place in the first 18.15% of the time it takes for the full diffusion path to come to a halt. Not only are the levels of adoption of interest but also the rates of market penetration - for instance, the length of time it takes for various percentages of total technology adoptions to occur. For 50% of total adoptions to occur (i.e. half of 18.78), it takes roughly 23% of the time it takes to complete the entire diffusion process (which is 440.4 periods). For reference, the time at which 50% of the market penetration occurs is the *median* passage time. The R&D sector (represented by variables such as z, A, and q) approaches its *neighborhood* of steady-state equilibrium much sooner than n approaches its *neighborhood* of final steady-state equilibrium. For most of the duration, z and A have a slight descent over time reflecting the fact as n increases, R&D returns fall so that R&D investment endogenously decreases. Note that in steady-state, $A = \theta$ since by then firms have discovered the true value of A.[10] During the transition, θ (the firms' estimate of A) catches up to the true value of A (the productivity potential of the new technology). The catch-up occurs roughly around period 80.

Next, the sensitivity of the results to alternative values of λ, the speed of learning, is investigated. The higher the value for λ, the quicker the firms' estimate of A(z) converges to the true value. Changes in the value of λ have no effects on the long run steady-state values of n, θ, A, z, and q. They affect the transitional dynamics. In particular, they affect the median passage time. Figure 3 illustrates two cases: $\lambda = 0.01$ and $\lambda = 1$. In both cases the long run level of adoptions continues to be 18.78. However, when $\lambda = 0.01$, the time for all 18.78 firms to adopt NT is greater (460.9 periods) than the time it takes when $\lambda = 0.1$ (which is 440.4 periods, as reported in Table 2). Market penetration is therefore slower under $\lambda = 0.01$. The median passage time, for example, is period 170 (or at the first 37% of the diffusion time path), which is absolutely and relatively greater than the median passage time under the benchmark case of $\lambda = 0.1$. In contrast, $\lambda = 1$ leads θ to converge rapidly to A. The catch-up occurs around period 40. The median passage time is period 70, or at the first 16.5% of the entire diffusion path. The bottom panels of Figure 3 show the relative speeds at which the gap between θ and A narrows for alternative values of λ. Variations in λ can proxy for the effect of government R&D demonstration projects and information services. The quality of information dissemination to the private sector is reflected in the value of λ.

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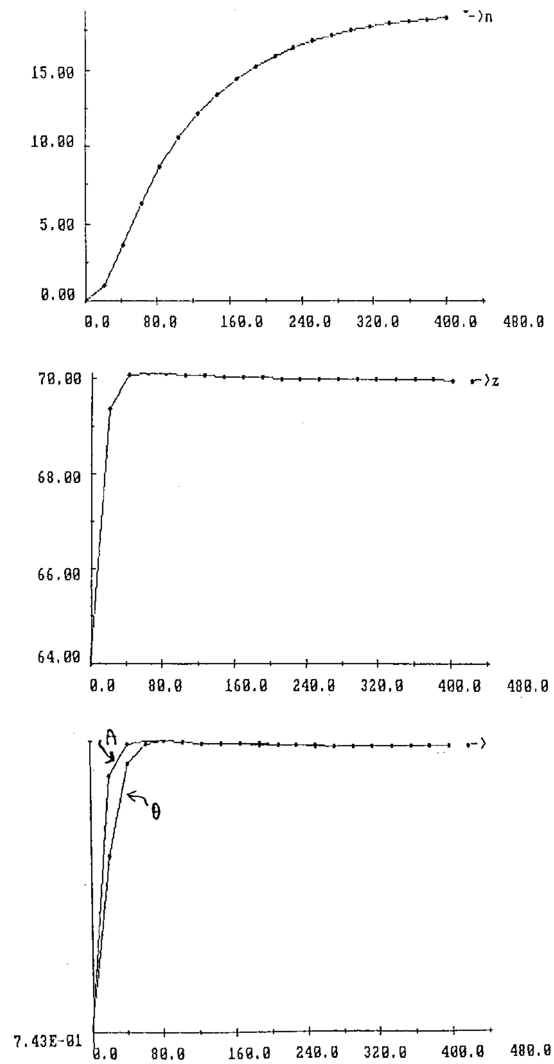


Fig. 2. Benchmark scenario. - Gross R&D Investment. Increase of 10% at Time 0.

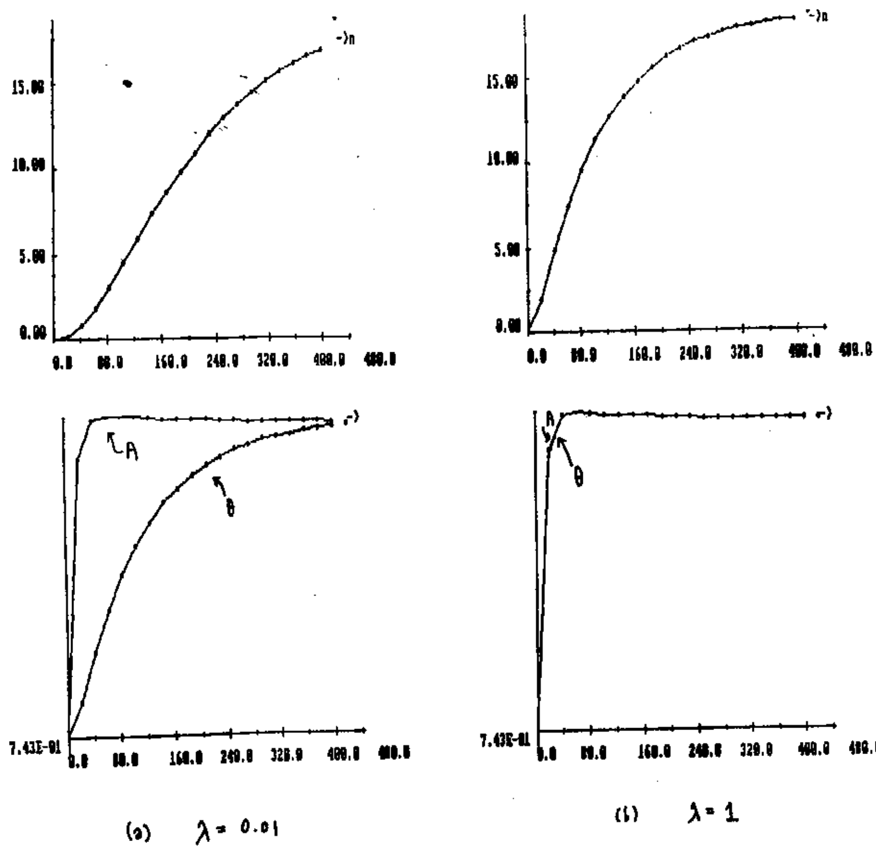


Fig. 3. Sensitivity to changes in λ (Speed of Learning).

Next the sensitivity of the results to alternative values of γ, the output elasticity of R&D capital z, is examined. Assume $\lambda = 0.1$ again. Recall that $\gamma < 1$ implies diminishing returns to R&D capital. This output elasticity indicates that a 1% increase in public R&D capital improves the performance of the new technology by γ%. If there are very large increasing returns (that is, $\gamma >> 1$) there is no guarantee the system will converge to steady-state: the system becomes explosive. For small increasing returns, however, the system will be (saddlepath) stable. Hence $\gamma = 1.1$ is chosen. In this case the long run values of q, n, A, θ, and z are affected. Figure 4 summarizes some of the results.

For the same 10% increase in exogenous R&D, the total level of firms adopting is more than double ($n = 40.55$) the level adopting when $\gamma = 0.333$, the benchmark case. The time to reach steady-state is 420 periods (sooner than the benchmark case) and the final values for the other variables are $z = 67.9$ and $A = \theta = 1.03$. The path to equilibrium for q, z, A, and θ is non-monotonic. The reason is that the presence of increasing returns makes the marginal value product of z rise with increases in z (not decline as in the case of diminishing returns), thus making q and z vary positively along the adjustment path. It also makes the return to R&D, given by q, initially very high, causing R&D investment to increase very rapid early on. For long run equilibrium to be reached, as n increases, q must fall (so that diffusion can slow down). But q can only decline along the adjustment path if z declines. Thus to ensure a long run dynamic adjustment path in which z declines, z grows initially above its long run steady-state level. The median passage time is sooner than that under diminishing returns, and occurs at the first 18% of the diffusion path (compared to 23% in the benchmark case). Thus increasing returns has a powerful effect on the *level* and *rate* of market penetration.

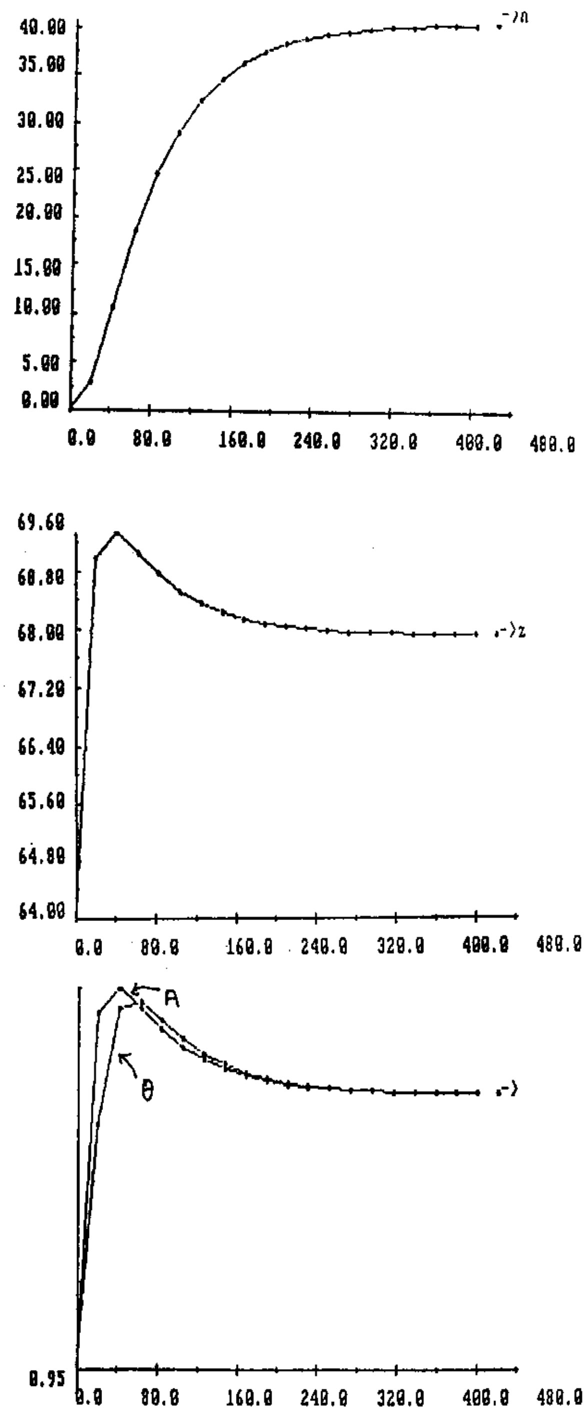
The next experiment to investigate is the impact of a rise in exogenous (gross) R&D spending by 20% (to compare it to the benchmark rise of 10%) - assuming $\gamma = 0.333$ again. This policy change has only a level effect. There is no change in the rate of diffusion. Instead the diffusion curve shown in Figure 2 shifts upward. The third column of Table 2 (under Policy B) summarizes the impacts.

Finally, experimenting with different parameter values for R_1, α, β, leads to no qualitative differences in the results. The absolute magnitudes differ by a scale. For instance a change in R_1 simply scales the value of q (provided R_1 is positive). Changes in α, β affect the speed at which p(n) and I(n) decline with n. The wider the gap between α and β, the quicker the diffusion process and the smaller the magnitude of market penetration. This is the case since $\alpha < \beta$, and $1/\beta$ determines the maximum level of adoptions before p turns negative. If the gap between α and β widens, increases in n will cause the price decreases to be more significant than the decreases in the fixed costs of adoption. Hence, a balancing of these intertemporal tradeoffs will involve diffusion taking place earlier and ending sooner.

Fig. 4. Increasing returns to R&D case. - Gross R&D investment.

Increase of 10% at Time 0.

$\gamma = 1.1$.



Conclusion

This paper has built upon the existing literature on technology adoption to examine how public RD&D can influence the adoption and diffusion of a new technology sponsored by the government. In the existing literature, adoption at the firm level is triggered when the firm obtains enough information to make an accurate estimate of the new technology's profitability, given search constraints. Information received is used to update the firm's prior estimates of profitability (in Bayesian fashion). In this paper, government RD&D influences adoption by improving the productivity of the innovation and by providing information about the innovation (thereby helping to reduce a firm's search costs).

Technology diffusion at the industry level occurs among homogeneous firms when there exist learning-by-doing and a market demand curve that declines with the cumulative level of adoptions. Learning-by-doing allows the fixed costs of adoption to be lower for future adopters, making later adoption more attractive. The declining market demand curve makes earlier adoption more attractive. In equilibrium these intertemporal gains and losses are balanced for every firm, and sequential adoption arises. If firms are heterogeneous, the additional firm heterogeneities will serve to vary the levels and rates of diffusion on top of what can be derived from a homogeneous pool of potential adopters.

The numerical simulations indicate that it is important to know how productive public R&D is in improving the performance and cost-effectiveness of a government innovation, since the market penetration level and rates depend on this information. For example, a higher technology output elasticity of public R&D capital increases the "level" and "rate" of market penetration. Increases in R&D investments have "level" effects only, while government R&D demonstrations (and other information services) have "rate" effects only.

An extension to this paper would be to carry out an econometric test and application of the theoretical model. The method of 'durations' would be one possible way to estimate the effects that changes in public RD&D have on the probability and timing of technology adoption, and on the rate and level of market penetration. It would also be useful to estimate the relationship between technology diffusion and productivity growth. A second extension is to study the implications of allowing the markets served by the new technology and by the conventional technology to be interdependent. A third extension is to consider welfare issues. Future analyses should investigate what the optimal government policies are that generate a technology diffusion path that is socially welfare-maximizing.

NOTES

1. With the exception of Stoneman (1987) and Lee (1985). Their focus is on the tradeoff a private firm faces between adoption and R&D: investing more in R&D may generate a better future technology. This paper has a different view: it looks at how R&D outside the firm (such as public R&D) affects private sector adoption behavior.

2. See Mansfield (1968).

3. It is possible to model the adoption decision without sunk costs, but the presence of sunk costs helps to explain why firms wait before committing to a new technology. It is also reasonable to assume that switching between technologies involves a fixed cost.

4. A seminal reference on Bayesian learning and optimal stopping is DeGroot (1970).

5. However, as McCardle (1985) points out, lower search costs alone are insufficient to produce early decisions since lower search costs work to prolong search. Only more precise information leads to earlier decisions (whether it be to adopt or reject), for this makes a firm more confident about its estimates of the profitability of NT.

6. Sveikauskas (1989) argues in favor of adding a depreciation or obsolescence rate to the evolution of (net) R&D capital. The assumption that $\delta = 0$ amounts to assuming that very old knowledge is still productive today.

7. Thus this framework is similar to the q-theory of physical capital investment.

8. See Markink and van der Ploeg (1989) *Policy Simulation with Rational Expectations Models* (PSREM). The idea is to solve the simulation model as a system of four ordinary differential equations, except that since one of the variables is forward-looking (namely q) and the rest backward-looking, convergence to steady-state occurs if the system is "saddlepath" stable (that is, if one of the eigenvalues or roots of the system is positive (unstable) and the rest negative (stable)). The parameter values chosen ensure one positive "root" and three negative. The initial conditions are just the initial steady-state values assumed by the variables (see Table 2) when n = 0.

9. Since min [$1/\alpha$, $1/\beta$] = 100, the maximum number of adoptions (before p turns negative) is 100. This maximum n is the market maximum. It does not represent the 'pool' of potential adopters; the pool is essentially infinite.

10. Since the analysis is focusing on the crossing of the upper threshold of the optimal stopping criterion, the new technology is assumed to be productive enough that the true value of A warrants adoption. Nonetheless there is some friction between the firms' estimate of A, given by θ, and the true value of A because in the neighborhood of the 'upper threshold' some firms are still learning about A.

11. The presentation is based on DeGroot (1970) Chapters 9 and 10.

APPENDIX

This Appendix[11] shows how Equation (12) in the text can be interpreted as a Bayesian learning process. Let $d = V_{NT} - I - V_{CT}$ and assume d(t) is normally and independently distributed over time with mean μ and variance σ^2 - i.e. $d(t) \sim N(\mu, \sigma^2)$. Assume that σ^2 is known. The adoption decision for a risk-neutral profit-maximizing firm is to adopt if $\mu > 0$, wait or reject otherwise. The firm is uncertain about the true value of μ and search activity is assumed to be costless. Let the firm's prior estimate of μ at time t be distributed as normal $N(\nu(t), \omega^2(t))$. The firm gathers information about μ which the firm can use to update its estimates of ν and ω^2, and thereby construct an estimate of the true mean of d. Suppose information arrives at time t and the firm observes a value x(t) which is assumed to come from the same distribution as d(t); that is, x(t) ~

$N(\mu, \sigma^2)$. This information x(t) can be used to update the firm's *prior* estimate of ν in order to get a *posterior* estimate of ν. Thus realizations of x will help the firm determine what the mean of d is.

By Bayes' rule, the prior distribution $N(\nu(t), \omega^2(t))$ becomes a posterior normal distribution with the following parameters:

$$= \left(\frac{\nu(t)}{\omega^2(t)} + \frac{x(t)}{\sigma^2} \right) \left(\frac{1}{\omega^2(t)} + \frac{1}{\sigma^2} \right)^{-1}, \; \omega^2(t+1) = \left(\frac{1}{\omega^2(t)} \right. \tag{A1}$$

Solving the Bayesian updating equation recursively from time 0 to the present gives:

$$\left(\frac{\nu(0)}{\omega^2(0)} + \frac{t\bar{x})}{\sigma^2} \right) \left(\frac{1}{\omega^2(0)} + \frac{t}{\sigma^2} \right)^{-1}, \; \omega^2(t) = \left(\frac{1}{\omega^2(0)} + \right. \tag{A2}$$

where

$$t\bar{x} = \sum_{i=1}^{t} x(i)$$

is the cumulative amount of information gathered since time t = 1, and $\nu(0)$ and $\omega(0)$ are the prior estimates of μ at time t = 0. Note that in the long run, the posterior distribution $N(\nu(t),$ $\omega^2(t))$ converges to $N(\mu, \sigma^2)$. This can be verified from (A2) by setting t to infinity. Thus when $\nu(t) < \mu$, $\nu(t)$ increases; when $\nu(t) > \mu$, $\nu(t)$ decreases. This dynamic adjustment process is the idea behind Equation (12).

In Section III, firms are trying to estimate A, the productivity parameter of the new technology. Their estimate of A is given by θ. When $\theta(t) < A$, $\theta(t)$ increases at the rate λ, and when $\theta(t) > A$, $\theta(t)$ decreases at the rate λ.

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