Adoption Costs
and the Rate of Return to
Research and Development

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by James Bessen*

Abstract: It is sometimes assumed that technology is a purely non-rival good. But this can be true only if adoption costs are negligible. This paper estimates a portion of the cost of adopting new technology in a panel of manufacturing firms. Specifically, it measures those adoption costs associated with a firm's own R&D, the internal adjustment costs of R&D investment. Using a flexible functional form, adjustment costs are found to exceed R&D spending and to nearly equal gross spending on physical capital. Each dollar of R&D generates $1.67 of adoption costs at the margin. This has strong implications for innovation and investment dynamics. For example, estimated private returns to R&D are typically much higher than risk-adjusted interest rates. This has been used to argue for R&D subsidies. But when adoption costs are considered, this premium disappears.

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I. Introduction

Is innovation predominately an activity of scientists and engineers, or does it also substantially depend on the contributions of marketing, manufacturing, customer service and other personnel? Recent management literature on innovation stresses the importance of non-technical personnel to successful innovation (for example, see Clark and Fujimoto, 1991). The implementation of new technology frequently involves learning curves and the development of new skills. The costs associated with these and other non-R&D activities—and the risks if they are not well-managed—can doom the introduction of a new technology.

From an economic perspective, the activity of non-technical personnel in implementing an innovation incurs adoption costs. Anecdotal evidence suggests that such costs are sometimes quite large. Many people who have installed new computer systems are well aware of significant adoption costs. However, there have been few attempts to assess the overall magnitude of these costs.

Yet the magnitude of adoption costs bears crucially on much economic analysis of technology and R&D. For example, much endogenous growth theory, following Romer (1990), views technology ("designs") as a non-rival good. Yet if the implementation of a technology requires substantial investment in new skills, then technology as a whole (as opposed to just the design) cannot be viewed as a non-rival good. Jovanovic (1997) argues that adoption costs are large and should play a critical role in endogenous growth models.

Adoption costs are also critical to analysis of R&D policy. It is widely accepted as a "stylized fact" that the rates of return to R&D are much larger than either the risk-adjusted cost of money or the rate of return on physical investment. Nadiri (1993) reviews the literature and finds typical rates of return ranging from 20% to 40%. This has been used to argue in favor of R&D tax credits or other subsidies (for example, Coopers and Lybrand, 1998). One analysis, using a 30% rate of return to R&D, suggests that R&D spending is one-quarter to one half of the optimal level (Jones and Williams, 1998).

Yet few empirical studies of R&D consider adoption costs.[1] If each dollar of R&D requires, say, an additional dollar of non-R&D investment in order to implement the technology, then the true rate of return on the total investment in innovation is only *half* the measured rate of

[1] Significantly, some of the studies that do consider R&D adjustment costs (which may be thought of as a kind of adoption cost) find smaller returns to R&D. For example, Mohnen et al (1986), using a dynamic factor demand model, find the net rate of return on R&D in the U.S. to be 11%. See discussion below.

return. This is because adoption costs strongly complement R&D expenditures and strong complements must be considered jointly; one cannot estimate the rate of return on mortar without considering the cost of bricks. Thus the policy implications of the measured rates of return to R&D depend very much on the magnitude of associated adoption costs.

This paper measures a portion of technology adoption costs for a balanced panel of U.S. manufacturing firms. Specifically, it measures those adoption costs arising from firms' own R&D. I obtain econometric estimates of adoption costs that are consistently large across a variety of specifications, nearly two dollars for each dollar of R&D at the margin. This corroborates survey evidence which, using a more restricted definition of adoption costs, finds about one dollar of adoption cost associated with each marginal dollar of R&D. In effect, formal R&D expenditures represent less than half of total firm spending on new technology developed in-house!

These results explain a long-standing anomaly in the empirical R&D literature. As Nadiri reports (1993), estimates of the *private* rates of return to R&D are quite high, typically 20% to 30%. Although high social rates of return might be explained by problems of appropriability, high private returns suggest either that firms act irrationally or that some major factor has not been included in the calculation. Two such factors have been suggested (Nadiri, 1993, p. 35, Griliches, 1995, p. 82). First, new technology may be associated with higher risk, requiring a higher rate of return. I explore this possibility below and find that risk can only explain a small portion of the gap between rates of return on R&D and rates of return on physical investment.

Second, it has been suggested that there may be large adjustment costs to R&D investment. The evidence developed here supports this hypothesis. Technology adoption costs associated with firms' own R&D are, in fact, internal adjustment costs. Adjusting the calculation of the rate of return to R&D to include these costs, I find that the corrected rate of return on R&D roughly equals the rate of return on investment in physical capital. This suggests that firms may optimize their investment in innovation as they optimize any other investment, taking the total cost of investment into account.

Several studies have developed dynamic factor demand models that also estimate internal R&D adjustment costs including Nadiri and Bitros (1980), Mohnen et al (1986), Bernstein and Nadiri (1989), and Hall (1993). Dynamic factor demand models require some rather strong assumptions and all of these studies impose a quadratic form on R&D adjustment costs. This paper differs in that R&D adjustment costs are modeled with a flexible functional form so that various specifications can be tested. In particular, the quadratic specification is strongly rejected and is found to substantially understate the magnitude of adjustment costs.

If technology adoption costs are substantial, several implications can be drawn for technology policy and growth models. First, although it may be desirable to subsidize innovative activity, the case for this is not easily made based only on the measured returns to R&D. Even estimates of the social returns to R&D (typically measured as industry-level returns) will not be nearly so large when adoption costs are taken into account.

Second, adoption costs may significantly enhance the appropriability of technology. Empirical researchers have long known that imitation costs are often quite large relative to the original costs innovation (Mansfield, Schwartz and Wagner, 1981). Large adoption costs suggest an explanation.

Finally, technology adoption needs to take a prominent place in growth and development theory. It has long been known that different nations sometimes achieve radically different results with the same technology (see, for example, Clark, 1987). The economic, institutional and social factors that influence the effective implementation of technology become an important part of the calculus of growth.

The paper proceeds as follows. Section II presents a simple model of adoption costs and estimates various specifications. Sections III considers the effects of adoption costs and risk on the rate of return to R&D relative to the rate of return on physical capital. Section IV concludes.

II. Estimating Own Adoption Costs

A Model of Production with R&D Adoption Costs

The adoption costs associated with a firm's own R&D can be considered adjustment costs of R&D investment. These are *internal* costs of adjustment. For example, such costs are incurred when productive resources are diverted to install and debug a new technology, to learn new skills, etc. These do not include external costs such as hiring fees paid to personnel search agencies.

Following the literature on internal adjustment costs (see Lucas, 1967, Treadway, 1971, and Mortensen, 1973; see Lichtenberg, 1988, for an empirical implementation), adjustment costs reduce potential output, that is,

(1) $$Q = Q^* - c\,,$$

where Q is actual output, Q^* is potential output, and c is total adjustment costs.

To model this, assume that potential output follows a Cobb-Douglas knowledge production function (Griliches, 1979) with two quasi-fixed factors, physical capital, C, and R&D capital, K, and two variable factors, materials, M, and labor, L. For the jth firm at time t,

(2) $$Q^*_{jt} = A_t \cdot M_{jt}^{\beta_M} \cdot L_{jt}^{\beta_L} \cdot C_{jt}^{\beta_C} \cdot K_{jt}^{\beta_K} \cdot e^{\mu_j} \cdot e^{\varepsilon_{jt}}$$

where the A_t represent exogenous Hicks-neutral productivity change, the β_i are constant elasticities, not necessarily constrained to constant returns to scale, μ_j represents a firm fixed effect, and ε_{jt} is a stochastic disturbance.

Adjustment cost, c, can be considered a function of present and past investment flows of both physical investment, $I_{C\,jt}$, $I_{C\,j,t-1},\ldots$, and R&D investment, $I_{K\,jt}$, $I_{K\,j,t-1},\ldots$. It is common, especially in dynamic factor demand studies, to assign c a symmetric quadratic form and to assume that the effects of different investments are separable. These assumptions are not made here; instead, c is assigned a flexible functional form and different specifications are tested. Initially, I assign c a simple linear form; other specifications are explored below.

For the moment, let c be a linear function of $I_{C\,jt}$ and $I_{K\,j,t-1}$. R&D investment is lagged to reflect the time from when the research is performed to the time when the technology is implemented (lags will also be explored below). I assume that $c = 0$ when $I_{C\,jt} = I_{K\,j,t-1} = 0$, so that

$$c\left(I_{C\,jt},\, I_{K\,jt-1}\right) = \gamma_C \cdot I_{C\,jt} + \gamma_K \cdot I_{K\,j,t-1}.$$

Substituting this expression into (1) and re-arranging gives

$$\begin{aligned} Q_{jt} &= Q^*_{jt} - \gamma_C \cdot I_{C\,jt} - \gamma_K \cdot I_{K\,j,t-1} \\ &= Q^*_{jt} \cdot \left(1 - \gamma_C \cdot r^*_{C\,jt} - \gamma_K \cdot r^*_{K\,j,t-1}\right), \quad r^*_{C\,jt} \equiv \frac{I_{C\,jt}}{Q^*_{jt}}, \quad r^*_{K\,jt-1} \equiv \frac{I_{K\,j,t-1}}{Q^*_{jt}} \end{aligned}$$

where $r^*_{C\,jt}$ and $r^*_{K\,j,t-1}$ can be interpreted as measures of physical investment intensity and R&D intensity (relative to *potential* output) respectively. Assuming that $Q^* \gg c$, so that $\ln\left(1 - \frac{c}{Q^*}\right) \approx -\frac{c}{Q^*}$, taking logarithms, and substituting from (2) yields

$$\ln Q_{jt} \approx \ln A_t + \beta_M \ln M_{jt} + \beta_L \ln L_{jt} + \beta_C \ln C_{jt} + \beta_K \ln K_{jt} + \mu_j - \gamma_C \cdot r^*_{C\,jt} - \gamma_K \cdot r^*_{K\,j,t-1} + \varepsilon_{jt} \quad (3)$$

This is the equation I would like to estimate.

Econometric Issues

Several econometric issues arise in implementing this model. First, the investment intensities, $r^*_{C\,jt}$ and $r^*_{K\,j,t-1}$, are not observed because potential output is unobserved. Since I have assumed that adjustment costs are small relative to potential output, however, these investment intensities can be approximated by the corresponding measures taken relative to *actual* output,

$$r^*_{C\,jt} \approx r_{C\,jt} \equiv \frac{I_{C\,jt}}{Q_{jt}}, \qquad r^*_{K\,j,t-1} \approx r_{K\,j,t-1} \equiv \frac{I_{K\,j,t-1}}{Q_{jt}}.$$

These variables, however, are negatively correlated with the stochastic error, ε, since the error term is included in the denominator (division bias). To correct for this potential bias, I instrument the investment intensities, using lagged right hand side variables as instruments.

More generally, other right hand variables may suffer from simultaneity bias (Marschak and Andrews, 1944; see Griliches and Mairesse, 1995, for a recent review) because measured input factors may include some response to exogenous shocks captured in ε. These variables will then be correlated with the error term, resulting in biased estimates of the coefficients. To correct for this bias, all of the right hand variables are treated as endogenous. Under the assumption that adjustments occur over time, lagged values of all of the right hand variables are used as instruments. Exogeneity tests are performed to verify that the more recent lags are orthogonal to the current error term.

Firm effects, μ_j, are eliminated by taking year-to-year first differences of equation (3).[2] First differencing does, however, tend to exacerbate measurement error problems (Griliches and Hausman, 1986). Because I use a balanced panel, efficiency can be improved by using the Generalized Method of Moments (GMM) to jointly estimate equations for different years. Mairesse and Hall (1996) have used this approach to estimate a knowledge production function and their approach is adopted here. Following Arellano and Bond (1991) and Schmidt, Ahn and Wyhowski

[2] A panel fixed effects model cannot be used because panel means cannot be estimated without potential simultaneity bias (see Mairesse and Hall, 1996).

(1992), they jointly estimate as many instrumented first difference equations as possible for a balanced panel, given the minimum lags in the instruments used. Details of the procedure used are described in the Appendix.

Implementation

The sample is a balanced panel of public R&D-performing firms derived from the NBER Manufacturing Masterfile (Hall, 1988) for the years 1983 – 1989. These data include deflated sales for Q, deflated age-adjusted net book value for C, average full time employees for L, and a measure of R&D stock constructed by the perpetual inventory method from deflated R&D spending depreciated at 15% per year. Investment measures include deflated gross investment in plant and equipment and deflated R&D spending.[3] Labor and physical capital have been corrected for "double counting" (Schankerman, 1981).[4] Observations were screened to exclude mergers and spin-offs and to exclude firms whose primary activity was R&D, not manufacturing. Also, because of possible measurement problems in deflators, SIC 357 (computers) was excluded.[5]

Note that gross investment measures are used even though some adjustment costs might arise from changes in net investment. Gross investment measures were chosen because of the lack of reliable depreciation data, especially for R&D. However, several estimations were performed using estimates of net investment. Also, estimates were made using R&D stocks constructed with depreciation rates of 5% and 25%. In all cases, the results were quite similar to those obtained using gross investment and an R&D depreciation rate of 15% (Bessen, 1998).

Also, note that the data set does not include a measure of materials, M. Materials are assumed to in constant proportion to output, $M_{jt} = k \cdot Q_{jt}$. Given this assumption, I actually estimate a first-differenced version of

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[3] Sales are deflated using the shipments deflator from the NBER Productivity Database (Bartelsman and Gray, 1996) (or the implicit GDP deflator when the firm is not assigned to a 3 digit SIC industry), capital and investment are deflated by the NIPA deflator for non-residential fixed investment, and R&D is deflated by the deflator in the NBER Masterfile. Physical and R&D stocks were measured as beginning-of-year stocks.

[4] Using the NSF figure that Schankerman cites that 46% of R&D is spent on labor, the number of R&D personnel were estimated by dividing 46% of nominal R&D spending by the average salary for non-production personnel in the NBER Productivity Database for the 3 digit SIC industry. Observations were excluded where the estimated R&D personnel exceeded 50% of the labor force. Physical capital was adjusted by the same proportion as labor.

[5] Observations were excluded where the year-to-year growth in C, L, or Q exceeded 100% or fell below –50%. Also excluded were observations where R&D exceeded 50% of sales. Many of the regressions were repeated including SIC 357 and the broad results were similar to those obtained without it, however, the coefficient of K tended to be larger if computers were included.

(4)
$$\ln Q_{jt} = b_0 + b_L \ln L_{jt} + b_C \ln C_{jt} + b_K \ln K_{jt} + \alpha_K \cdot r_{Kj,t-1} + \alpha_C \cdot r_{Cjt} + \mu_j + \varepsilon_{jt}$$
$$b_0 = \frac{a_t + \ln k \cdot \beta_M}{1-\beta_M}, \quad b_i = \frac{\beta_i}{1-\beta_M}, \quad \alpha_K = -\frac{\gamma_K}{1-\beta_M}, \quad \alpha_C = -\frac{\gamma_C}{1-\beta_M}$$

in lieu of (3). The value of .53 was used for β_M ; this was obtained as the materials share of output for 1989 from the NBER Productivity database.

The balanced panel includes 3,297 observations on 471 firms. Mean values of the variables are shown in Table 1. These firms tend to be somewhat larger and somewhat more R&D-intensive than the average firm in the NBER Manufacturing Masterfile. However, the balanced panel accounts for over 90% of the R&D performed in the total sample in any given year and therefore should accurately capture the effects of R&D spending overall.

Estimates

Table 2 presents estimates of the linear specification, (4), and also specifications with other lagged values of R&D intensity. Following the above analysis, all right hand variables were treated as endogenous and were instrumented. Instruments included lagged values of log labor, capital and R&D stock and lagged values of investment intensity for gross R&D and physical capital. [6] Prior to estimation, a series of specification tests confirmed that instruments lagged one year and longer were exogenous (see Bessen, 1998, for details of these tests). Consequently, instruments lagged one year and longer (from the earlier year in each difference equation) were used in the GMM estimations.

As can be seen, in all specifications the coefficient for R&D intensity with a one-year lag is large and highly significant. In most specifications, the coefficient capturing adjustment costs for physical capital is significant, but not as large. The R&D intensity with a one-year lag has a consistently larger coefficient than other lags across specifications. Current R&D intensity has only a weak effect and after one year, the coefficients drop off sharply. The bottom row presents the results of tests restricting some of the coefficients to zero. The addition of a three year lag is rejected both by this specification test and by the coefficient *t* test, but apparently a significant

[6] Both net and gross intensities for physical capital were used as instruments where the intensity of net physical capital is defined as the year-to-year change in net physical capital divided by output. Specification tests confirmed the validity of this instrument.

adjustment effect is measured for up to two years after R&D funds are spent.[7] Considering this pattern, the analysis below only uses terms involving the R&D investment lagged one year.

The overall picture, then, is that the main adoption costs occur a year after R&D spending, but some significant costs still occur for up to two years. Pakes and Schankerman (1984) have estimated a lag between the onset of R&D spending on a project and manufacturing production from 1.2 to 2.5 years. But Mansfield et al (1971) found that most of the R&D spending occurs during the latter stages of this R&D lag. Thus the results obtained here are roughly consistent with these sources.

A virtue of the approach taken here is that adjustment costs may be assigned a flexible functional form and different specifications tested. A simple Taylor series expansion around the zero investment point (where c is assumed to be zero) generates higher order terms. I tested specifications involving second order terms, including an interaction term between physical and R&D investment, and also both absolute and relative (to capital stock) measures of R&D intensity:[8]

$$\begin{aligned} c\left(I_{Ct}, I_{Kt-1}, C, K\right) = {} & \gamma_C I_{Ct} + \gamma_K I_{K,t-1} + \gamma_{CK} I_{Ct} I_{K,t-1} \\ & + \beta_C \frac{I_{Ct}}{C_t} + \beta_K \frac{I_{K,t-1}}{K_{t-1}} + \beta_{CC} \frac{\left(I_{Ct}\right)^2}{C_t} + \beta_{KK} \frac{\left(I_{K,t-1}\right)^2}{K_{t-1}} \end{aligned} \tag{5}$$

Estimates using this expanded specification of c are shown in the fifth column of Table 3. These estimates used the same instruments as with the linear model, but also included lagged values of the new right hand variables. The second order terms are all significant. The interaction coefficient, γ_{CK} , is statistically significant, but small in magnitude, hence the adjustment costs associated with physical capital and R&D are more or less separable. In this specification, adjustment costs on both types of investment are substantially concave, contrary to common assumption.

Several restricted specifications are also estimated and the restrictions tested, including a standard quadratic specification (column 3), the linear specification (column 2) and a specification without adjustment costs (column 1). All restrictions shown are rejected at the 1% level.

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[7] Moreover, multi-collinearity problems appear modest. The condition number (Belsey et al, 1980) for the fifth column is 2.9.

[8] A variety of other terms were also tested; these are the most significant.

Taking partial derivatives of (5), one can calculate the marginal adjustment costs of R&D and physical investment for each year of each plant in the sample. Examining (5), one can see that for $K_{t-1} \approx 0$, estimates of marginal adjustment cost will be extremely large. Since plants with near-zero R&D stock can be assumed to obtain their technology from sources not explicitly included in the model (licensing, embodied technology, etc.), cases with small K are, in effect, mis-measured. Such measurement error will skew the estimates of marginal adjustment costs. To avoid this, the median value is used to indicate central tendency. Median values will be less than the true mean values and so will understate the magnitude of marginal adjustment costs.

Median values are displayed in the lower portion of Table 3. As can be seen, for the preferred specification, an additional dollar of R&D incurs $1.67 in adjustment costs at the median plant. A marginal dollar of gross physical investment incurs 21 cents in adjustment costs. This latter figure corresponds to Lichtenberg's estimate (1988) of the marginal internal adjustment cost generated by replacement investment, although his estimate for new investment is higher (replacement typically constitutes the majority of gross investment).

Note that the marginal adjustment costs vary across specifications. Both measures are particularly small for the quadratic specification; this is not surprising given that the preferred specification is quite concave. This suggests that estimates of adjustment costs in dynamic factor demand models that assume quadratic adjustment costs may be substantially understated.

Finally, using the parameter estimates in (5), one can calculate internal adjustment costs as a percent of output for each year of each plant. Median values of this percentage are also shown in Table 3. Compared to the investment intensities in Table 1, adjustment costs represent a large implicit investment flow, larger than R&D investment and nearly as large as the gross investment in physical capital.

Other Evidence of R&D Adoption Costs

Prior to the twentieth century, scientists and engineers were only involved with a small percentage of innovations. Few firms had scientific and engineering personnel dedicated to product or process innovation. Many of the major technological innovations of the Industrial Revolution were made by hands-on manufacturing people who were also tinkerers, such as Hargreaves and Crompton. So the question of whether non-R&D personnel play an important role in innovation is only relevant for the last century or so. The more general question is whether or not formal R&D activities have largely supplanted non-R&D innovative activity.

Some of the clearest evidence that large adoption costs persist today comes from a survey of product innovation in the chemical, machinery and electronics industries conducted by Mansfield et. al. (1971). They break the entire activity related to product innovation into different stages and assess the role of non-R&D personnel at each stage. During the project specification phase, marketing personnel evaluate product features and manufacturing personnel evaluate manufacturability. Manufacturing personnel are also typically involved during prototype design, construction and testing, during production planning, tooling, and during construction and installation of manufacturing facilities. During the start-up phase, prior to routine production, production workers are trained, the process is "debugged," and some production may take place until acceptable quality levels are reached. Marketing start-up includes market research, distribution setup, training the sales force, and introductory advertising.

Using NSF definitions of R&D activity, Mansfield et al allocate costs between R&D and non-R&D functions. They find that each dollar of R&D spending requires $1.34 of non-R&D in the chemical industry, 94¢ of non-R&D in the machinery industry and 97¢ in the electronics industry. They conclude,

> "Economists sometimes have assumed that research and development expenditures could be treated as synonymous—or nearly so—with the costs of product innovation. Judging from our data, this assumption is a poor one, since an amount approximately equal to the R and D expenditures must be spent on non-R and D innovative activity in the case of the typical commercialized product."

These estimates of adoption costs are slightly lower than our econometric estimates. Note, however, that Mansfield et al do not consider any costs incurred after the onset of routine production. The possibility of learning-by-doing implies that some additional adoption costs may be generated during routine production. Considering some role for such costs, the econometric estimates correspond with the survey evidence.

A second piece of indirect evidence derives from survey data on the costs of imitation. If a firm incurs large costs adopting its *own* technology, then it seems likely that firms who imitate that technology will also incur large adoption costs. If one assumes that an imitator pays nothing for the knowledge developed by the innovating firm's R&D personnel, but must still pay the same adoption costs, then (using the estimate of $1.67 of adoption costs per dollar of R&D) imitation costs should run about 60% of the original cost of innovation. In fact, in another survey study, Mansfield, Schwartz and Wagner (1981) found that imitation costs are estimated to run about two thirds of the cost of original innovation. Hence the estimates derived here are consistent with the finding of large adoption costs.

Thus multiple sources suggest substantial adoption costs to technology. From a historical perspective, it appears that R&D has not completely supplanted all other forms of innovative activity and these other activities complement the work of scientists and engineers. Moreover, the adoption costs associated with these activities represent an intangible investment that is large relative to R&D spending and to gross physical investment.

III. The Returns to Innovative Activity

Adoption costs and the required rate of return

As noted in the introduction, adoption costs, viewed as an adjustment cost of R&D investment, may explain why estimates of the returns to R&D seem so high. Adoption costs increase the total expenditure required to generate the additional output associated with an R&D project. Adoption costs are a strong complement to R&D spending and must be included in the calculation of required returns. A marginal dollar of R&D incurs a total marginal cost of

$1 + \dfrac{\partial c}{\partial I_K}$ and generates additional output each year of $\dfrac{\partial Q^*}{\partial K}$.

Therefore, the rate of return on the marginal project, net of depreciation δ, is

$$R = \frac{\partial Q^*}{\partial K} \cdot \frac{1}{1+\partial c/\partial I_K} - \delta = \beta_K \cdot \frac{Q^*}{K} \cdot \frac{1}{1+\partial c/\partial I_K} - \delta . \tag{6}$$

This is the rate of return that can be compared to net rates of return on physical capital or to returns on financial instruments.

Clearly adoption costs can have a large impact on estimated returns. For example, assume that R&D assets depreciate at 15% per year and that the net marginal return on R&D is measured at 40% without considering adoption costs (gross return of 55%). Using our best estimate of adoption costs, the total marginal expenditure is $1 + 1.67 = 2.67$, so that the true required net return is only $55\% / 2.67 - 15\% = 6\%$. Of course, if the estimated return of 40% was derived from an econometric analysis that omitted adoption costs, then the situation is complicated by possible omitted variable bias. Depending on how R&D spending correlates with other right hand side variables, the correct result might be larger than 6%.

Using (6), one can calculate the net marginal return on total innovation (assuming 15% depreciation of R&D stock) for each plant in each year of the pooled sample. Again, any mis-measurement of K at small values will skew estimates upwards and so medians are used, although they may understate the rates of return. Median values are reported in Table 3. Column 1 reports a specification without adoption costs; the estimated net return is over 33%, a typical result for studies that omit adoption costs (Nadiri, 1993). For specifications that include adoption costs, however, the estimates range only from 5% to 14%, with a net return of 6% for the preferred specification.[9] These results suggest that when adoption costs are included, the private rates of return on innovation spending roughly equal the rates of return on physical capital and the risk-adjusted interest rates of corporate financial instruments.

The *social* returns to innovative activity may be higher, of course. Note, however, that accurate estimates of social returns are made more difficult by consideration of adoption costs. The total social cost of innovation includes not only the cost of R&D and firms' cost of adopting their own R&D; it also includes the cost of adopting technology developed by other firms, either by imitation, by licensing technology or by purchasing products embodying that technology. Some studies have attempted to measure social returns by estimating industry-level returns to R&D (see Nadiri, 1993, for a review). The finding of substantial adoption costs at the firm level, however, suggests that such studies need to consider adoption costs. A similar consideration applies to studies that attempt to measure the returns to basic research or to federal R&D spending without including the total costs of implementing that research.[10]

Risk and the relative returns to R&D and physical capital

An alternative explanation for the high estimates of private returns to R&D has been suggested by Nadiri (1993, p. 35) and Griliches (1995, p. 82). They propose that greater risk associated with R&D might require a higher hurdle rate for investment. In this case, net returns to R&D might substantially exceed net returns on physical capital. This section considers whether the high measured returns to R&D can be explained by risk instead of adoption costs.

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[9] If instead of a median, one takes the mean, but excludes from the sample all observations where $K < .01*Q$, then the net return on the preferred specification is 11.2%. Other measures are also higher.

[10] Social returns to R&D may nevertheless be substantial. For example, some evidence of R&D complementarities is unaffected by consideration of adoption costs, as in Jaffe (1986).

It is well-known that R&D projects are risky in the sense that only a fraction are successfully commercialized. This may generate a greater variance in profits for firms that invest heavily in R&D. Greater profit variance may affect the required returns to R&D in two ways. First, given a fixed cost of money and irreversible investment, greater profit variance may lead to a higher hurdle rate for investment. Second, if the stochastic returns to R&D tend to be pro-cyclical (that is, if they are correlated with returns to a market portfolio), then the R&D intensive firms will have higher stock market betas and will face a higher costs of funds.

The first effect, however, does not generate a *differential* between the required return on R&D and the required return on physical investment. Calculations based on a real options model of investment show that investment hurdle rates rise *equally* for R&D and physical investment when variance of profits increases.[11] Intuitively, the risk of irreversible investment applies whether the investment being considered is physical capital or R&D capital or both.

The second effect does generate a differential as demonstrated by the following. Define the portion of total capital invested in R&D as ϕ. Let the stock market beta be an increasing function of ϕ. Then by the Capital Asset Pricing Model,[12] the firm's required return is

(7) $$r_f(\phi) = r_0 + \beta(\phi)\cdot(r_m - r_0)$$

where β is the stock market beta value, r_0 is the risk-free rate of return and r_m is the expected return on a market portfolio. Define total capital $T \equiv C + K$ so that $K = \phi\cdot T$ and $C = (1-\phi)\cdot T$. Then, using production function (2), and assuming no adjustment costs, profits are

$$\pi = p\cdot Q - w_m\cdot M - w_l\cdot L - r_f(\phi)\cdot T$$

where p is product price and the w_i are factor costs. The first order condition for maximizing profits with respect to ϕ is

$$\frac{\partial\pi}{\partial\phi} = 0 = p\cdot\frac{\partial Q}{\partial K}\cdot\frac{\partial K}{\partial\phi} + p\cdot\frac{\partial Q}{\partial C}\cdot\frac{\partial C}{\partial\phi} - \frac{\partial r_f}{\partial\phi}\cdot T = p\cdot T\cdot\left(\frac{\partial Q}{\partial K}-\frac{\partial Q}{\partial C}\right) - \frac{\partial r_f}{\partial\phi}\cdot T$$

or

[11] Details available from the author. This model assumes that the cost of funds is fixed, investment is irreversible, profits per unit of capital evolve according to a geometric random walk and the variance of this process is an increasing function of R&D. Also, note that an elevated hurdle rate only indirectly translates into an elevated *average* rate of return.

[12] Since our sample consists of public firms, the Capital Asset Pricing Model is assumed to apply.

(8) $$R_K - R_C = \frac{\partial r_f}{\partial \phi} = \frac{\partial \beta}{\partial \phi} \cdot (r_m - r_0)$$

where R_K and R_C are the marginal revenue products of R&D capital and physical capital, respectively. The differential in required rates of return equals the increase in the cost of funds arising from a marginal increase in the R&D share of capital.

The marginal increase in beta value has been the focus of two studies. Statman and Tyebjee (1984) performed a regression analysis but failed to find a significant relationship. However, Wedig (1990) analyzed a panel of 214 manufacturing firms and included terms representing interactions between ϕ and firm size and industry concentration. Using a fixed effects model Wedig obtained estimates of $\frac{\partial \beta}{\partial \phi}$ from .48 to .62 for large firms (.79 to .93 for small firms) depending on whether they were in concentrated or unconcentrated industries.[13] The appropriate value for the equity risk premium, $(r_m - r_0)$, has been a subject of some controversy (Annin and Falaschetti, 1998). However, a range from 4% to 8% brackets many estimates. Assuming that Wedig's large firm coefficients are most representative for our sample, this generates a risk differential ranging from 2% to 5%. That is, the required rate of return on R&D investment is only 2% to 5% larger than the required rate of return on physical investment.

Thus risk only appears to account for a minor fraction of the difference between the estimated rates of return to R&D and the rates of return on physical capital. Adoption costs appear to generate the major portion of this differential.

IV. Conclusion

It is much easier to measure research and development expenditures than to measure adoption costs. R&D appear as an item in financial statements, but adoption costs include disparate, sometimes unpredictable activities that are hard for firms to monitor and harder yet for economists to gauge. Indeed, firms seem to resort to rough rules of thumb when adopting new technologies—e.g., budgeting rules for projects involving new technology often require a two to

[13] Wedig also performed employed a random effects model that generated somewhat higher coefficients, but this model was rejected by a Hausman specification test. Wedig also used a 20% depreciation rate for R&D capital as opposed to the 15% rate used here. If the true rate is 15% Wedig's results are overstated.

three year payback.[14] Yet the lower visibility and difficulty of measuring adoption costs does not make them any less significant.

It is also hard to observe the costs of adopting technology developed by *other* firms. The large adoption costs from own-R&D suggest that adoption costs may make it substantially more difficult for competitors to imitate a new technology. Adoption costs may also hinder the acceptance of products embodying new technology by consumers and downstream producers.

A rich and complex picture of the innovation process emerges from consideration of these adoption costs. The innovativeness of firms and nations may depend on how well they manage adoption of new technologies and this may depend, in turn, on organizational, institutional, and historical factors. Innovation is simply a much broader process than research and development. It involves not only scientists and engineers, but also marketers, managers, production workers, service technicians and customers. Endogenous growth models that look only at the costs and incentives of R&D miss the major part of the story. Growth models and innovation policy must address all of the issues that affect the adoption of new technologies, and these are, perhaps, much more complex.

Appendix

The GMM estimates are derived by jointly estimating difference equations for each year in the panel using lagged right hand side variables as instruments (excluding equations that do not have lagged instruments in the panel). For example, using instruments lagged one year or more, we estimate T = 5 difference equations, each taking the difference between year t + 1 and year t where t = 1984 – 1988. Given m instrumental variables, $z_{is}^1,\ldots,z_{is}^m$ for the ith firm at year s ($s = t$ – 1983 = 1,…,T), the sth difference equation has instruments $z_{is} = \left(z_{i0}^1,\ldots,z_{i0}^m,\ldots,z_{i,s-1}^1,\ldots,z_{i,s-1}^m\right)$. The variables used as instruments are logs of capital, labor and R&D stock, the intensity of R&D spending, and the intensities of gross and net physical investment. The non-linear specifications (Table 3) also used lags of the non-linear right hand variables.

Designate the residual of the sth equation for the ith firm as $u_{is}(\beta)$, a function of the parameter vector β. This implies $m \cdot s$ orthogonality conditions for each equation, $E\left(u_{is} \cdot z_{is}\right) = 0$,

[14] Adoption costs may explain a large portion of these elevated hurdle rates. Another portion may arise from risk considerations.

for a total of $m \cdot T(T+1)/2$ moment conditions for all T equations. I presume the disturbances are independent across firms, $E(u_{is} \cdot u_{jt}) = 0,\ i \neq j$, but I allow for serial correlation, $E(u_{is} \cdot u_{it}) \neq 0$, and heteroscedasticity, $E(u_{is}^2) \neq E(u_{jt}^2)$. The GMM procedure used (in TSP 4.4) initially obtains consistent parameter estimates using 3SLS. Under these assumptions, the residuals from this step are used to estimate a full covariance matrix for the orthogonality conditions. The inverse of this matrix is then used as the weighting matrix in the GMM estimation (see Mairesse and Hall, 1996 for further details).

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Table 1. Sample means

	Balanced Panel 1983 - 1989
Number of observations	3,297
Number of firms	471
Q = Sales (millions 1987 $)	2,362.5
C = Net plant and equipment (millions 1987 $)	1,297.2
L = Full-time employees (1,000s)	15.2
K = R&D stock (millions 1987 $)	305.3
I_K = R&D spending (millions 1987$)	57.8
I_C = Gross capital spending (millions 1987 $)	194.8
$r_K = I_K / Q$, R&D intensity	3.0%
$r_C = I_C / Q$, Gross investment intensity	6.6%

K is deflated R&D capital stock constructed by the perpetual inventory method at 15% depreciation. Both capital stock measures are beginning-of-year stocks. Labor and physical capital have been corrected for the “double counting” contribution of R&D labor and capital. Sample excludes observations with missing data, large year-to-year size changes (likely merger or spin-off), and firms where R&D exceed 50% of sales (see text). Also, SIC 357 (computers) has been excluded.

Table 2. Production Function Estimates with Linear Adjustment Costs

Column	1	2	3	4
Ln C	.035 (.052)	.037 (.055)	-.045 (.057)	-.044 (.065)
Ln L	.328 (.055)	.308 (.058)	.433 (.065)	.441 (.073)
Ln K	.112 (.027)	.110 (.027)	.096 (.028)	.096 (.034)
I_C/Q	-.229 (.112)	-.115 (.116)	-.342 (.115)	-.371 (.125)
$I_{K,t}/Q$		-1.636 (.513)	-.470 (.674)	-.070 (.779)
$I_{K,t-1}/Q$	-2.156 (.339)	-1.825 (.390)	-1.413 (.404)	-1.545 (.460)
$I_{K,t-2}/Q$			-.678 (.225)	-.316 (.312)
$I_{K,t-3}/Q$				.250 (.366)
Number of equations	5	5	4	3
Test of over-identifying restrictions (Sargan) Chi squared [deg. free]	99.9 [85] P = .129	108.9 [84] P = .036	90.7 [77] P = .136	76.2 [64] P = .142
Test of restrictions Chi squared [deg. free]	--	Lag 0 = 0 11.4 [1]* P = .001	Lag 2 = 0 11.2 [1]* P = .001	Lag 3 = 0 0.9 [1] P = .347

Notes: Asymptotic, heteroscedastic-consistent standard errors in parentheses, degrees of freedom for chi squared statistics in brackets. A “*” indicates the null hypothesis is rejected at the 1% level.

Sample is a balanced panel of 471 firms from 1983 to 1989. Dependent variable is deflated sales, Q. Right hand variables include physical capital, C, labor, L, R&D capital, K, and investment intensities based on gross physical investment, I_C, and gross R&D investment, I_K including lagged values. All variables have year means removed (equivalent to year dummies).

The coefficient estimates are derived by jointly estimating *n* difference equations between the production function at time $t + 1$ and time t where $t = (1989 - n)\ldots 1988$ using GMM. The instruments include lagged log capital, labor and R&D stock and lagged R&D intensity and gross and net physical investment intensity. Instruments are lagged values from periods $t - 1$ and earlier.

The Sargan test (over-identifying restrictions) provides a measure of fit. The last row tests the null hypothesis that the coefficient of R&D intensity with the indicated lag is 0, using the weighting matrix from the unrestricted regression (restricted regressions not shown).

Table 3. Production Function Estimates with Non-Linear Adjustment Cost Specifications

Independent variable	1	2	3	4	5
Ln C	-.010 (.045)	.035 (.052)	.062 (.042)	.060 (.038)	.140 (.025)
Ln L	.446 (.050)	.328 (.055)	.468 (.049)	.384 (.040)	.275 (.034)
Ln K	.093 (.025)	.112 (.027)	.065 (.023)	.122 (.025)	.097 (.024)
I_C/Q		-.229 (.112)		-.631 (.151)	-.616 (.141)
I_K/Q		-2.156 (.339)		-8.274 (.783)	-8.905 (.671)
$I_K \cdot I_C/Q$					.0005 (.0001)
$I_C/(Q \cdot C)$					.266 (.461)
$I_K/(Q \cdot K)$					-5.670 (.859)
$I_C^2/(Q \cdot C)$			-.220 (.057)	.372 (.155)	.405 (.131)
$I_K^2/(Q \cdot K)$			-3.684 (.524)	13.104 (1.562)	15.070 (1.323)
$\partial c/\partial I_K$	--	1.01	.66	1.56	1.67
$\partial c/\partial I_C$	--	.11	.04	.23	.21
Total adjustment cost / output	--	2.5%	0.7%	6.0%	6.3%
Total net return to R&D	33.7%	14.0%	5.4%	12.7%	6.3%
Test of over-identifying restrictions (Sargan)	94.7 [87] P = .269	99.9 [85] P = .129	104.7 [90] P = .138	135.7 [103] P = .017	151.5 [130] P = .095
Test versus column 5 Chi squared [degrees freedom]	649.6 [7] P = .000	426.3 [5] P = .000	557.1 [5] P = .000	97.8 [3] P = .000	--

Notes: Asymptotic, heteroscedastic-consistent standard errors in parentheses, degrees of freedom for chi squared statistics in brackets.

Sample is a balanced panel of 471 firms from 1983 to 1989. Dependent variable is deflated sales, Q. Right hand variables are constructed from physical capital, C, labor, L, R&D capital, K, and investment intensities based on gross physical investment, I_C , and gross R&D investment (lagged once), I_K . All variables have year means removed (equivalent to year dummies).

The coefficient estimates are derived by jointly estimating 5 difference equations between the production function at time t + 1 and time t where t = 1984…1988 using GMM. The instruments include all lagged right hand variables. Instruments are lagged values from periods t – 1 and earlier.

Marginal effects, adjustment cost as a percent of sales, and total net return on R&D are median values for entire sample (pooled). Total net return on R&D includes marginal adjustment costs and 15% depreciation. The Sargan test (over-identifying restrictions) provides a measure of fit. The last row tests the null hypothesis that the coefficient restrictions relative to the fifth column are not significant. These tests use the weighting matrix from the unrestricted regression (test regressions not shown).