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Final Project Report:

UNDERSTANDING DIFFERENCES IN THE DIFFUSION OF ENVIRONMENTALLY
BENEFICIAL TECHNOLOGY
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AIMS OF THE PROJECT

The factors affecting the diffusion of technical discoveries among firms and nations remain one of the most interesting and important but least understood elements of economic behavior. For many years scholars have been interested in technology diffusion because of its implications for the profitability of firms or industries, and the competitiveness and overall well-being of societies as a whole.¹ More recently, interest in technology diffusion has been heightened by a recognition that the spread of technologies could have important implications for environmental quality as well as for market goods and services.

A specific motivation for this study was the question of how rapidly technologies that reduce greenhouse gas emissions might diffuse. Technologies in this category include technologies that improve the efficiency of fossil energy use or promote the substitution of renewable energy resources.² The speed with which these technologies spread could have a significant effect on the rate of accumulation of carbon in the atmosphere. From a modeling perspective, the rate of innovation and diffusion of carbon-reducing technology is known to be a crucial parameter in integrated assessments of climate change risks and policy responses. Thus, a better understanding of factors that might influence the spread of carbon-reducing technologies could be valuable in studies of long-term global change and policy assessments.

It has long been recognized that better understanding the dynamics of technology adoption is a complex problem that requires careful analysis of individual firm decisions. Indeed, DOE currently is supporting several studies that attempt to shed light on the issue with micro-level studies, focusing mostly (though not entirely) on the US. Results for other countries will be even slower in coming given that micro-level data is even less available and reliable outside the US.

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¹In the late 19th century, Alfred Marshall's pioneering analysis of microeconomic behavior recognized the importance of technical innovation as a dynamic process that went beyond the attempts to model economic systems by analogy with classical mechanics. Later, Schumpeter (1942) further developed the idea of technical (and thus social) innovation as an active, almost biological process.

²Carbon-sequestering or other "exotic" technologies for slowing global warming also could be included, but our primary interest is in information that could be relevant to the diffusion of lower-carbon-producing techniques. Reforestation also is relevant, but this technology has been studied to a considerable extent; we focus more on industrial process and other production technologies.

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In light of these difficulties, and the perceived high value of better understanding of the international diffusion rates for lower-emissions technologies, this study sought to take a more heuristic approach. It is a widely accepted stylized fact that the diffusion of new technologies follows a predictable temporal pattern -- technologies are adopted quite slowly at first, then more rapidly, and then slowly again as a technology specific "adoption ceiling" is reached. Thus, a plot of the number (or the proportion) of adopters over time has the "S" shape of a logistic curve. A variety of theoretical explanations for this pattern can be offered, including learning-by-doing or differences in individual firm diffusion patterns that reflect differences in their characteristics.³

If one starts with the assumption that this stylized adoption pattern is applicable internationally, one can then ask: what affects the speed and ultimate level of adoption of lower-emissions technologies in different countries?⁴ The goal of this project was to gain some understanding of these differences through international comparisons of adoption patterns for technologies in wide use. We focused on several production technologies for which data on technology use could be secured and which seemed sufficiently analogous to carbon-reducing technologies that lessons learned from our study could have some applicability to the greenhouse issue. The technologies we have considered include the basic oxygen furnace and continuous casting in steel production, and alternative methods for textile production -- shuttleless looms and open-ended rotor spinning. The former technologies are substantially more capital-intensive than the latter two, which rely upon a more skilled workforce. This gave us the prospect of being able to compare results across technologies of different types. While some carbon-reducing technologies (such as more efficient power plant boilers or large-scale production of biomass fuels) are highly capital-intensive, many energy-efficiency technologies are far more labor-intensive. The range of technologies we consider here seemed to include both aspects.

GENERAL APPROACH TAKEN

Technology diffusion ultimately comes down to a set of profitability decisions by individual users of competing technologies. A new technology will be adopted if and only if, in the estimation of users, the expected present value of net revenues with the new technology exceeds that obtainable under the old technology. Thus, ideally we should study the process of technology diffusion at the level of individual users. Unfortunately, this is difficult to do systematically at the international level because of severe data limitations.

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³ For further discussion of the influences on adoption decisions see Mansfield et al (1977), Landau and Rosenberg (1986) (especially the chapters by David and Mansfield), Silverberg, Dosi, and Orsenigo (1988), and Rose and Joskow (1990). Early important applications of the S-shaped pattern can be found in Griliches (1957) and Mansfield (1961). Note that the logistic model is analogous to biological processes such as species growth in a constraining ecosystem or the spread of infection. Scherer (1984) discusses the relationship between market structure and innovation.

⁴ For an early attempt to understand international differences, see Nabseth and Ray (1974); for more recent work, see Lücke (1993, 1994).

Because technology users differ in the basic characteristics that influence the profitability of new versus old technology, we would expect variation across users within and among countries in the propensity to adopt. Moreover, the adoption decision is predicated on a set of future expectations that may in turn reflect much uncertainty. Over time the information used to develop expectations of profitability will change, so we would also expect variation over time in the time path of adoption decisions (changes in the shape of the logistic curve).

The economic theory of technology diffusion has developed a variety of explanations for differences among firms in an industry in the rate of new technology adoption (see the references in footnote 3 above). Although our focus in this study was on international differences, it is still useful to summarize the rationales for interfirm differences because they provide a basis for understanding some of the variation across countries. It is important to note, however, that many of the hypotheses enunciated below are quite heuristic since they do not derive explicitly from a description of optimizing decisions by firms. One of the problems with this approach is that it is ad hoc, and plausible stories can be told for a number of hypotheses that may not be consistent with each other.

Keeping in mind that the basic determinant of technology switching is relative profitability, one set of influences on adoption propensities is the collection of factors affecting the general propensity to invest. These factors include the vintage of firms' existing capital stock, the rate of sectoral growth, and the intensity of R&D efforts. The cost of capital (both in terms of observed interest rates and less-easily observed constraints on credit) and other inputs also will affect investments, as will the level of labor force skill and productivity and the level of public infrastructure available to support new investment.

A second, overlapping set of considerations has to do with firm size and market structure. Other things equal, large firms may have a larger adoption propensity than small firms. This could reflect fewer problems of indivisibility in physical capital investment and in human capital (e.g., large firms can afford greater engineering staffs in their overhead budgets), more opportunities for technological risk diversification and learning by doing, and greater exploitation of scale economies. On the other hand, larger firms may be more insulated from competitive pressures and less dynamic in their innovativeness.

Market structure considerations can arise at the level of the industry or the economy as a whole. The effect of competitiveness within an industry seems to be ambiguous both conceptually and empirically; arguments can be made that firms in more competitive environments are faster to adopt, or slower. At the level of the economy as a whole, the existence of greater specialization in the production of capital goods may promote greater rapidity of diffusion as well as innovation, in part because the specialized sectors will aggressively seek to expand markets. This could be one reason (among many) why diffusion rates are higher in modern industrial economies than in less

developed economies with lower levels of economic specialization. In addition, some recent research suggests that economic growth may best be modeled as an endogenous phenomenon, in which technological innovation and diffusion are self-perpetuating, with advances made by a single firm or industry spurring related developments throughout the economy.

A variety of institutional factors also may influence the spread of technologies within and across industries. Examples include regulation, taxation, and any other influences that could significantly affect investment incentives. Another influence could be the pattern of resource ownership in the economy -- if, for example, public ownership weakens incentives for profit maximization, adoption incentives correspondingly would be reduced.⁵

There is no direct analogue at the national level to the argument that larger firms might adopt more quickly. However, it seems reasonable to suppose that more rapidly growing economies also are more likely to adopt sooner and faster, since they are more likely to be modernizing capital and may experience fewer divisibility problems in establishing the domestic infrastructure for supporting a new technology. The degree of openness of an economy in general and of an adopting industry in particular also could be relevant, since it gives some indication of the degree of competition faced by firms in that country, though as noted above the effect on adoption of competitiveness is still unclear. Finally, a variety of national policies (beyond those directly affecting factor costs and risks) could be relevant. These would include intellectual property laws (which influence the cost of acquiring new technology) and laws related to foreign investment and business operation (which affect the cost of capital as well as information).

No measures are available internationally for many of these factors, and many other variables for which some data are available exhibit problems of measurement. Even more serious is the problem of attempting to analyze at the aggregate level a process that fundamentally operates at the more disaggregated level of the firm. The heuristic analysis attempted in this project ultimately did not bear much fruit, and in retrospect we believe that there is no substitute for the more difficult micro-level analysis. This is not a very encouraging conclusion in that it seems reasonable intuitively that there would be differences internationally in the forces driving the spread of environmentally friendly technology. If these factors cannot be identified at the aggregate level, as we have concluded, then the lack of micro-level data outside the US seems likely to severely limit the conclusions that can be drawn about international technology diffusion patterns for a number of years.

EMPIRICAL METHODS AND PITFALLS

In addition to problems of measuring key variables, there are basic econometric problems that stymied the achievement of empirical results with the national aggregate

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⁵In assessing this influence one needs to control for other factors, such as the possibility that a publicly owned sector of the economy also benefits more from public R&D expenditure.

data used in this study. As noted above, the most common functional form used to describe this "S" shaped temporal pattern is the equation for a logistic curve:

$$p_{it} = k_i / [1 + \exp(-a_i - b_i t)] \quad (i = 1, 2, \dots, n) \quad (1)$$

where "i" is an index of "n" subsets of potential adopters, "t" is an index of time, " p_{it} " is the number or fraction of firms in subset "i" that have adopted the new technology at time "t", and " k_i ", " a_i ", and " b_i " are parameters. The parameter " k_i " shifts the upper asymptote of the curve and is therefore interpreted as the adoption ceiling; " b_i " shifts the curve to the right or left and is therefore interpreted as a measure of the date of first adoption; and " a_i " dictates the slope of the curve, and is therefore interpreted as a measure of the speed of diffusion. Note that " p_{it} " may be interpreted as the cumulative probability of adoption at time "t;" if we normalize k_i to lie between zero and one, we can interpret p_{it} as the fraction of adopters.

One branch of the empirical literature on diffusion has focused on trying to explain variation in estimates of the parameters " k_i ", " a_i ", and " b_i " across different sets of potential adopters. There are three widely used econometric methodologies for doing this. The oldest is a two-stage method used in the seminal work by Griliches (1957) and Mansfield (1961) that, despite a number of weaknesses, is still in use today (see, e.g., Lücke 1993). First, the adoption ceiling, " k_i ", is estimated by some ad hoc method -- often visual inspection or the assumption that all firms will eventually adopt the new technology -- so that equation (1) can be expressed as a linear function of transformed variables:

$$\ln (p_{it} / k_i^* - p_{it}) = -a_i - b_i t \quad (i = 1, 2, \dots, n). \quad (2)$$

This equation is estimated using ordinary least squares (OLS), sometimes with a correction for autocorrelation (see, e.g., Sahal 1981). In the second stage, the estimated parameters are used as independent variables in the regressions:

$$[a_i \ b_i] = [X^a \beta^a \ X^b \beta^b] \quad (3)$$

where X^a is a vector of independent variables presumed to be related to the date of first adoption, X^b a vector of independent variables presumed to be related to the speed of diffusion and β^a and β^b corresponding vectors of parameters. Note that X^a and X^b may have some common influences as well as differing components. Least squares is generally used in the second stage, sometimes with a correction for heteroskedasticity (see, e.g., Saxonhouse 1977).

The two-step approach suffers from a number of serious weaknesses. First, the adoption ceiling is estimated in an ad hoc manner. Second, the estimated parameters of the logistic curve which serve as dependent variables in the second stage presumably capture information about a diffusion process that has occurred over the course of several

decades; but the independent variables that are meant to explain them are point estimates of firm characteristics which contain scant information about changes over time. Third, and perhaps most important, it is now widely acknowledged that using estimated parameters as dependent variables leads to heteroskedasticity that can undercut the precision of standard error estimates and the strength of inferences (Hanushek 1974, Saxonhouse 1976, Edmonds and Meisel 1992).

A second popular methodology for explaining the variations in logistic diffusion curves is to estimate the parameters of the differential equation derived from equation (1),

$$dp_{it}/dt = b_i p_{it}(k_i - p_{it}) \quad (i = 1, 2, \dots n). \quad (4)$$

The time derivative, dp_{it}/dt , may be interpreted as the instantaneous probability that a firm adopts in time t ; the intuition for the "Bass model" widely used in the marketing literature (Srinivasan and Mason 1986). First differences are used to approximate the time derivative:

$$p_{it} - p_{it-1} = b_i p_{it-1}(k_i - p_{it-1}) \quad (i = 1, 2, \dots n). \quad (5)$$

With this formulation as a starting point, researchers have attempted to explain variation in both the adoption ceiling, k_i , and the rate of diffusion, b_i (see, e.g., Knudsen 1991, Mahajan and Peterson 1978, Chow 1967, Williams 1972, Brewley and Fieberg 1988, Labson and Gooday 1994). One hypothesis is that the adoption ceiling is a linear function of a vector of contemporaneous variables, X^k , that is,

$$k_i = X^k \beta^k, \quad (i = 1, 2, \dots n) \quad (6)$$

(where β^k is a row vector of parameters) and the researcher tests for a correlation between these supply variables and the adoption ceiling by substituting equation (6) into equation (5) and using ordinary least squares to estimate the resulting relationship:

$$p_{it} - p_{it-1} = b_i p_{it-1}(X^k \beta^k - p_{it-1}) \quad (i = 1, 2, \dots n). \quad (7)$$

Similarly, one can hypothesize that the rate of adoption, b_i , is a linear function of a vector of variables, Y , that is,

$$b_i = Y\gamma \quad (i = 1, 2, \dots n) \quad (8)$$

(where γ is a row vector of parameters). A two stage procedure can be used to test this hypothesis. In the first stage, use equation (5) to obtain estimates of the adoption ceiling, k_i^* and in the second stage substitute out " b_i " in equation (5) using (8) and employ k_i^* to obtain

$$p_{it} - p_{it-1} = Y\gamma p_{it-1}(k_i^* - p_{it-1}) \quad (i = 1, 2, \dots n) \quad (9)$$

which can be estimated using least squares.

Despite the advantages of the differential equation approach -- the use of time series data on the right hand side so that more data can be brought to bear on the problem, and the ability to use simple least squares estimation routines -- there are a couple of practical problems. First, to test for the determinants of the rate of diffusion, one must make ad hoc assumptions about the adoption ceiling, k_i^* . Second, if OLS is used, a "time interval bias" is introduced because discrete time series data are used to estimate a continuous time model (Schmittlein and Mahajan 1982).

The third procedure for explaining variation in logistic diffusion curves is to use non-linear least squares (NLS) to estimate the parameters of a cumulative logistic function (equation 1 above). There would seem to be a consensus among empirical analysts addressing the issue that NLS is the best means of obtaining accurate parameters estimates and standard errors. As Oliver noted in 1964, "[T]here is no substitute for full least squares in estimating the logistic growth function...Other methods of fitting are inefficient and can give diverse estimates of the parameters (quoted in Dixon 1980, p. 1455). Using data on hybrid corn (an updated version of the data that Griliches used in his seminal 1957 study), Dixon (1980) compares parameter estimates obtained using OLS and estimates obtained using NLS and concludes (p. 1460) that "[T]he diffusion parameters ... derived by application of an iterative nonlinear least squares technique should be preferred to the logit parameters set derived by indirect means." Srinivasan and Mason (1986) compare estimates of diffusion parameters for four different product types and conclude (p. 178) that "The key advantage of NLS is obtaining valid standard error estimates. ... In terms of fit and predicative validity the NLS ...[outperforms] the OLS regression which has a time aggregation bias." But while there seems to be agreement that NLS is preferable method for obtaining consistent and efficient estimates, NLS has been used (to our knowledge) in only one study (Dixon 1980) to assess the determinants of these parameter estimates; and that study uses a two-stage procedure that is subject to some of the same criticisms as the first procedure discussed above.

A seemingly straightforward means of avoiding these difficulties is to estimate an expanded flexible form of equation (1) using NLS. More specifically, we assume that both the adoption ceiling, " k_i ", and the rate of adoption, " b_i ", are linear functions of a set of contemporaneous independent variables, i.e.,

$$[b_i \ k_i] = [X^b \beta^b \ X^k \beta^k] \quad (10)$$

and we substitute these functions into equation (1) to arrive at:

$$p_{it} = X^b \beta^b / [1 + \exp(- a_i - X^k \beta^k t)] \quad (i = 1, 2, \dots n), \quad (11)$$

which we estimate using NLS.

SUMMARY OF EMPIRICAL RESULTS FROM THIS STUDY

A short paper (enclosed) prepared during the course of the project reported the results of using the two-step procedure discussed above to estimate how adoption profiles might vary internationally. Unfortunately, the results were largely negative in that the estimating equations had little explanatory power, and the signs of at least some coefficients were counterintuitive. Attempts to improve on these results were later attempted using some of the more sophisticated methods discussed above. Additional explanatory variables also were incorporated, such as the share of government expenditure in national income, the aggregate capital-labor ratio, a measure of the unit cost of investment goods, and the degree of openness of the economy (as indicated by the sum of exports and imports divided by national income). These methods generated some improvement in the results, and some work continues to refine them, but the results still were not robust.

The overall conclusion drawn from these negative empirical findings is that it is not possible to fully and reliably identify international differences in technology adoption profiles with simple heuristic models and national data. The data must be disaggregated to firm-level decisions and coupled with a theoretical model of individual firm decisionmaking that makes it possible to identify clearly testable hypotheses. Until such work can be accomplished -- and experience suggests that progress in this area will require considerable time and money, especially to highlight the effects of the substantial international differences in market performance and institutions -- integrated assessment models will have to rely on educated guesses and sensitivity analysis to parametrize emissions-reducing technical progress.

RELATED RESEARCH APPROACHES

In addition to the work reported here and in the paper attached, several other research strategies were explored in the second year of the project as possible ways to address issues of technology diffusion. Limited second year resources and data availability did not allow us to pursue these alternatives far enough to produce formal outputs. Nonetheless, at least one potentially promising option was identified on which future research might be useful. This is in the area of endogenous growth models.

Models of growth with perfect competition, complete markets, and non-increasing returns are useful and have some predictive power. They also have some important practical limitations, however. Perhaps most importantly, their predictions may be at variance with real-world phenomena: the benefits of knowledge are imperfectly appropriated, factor prices are not equalized across nations, and, if the economic welfare of nations converges at all, it must only do so very, very, slowly.

A number of recent contributions to the literature on economic growth have explained these stylized facts using conceptual models in which technological innovation and diffusion are modeled explicitly (see, e. g., Romer, 1986, 1990, 1994; Grossman and

Helpman, 1991a, 199b, 1994; Lucas, 1988, 1990).⁶ Such models might be useful for integrated assessment modeling in that they might afford opportunities to represent a country's "technological uptake capacity" as a relatively simple function of measures of its macroeconomic performance. If such "reduced form" correspondences could be identified, the paucity of detailed microeconomic data that has stymied the research efforts reported above might be obviated. These notions remain untested conjectures, however, although one result of the work that has been done under this grant is to suggest that further inquiries into the implications of endogenous growth models for integrated assessment modeling might be useful.

ADDENDUM

In addition to the main body of work described above, DOE also provided a moderate amount of support for one of the investigators (Toman) to provide analytical input to staff in the DOE Policy Office on how policies to promote the development and diffusion of lower-emissions technologies might interact with incentive-based and regulatory policies to reduce greenhouse gas emissions. The broad question being addressed was, what kinds of policy "portfolios" make sense for greenhouse gas mitigation?

The investigator provided to the DOE Policy Office a draft report arguing that technology-promoting policies complement emissions reduction policies, but that the degree of complementarity (versus overlap) depended on how much ex ante inefficiency one expected to find in energy markets. In particular, if markets leave relatively few truly profitable energy-saving or energy-switching opportunities behind, then economic incentives to reduce emissions also will motivate substantial innovation and diffusion of new technology, with technology policy needed mainly to finance basic R&D and spread information. If, on the other hand, one believes that private market are quite unresponsive to economic inefficiencies then one believes in the necessity for regulatory mandates and more aggressive programs for government-sponsored technology diffusion. Material from the draft report was absorbed into DOE's final published report, "Policies and Measures for Reducing Energy Related Greenhouse Gas Emissions" (Technical Document DOE/PO-0047, July 1996).

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⁶ It must also be noted, however, that the empirical evidence for these new models is itself mixed, at best. For skeptical empirical treatments, see, e. g., Mankiw, Romer, and Weil (1992), Pack (1994), and Jones (1995a, 1995b).

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