THE JOURNAL OF INDUSTRIAL ECONOMICS 0022-1821
Volume XLIX September 2001 No. 3

ADOPTION OF A PROCESS INNOVATION WITH LEARNING-BY-DOING: EVIDENCE FROM THE SEMICONDUCTOR INDUSTRY*

Ricardo Cabral† and Michael J. Leiblein‡

This article analyzes the adoption of a new process technology in the global semiconductor manufacturing industry. The paper extends research on the relationship between learning-by-doing and technology adoption by examining the stability of learning effects across technological generations. While the results indicate that production experience with the immediately preceding technological generation is associated with a higher likelihood of adoption, we find no evidence that experience with older technologies or regional knowledge spillovers influence adoption. Finally, the results indicate that large firms and memory manufacturers have a higher likelihood of adoption than small firms and non-memory manufacturers, respectively.

I. INTRODUCTION

Recent work has argued that inter-firm differences in technological knowledge represent one of the most critical drivers of new technology adoption (e.g., Jovanovic and Lach [1989], Irwin and Klenow [1994], Parente [1994]). This paper empirically examines how the adoption of process technology used to manufacture semiconductor devices with 0.5 micron feature sizes varies with production experience derived from prior generations of process technology as well as access to geographic knowledge spillovers. Our results indicate that while a firm's cumulative production experience with the previous 0.6 to 0.75 micron generation of process technology has a statistically significant effect on the likelihood that the 0.5 micron technology will be adopted, no significant correlation

* The authors gratefully acknowledge financial support from PRAXIS XXI, Portugal, grant no. BD/2587/93, the Purdue Research Foundation, the Center for the Management of Manufacturing Excellence at Purdue University, and the Centers for International Business Education and Research at the University of South Carolina and the Ohio State University. The authors wish to thank Henry Chappell, Kin Blackburn, Jay Barney, Konstantina Kiousis, Jeffrey Reuer, the editor David Genesove, and two anonymous referees for helpful comments. The authors remain solely responsible for any errors. The views expressed in this paper are those of the authors and do not necessarily reflect those of Siemens AG.

† Authors' affiliations: Siemens AG, ICM CA CV B14, Otto-Hahn-Ring 6, D-81739 Munich, Germany.
email: ricardo.cabral@icn.siemens.de

‡ Fisher College of Business, The Ohio State University, Columbus, OH 43210-1399, USA.
email: leiblein.1@osu.edu

exists between adoption and cumulative production experience with earlier generations of the technology. Further, we find no evidence that spillovers within geographic clusters significantly affect adoption. The empirical analyses include controls for the influence of firm size, product market characteristics, and industry characteristics that have been highlighted in the existing empirical literature (e.g., Hannan and McDowell [1984], Levin, Levin, and Meisel [1987], Rose and Joskow [1990], Karshenas and Stoneman [1993], Dunne [1994], Baptista [2000]).

The paper proceeds as follows: Sections II and III describe the importance of process technology in the semiconductor industry and the data used in our empirical analyses. Section IV summarizes the statistical methodology used in this paper and presents our results. Section V concludes with a discussion of the findings and their implications for theory development as well as future empirical research.

II. TECHNOLOGY

The empirical setting for this paper is the adoption of a process technology used to manufacture semiconductor devices with sub-0.5 micron feature sizes. New semiconductor process technologies reduce the size of device components such as transistors allowing them to run faster while generating less heat. Improved speed and temperature characteristics have been shown to allow firms to enter into premium product-markets (Hazewindus and Tooker [1982, p. 88]), to improve production efficiency (Hazewindus and Tooker [1982, p. 86]; Gruber [1994]), and to displace products based on older process technologies (Gruber [1994, p. 9]). While desirable, the adoption of improved process technology is typically constrained by the production process quality or yield.[1] Previous research has shown that the yield rises with cumulative output (e.g., OECD [1985], Dick [1991], Irwin and Klenow [1994]).

While new process technology can be used in the production of different types of semiconductors (i.e., memories, microprocessors, analog integrated circuits, etc.) these sub-markets have different market structures.[2] For instance, while memory devices are frequently considered as commodities, there is significant product differentiation within the microprocessor industry. Intel is the dominant firm in the market for x86 compatible microprocessors, with 80% of worldwide sales (*The Economist*,

[1] The yield is the percentage of usable (good) semiconductor devices (chips) in a wafer at the end of the manufacturing process. In initial production runs the yield can be as little as 10% (Irwin and Klenow, [1994]; Dick, [1994]).

[2] Worldwide semiconductor sales in 1995 are estimated at US $150 Billion, with DRAM sales estimated at US $40 billion (Moody's Investor Service report 'Semiconductor Outlook for U.S. Based Companies,' April, 1998). X86 compatible microprocessor sales are estimated at US $15.4 Billion in 1996.

June 13, 1998, p. 62). Several fringe firms in the x86 market (e.g., AMD, CYRIX, and IBM) along with other firms that offer competing microprocessor architectures (e.g., Macintosh's PowerPC, Sun's Sparc, Digital's Alpha, and Transmeta's Crusoe) comprise the bulk of remaining industry sales (see also Diefendorff, 'Are there too many processors?' *Microprocessor Report*, v. 14, February 2000.). Thus, while the memory 'industry' is perceived to be quite competitive, the microprocessor 'industry' is perceived to be oligopolostic.

III. DATA

The data were obtained from a series of reports published by Integrated Circuit Engineering Corporation, VLSI Research, and Strategic Marketing Associates. These data provide firm-level accounting information as well as plant-level product-market, process technology, and production capacity data. This information is available for 152 U.S., European, and Asian semiconductor manufacturing firms for the years 1990 through 1995. The sample data represent nearly 60% of the semiconductor manufacturers in the world and each of the ten largest manufacturers as determined by annual revenue. North American firms constitute approximately half of the sample, with the remainder being evenly divided between Europe, Japan, and Southeast Asia. Nine of the original 152 firms were eliminated from the sample since they used a manufacturing process based on Gallium Arsenide (*GaAs*) rather than Silicon.[3] An additional 7 firms were deleted because they were formed after 1990 and thus represented a potential source of left-censoring bias. The final sample thus includes data for 136 firms from 1990 through 1995. Each firm that was acquired by another firm, or otherwise disappeared from the sample was treated as succumbing to a competing event and coded as censored. Firms that adopted the new technology are coded as right-censored in the adoption year. After controlling for censored observations the sample yields a total of 652 firm-year observations. From 1990 to 1995, 55 (41%) of the firms in the sample adopted sub-0.5 micron process technology.

Table I provides the definitions of the variables used in the empirical analysis. The table indicates that the variables used to measure production experience are based on plant-level production capacity cumulated over time. Since the number of semiconductor devices is a function of the size of the processed semiconductor wafer and the size of wafers varies across plants and over time, we normalize cumulative capacity as a function of wafer size. Where capacity data is missing, we estimate capacity as equal

[3] Gallium Arsenide (GaAs) is used primarily in high frequency applications (e.g. opto-electronics), requiring a substantially different fabrication process. Typically, GaAs plants adopt higher resolution technology earlier than Silicon plants.

TABLE I
SUMMARY OF VARIABLES

Variable Name	*Definition*
Adoption	Dependent variable. Adoption is set to 1 in the first year a firm adopts a sub-0.5 micron process technology, 0 otherwise.
Covariates used to estimate baseline hazard in semi-parametric models	
1990 to 1995	Year dummies for 1990, 1991, 1992, 1993, 1994, and 1995.
Industry-wide covariates used in fully-parametric models	
Log WorldExp	Worldwide experience with sub-0.5 micron process technology. Defined as the logarithm of the sum of cumulative production capacity with sub-0.5 micron technology across all firms.
Market Growth	Market growth for sub-0.5 micron semiconductor production capacity is proxied by the yearly percent change in worldwide contracted capacity for sub-0.7 micron production with respect to the two-year average production levels.
Time	Number of years since 1990. Used to parametrize a Gompertz baseline hazard.
Log Time	Logarithm of years since 1990. Used to parametrize a Weibull baseline hazard.
Firm-specific covariates used in semi- and fully-parametric models	
Log Firm Exp	Generic fabrication experience. Equal to the logarithm of total cumulative production experience (capacity) with all prior process technologies.
Log Firm Exp 1	Logarithm of the firm's cumulative experience with 1 micron and higher production process technologies (earliest process technology generation).
Log Firm Exp 2	Logarithm of the firm's cumulative experience with 0.75 - 1.0 micron production process technologies.
Log Firm Exp 3	Logarithm of the firm's cumulative experience with 0.6 - 0.75 micron production process technologies (most recent process technology generation).
Log Region Exp	Logarithm of the regional cumulative experience with sub-0.5 micron production process technology, where the regions are broadly defined as the U.S., Europe, Japan, and Rest of the World.
Small Medium Large	Following previous work (Angel, [1994], p. 93) and industry press (e.g., Dataquest) firms were classified as small, medium, or large. Small firms had sales under \$200m. Medium sized firms had sales between \$200m and \$1b. Large firms had sales above \$1b.[4]
Mem Product	Memory Product Market dummy. Equal to 1 for firms that manufacture memory devices and to 0 otherwise.
Micro Product	Microprocessor Product Market dummy. Equal to 1 for firms that manufacture microprocessors or digital signal processors (DSPs), and to 0 otherwise.

[4] Firm size is an endogenous covariate. Therefore, there is the potential for reverse causality. Sensitivity analysis using lagged size dummies showed that the results are not substantially affected by reverse causality. If lagged size dummies are used, the size dummies coefficient estimates are still strongly statistically significant, but large firms have a relatively lower hazard of adoption.

TABLE II
DESCRIPTIVE STATISTICS FOR FIRM-LEVEL VARIABLES[a]

	All Firms ($N = 136$)				Large-sized Firms ($N = 21$)				Medium-sized Firms ($N = 21$)				Small-sized Firms ($N = 94$)			
Variable	Mean	Stand. Error	Min	Max	Mean	Stand. Error	Min	Max	Mean	Stand. Error	Min	Max	Mean	Stand. Error	Min	Max
Log Firm Exp	3.748	2.637	0	8.900	7.167	2.012	0	8.900	4.494	2.414	0	7.140	2.817	2.081	0	7.150
Log Firm Exp 1	3.295	2.689	0	8.600	6.585	2.450	0	8.600	3.295	2.716	0	6.570	2.560	2.151	0	7.150
Log Firm Exp 2	0.781	2.070	0	8.680	2.891	3.514	0	8.680	1.542	2.562	0	7.030	0.140	0.776	0	4.560
Log Firm Exp 3	0.208	1.023	0	7.140	0.530	1.680	0	5.960	0.340	1.558	0	7.140	0.106	0.594	0	4.020
Mem Products	0.434	0.497	0	1	0.810	0.402	0	1	0.571	0.507	0	1	0.319	0.469	0	1
Micro Products	0.301	0.461	0	1	0.667	0.483	0	1	0.524	0.512	0	1	0.170	0.378	0	1

[a] Statistics describe the sample at the onset of data collection, in the year 1990.

to the reported capacity for the same plant in the subsequent year. If a plant opened before 1990 and its production start date is missing, we assume that production began in the year 1985. Sensitivity tests indicate that our results are robust to changes in assumed production start-year.

Following industry convention and prior work (e.g., Angel [1994]), we classified all firms in the sample as small, medium, or large based on their reported semiconductor revenue. Where sales data was missing, firms are classified according to the sales value in the most recent year reported. Similar to the results reported in Angel [1994], the vast majority of firms that fail to report sales data are recent start-ups. Since we expect smaller firms to have a lower hazard of adoption, eliminating these observations would have biased the results against finding statistical significant effect of firm size on adoption. Of the 136 firms in the sample, 74 were classified as 'small' during each of the six years of our study. Of these 74 firms, 11 adopted sub-0.5 micron process technology during the sample frame. An additional 13 firms were classified as medium-sized, 8 of which adopted. Another 21 firms were classified as large, of which 17 adopted. In addition, there were 22 firms that changed in classification between small and medium, of which 13 eventually adopted sub 0.5 micron technology. Five firms changed classification between medium and large. Each of these five firms adopted the technology. One firm changed from small to medium and then to the large category. This firm also adopted sub-0.5 micron technology. There was no contracted capacity of this technology prior to 1990, the first year of our data, for any of the firms in our sample. Table II presents descriptive statistics for the firm-level variables included in our analysis.

IV. RESULTS

For the empirical estimation, we assume that the adoption of a new process technology is generated by Cox's proportional hazard model (Kiefer [1988]). In order to estimate the results we use the complementary log-log discrete survival model (Allison [1982]), which is given as:

$$(1) \qquad \log[-\log(1-h_{it})] = \alpha_t + \beta_1 \cdot \mathbf{x}_{it1} + \cdots + \beta_K \cdot \mathbf{x}_{itK}$$

where h_{it} is the probability that firm i adopts the innovation in year t, given it had not yet adopted the innovation, K is the number of covariates, and x_{itn} are the covariates. The β_i coefficients are identical to the coefficients in the underlying proportional-hazards model, meaning that they have the same relative risk interpretation (Prentice and Gloeckler [1978]). The model is estimated by a maximum likelihood method.

Table III presents the non-parametric estimates of the hazard rate and the survivor function. The results are suggestive of an 'S-curve' adoption

TABLE III
NON-PARAMETRIC HAZARD AND SURVIVOR ESTIMATES

Spell Length	*Number of Firms At Risk*	*Number of Firms that Adopted*	*Number of Firms Censored*	*Hazard Rate*	*Survivor Function*
1	136	1	1	0.0074	0.9926
2	134	9	6	0.0672	0.9259
3	119	11	3	0.0924	0.8403
4	105	13	4	0.1238	0.7363
5	88	13	5	0.1477	0.6275
6	70	8	62	0.1143	0.5558
Totals	652	55	81		

pattern with very few firms adopting the new technology at its inception, a sharp increase in the hazard of adoption in years two through four, and evidence of a decline in the hazard rate in year six.

Table IV presents the results estimated with a series of parametric specifications. In Models I and II of Table IV we assume semi-parametric specifications that allow estimation of the underlying hazard function (Kiefer [1988]). In these two models we test arguments relating firms' adoption of new technology to asymmetries in the possession of stocks of related knowledge (e.g., Chari and Hopenhayn [1992], Irwin and Klenow [1994], Jovanovic and Lach [1989], Jovanovic and MacDonald [1994]). Model I examines the influence of experience with any prior technology on the likelihood of adoption. Model II examines the influence of experience for each specific generation of technology on adoption. The likelihood ratio test between the semi-parametric specifications (Models I and II) and the non-parametric estimator of Table III indicates that both Model I and II provide significantly better statistical fit than the non-parametric specification at the 1% level. Moreover, while Model I indicates that generic fabrication experience has no statistically significant impact on the hazard of adoption, Model II indicates that only experience with the most recent generation of technology affects adoption. A likelihood ratio test between the two models suggests that Model II is most appropriate and serves hereafter as the basis of discussion.

The results presented in Model II indicate that the hazard of adoption increases by approximately 12.6% with each doubling of cumulative output in the most recent generation of technology. While this finding suggests there is a linkage between learning-by-doing and process technology adoption, this result may also be due to the existence of other, unobservable, firm-specific cost efficiencies. For instance, firms endowed with this advantage would have lower marginal costs, higher market share, and thus a higher cumulative experience. In an influential paper that speaks to this possibility, Irwin and Klenow [1994] demonstrated that

TABLE IV
ESTIMATION FROM PARAMETRIC MODEL SPECIFICATIONS[b]

Variable	*Model I Generic Learning*	*Model II Generation-specific Learning*	*Model III Gompertz Distribution*	*Model IV Weibull Distribution*
1990 Dummy	−7.22** (1.13)	−6.61** (1.09)	—	—
1991 Dummy	−5.00** (0.62)	−4.39** (0.56)	—	—
1992 Dummy	−4.51** (0.70)	−4.15** (0.62)	—	—
1993 Dummy	−4.11** (0.76)	−3.88** (0.70)	—	—
1994 Dummy	−3.83** (0.83)	−3.63** (0.78)	—	—
1995 Dummy	−3.99** (0.90)	−3.81** (0.85)	—	—
Intercept	—	—	−1.55 (2.82)	−3.34 (1.58)
Time	—	—	0.83 (0.54)	—
Log Time	—	—	—	2.65* (1.30)
Log WorldExp	—	—	−0.62 (0.57)	−0.49 (0.37)
Market Growth	—	—	−0.01 (0.00)	−0.01 (0.01)
Log Firm Exp	0.11 (0.09)	—	—	—
Log Firm Exp 1	—	−0.02 (0.06)	−0.01 (0.06)	−0.01 (0.06)
Log Firm Exp 2	—	−0.01 (0.06)	−0.01 (0.06)	−0.01 (0.06)
Log Firm Exp 3	—	0.17** (0.06)	0.18** (0.06)	0.18** (0.06)
Log Region Exp	−0.01 (0.08)	0.02 (0.08)	0.01 (0.08)	0.01 (0.08)
Medium	1.70** (0.40)	1.69** (0.39)	1.67** (0.40)	1.67** (0.40)
Large	1.95** (0.52)	1.97** (0.54)	1.91** (0.55)	1.93** (0.54)
Mem Product	1.23** (0.41)	1.06** (0.41)	1.07** (0.41)	1.06** (0.41)
Micro Product	−0.33 (0.37)	−0.19 (0.40)	−0.27 (0.40)	−0.25 (0.40)
Log likelihood	−136.8	−133.8	−137.6	−135.0

[b] Standard errors are reported in parentheses.
* Statistically significant at the 5% level; ** Statistically significant at the 1% level.

production experience with the previous generation of Dynamic Random Access Memory devices (DRAMs) was associated with a lower marginal cost of production for the current generation of DRAMs. When this finding is coupled with our results, we are confronted with two pieces of evidence that suggest that experience provides firms with efficiency advantages that frequently allow firms to adopt new processes earlier than their competitors.

Moreover, in contrast to the typical presentation of experience effects as stable, the results in Model II indicate that the relationship between experience and new technology adoption is relatively short-lived. This finding parallels the relationship between production experience with the previous generation and the marginal cost of production with the current generation of DRAMs shown in Irwin and Klenow [1994]. The statistical insignificance of experience with older technologies suggests that knowledge derived from learning-by-doing rapidly becomes obsolete. Apparently, even if firm-specific effects exist, they dissipate within a few generations if not exploited.

Based on predictions from the agglomeration literature (e.g., Porter [1990]), we anticipated that knowledge spillovers within geographic regions where many participants were working on a new technology would enhance the likelihood of new technology adoption for all members of the region. However, the coefficient associated with our regional experience variable in Model II is not statistically significant. While contrary to our expectations as well as findings presented in Baptista [2000], this is in line with Irwin and Klenow's finding that learning spillovers between firms from different countries are not different from those between firms from the same country. These results may also indicate that the form of technological knowledge that drives early adoption of new processes is not readily transferable across firms and must be derived experientially. Such a result would support the notion of tacit, non-codifiable knowledge emphasized by Polanyi [1967].

The results presented in Model II also indicate that *Medium* and *Large* firms are 5 to 7 times more likely to adopt the new process technology than *Small* firms. This result is consistent with the Schumpeterian hypothesis and with earlier empirical research (e.g., Hannan and McDowell [1984, 1987], Levin, Levin, and Meisel [1987], Karshenas and Stoneman [1993], Baptista [2000]). Model II also indicates that memory device manufacturers are 2.9 times more likely to adopt the new process technology than non-memory manufacturers. This finding is consistent with arguments suggesting that product-market characteristics affect new technology investment as well as anecdotal evidence suggesting that it is both easier and less costly to introduce new semiconductor process technologies in memory devices due to their relatively simple product designs (e.g., Flamm [1993], Gruber [1994]). Contrary to the popular contention that microprocessor manufacturers are process technology leaders, our results do not suggest that the likelihood of adoption for microprocessor device manufacturers is statistically different from zero. In retrospect, this non-finding may be the result of the more complex design characteristics of microprocessors. These characteristics may increase the cost of adoption and may at the same time provide microprocessor manufacturers with other means of differentiation.

Models III and IV assume parametric specifications of the underlying hazard, both to facilitate comparison with prior work, and to introduce industry-level covariates. Importantly, the estimates of the firm-specific experience effect that are central to this study are robust across all model specifications. The results presented in Model III also suggest a 79% reduction in the adoption hazard with each doubling of worldwide experience with the new process technology. However, neither the cumulative number of adopters nor the rate of growth in demand have a significant effect on adoption. Prior studies have reported mixed results for these variables (e.g., Hannan and McDowell [1984, 1987], Levin, Levin, and Meisel [1987], Karshenas and Stoneman [1993], Baptista [2000]).

V. CONCLUSIONS

This article provides basic evidence on the drivers of new technology adoption in a sample of worldwide semiconductor firms. Following recent studies that have emphasized the relationship between a firm's stock of technological knowledge and the likelihood that it will adopt a new technology, the paper provides a test of the relationship between adoption and two important precursors to knowledge development: experience and access to knowledge spillovers. The primary result is that the relationship between new technology adoption and experience varies across generations of experience. Specifically, only experience with the immediate generation of technology significantly enhances a firm's likelihood of adopting a new technology. This suggests that the advantage associated with experience becomes rapidly obsolete. The paper also examines the extent to which the likelihood of new technology adoption is associated with potential knowledge spillovers within a geographic cluster of firms. No evidence is found to suggest that regional knowledge spillovers influence new technology adoption in the worldwide semiconductor industry.

The finding of differential firm experience suggests that different types of knowledge may be accumulated with experience in each given generation of semiconductor technology. In addition to suggesting that experientially generated advantages rapidly obsolesce, this finding calls into question the generalizability of findings on the role of 'generic' experience found in studies conducted in less technologically complex industries. Thus, one promising avenue for future research would be to identify the types of knowledge that easily spill across generations of technology or geographic regions from those types of knowledge that must be continually re-developed, generation by generation.

REFERENCES

Allison, P., 1982, 'Discrete-Time Methods for the Analysis of Event Histories', in Leinhardt, S. (editor), *Sociological Methodology,* (Jossey-Bass), pp. 61–97.

Angel, D. P., 1994, *Restructuring for Innovation: The Remaking of the U.S. Semiconductor Industry* (Guilford Press, New York).

Baptista, R., 2000, 'Do Innovations Diffuse Faster within Geographical Clusters?', *International Journal of Industrial Organization*, 18, pp. 515–535.

Chari, V. V. and Hopenhayn, H., 1991, 'Vintage Human Capital, Growth, and the Diffusion of New Technology', *Journal of Political Economy*, 99, No. 6, pp. 1142–1165.

Dick, A. R., 1991, 'Learning by Doing and Dumping in the Semiconductor Industry', *Journal of Law and Economics*, 34, pp. 133–159.

Dunne, T., 1994, 'Plant Age and Technology Use in U.S. Manufacturing Industries', *RAND Journal of Economics*, v. 25(3), pp. 488–499.

Flamm, K., 1993, 'Semiconductor Dependency and Strategic Trade Policy', *Brookings Papers on Economic Activity: Microeconomics*, No. 1, pp. 249–333.

Gruber, H., 1994, *Learning and Strategic Product Innovation: Theory and Evidence for the Semiconductor Industry* (North-Holland).

Hannan, T. and McDowell, J., 1984, 'The Determinants of Technology Adoption: The Case of the Banking Firm', *RAND Journal of Economics*, 15, pp. 328–335.

Hannan, T. and McDowell, J., 1987, 'Rival Precedence and the Dynamics of Technology Adoption: an Empirical Analysis', *Economica*, 55, pp. 155–177.

Hazewindus, N., with J. Tooker, 1982, The U.S. Microelectronics Industry: Technical Change, Industry Growth and Social Impact (New York: Pergamon Press).

Irwin, D. A. and Klenow, P. J., 1994, 'Learning-by-Doing Spillovers in the Semiconductor Industry', *Journal of Political Economy*, 102, pp. 1200–1227.

Jovanovic, B. and Lach, S., 1989, 'Entry, Exit, and Diffusion with Learning by Doing', *American Economic Review*, 79, No. 4, pp. 690–699.

Jovanovic, B. and MacDonald, G., 1994, 'Competitive Diffusion', *Journal of Political Economy*, 102, No. 1, pp. 24–52.

Karshenas, M. and Stoneman, P., 1993, 'Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model', *RAND Journal of Economics*, 24, pp. 503–528.

Kiefer, N., 1988, 'Economic Duration Data and Hazard Functions', *Journal of Economic Literature*, 26, pp. 646–679.

Levin, Sharon, Levin, Stanford and Meisel, J., 1987, 'A Dynamic Analysis of the Adoption of a New Technology: The Case of Optical Scanners', *Review of Economics and Statistics*, 69, pp. 12–17.

Organization for Economic Cooperation and Development, 1985, *The Semiconductor Industry: Trade Related Issues* (OECD, Paris).

Parente, S. L., 1994, 'Technology Adoption, Learning-by-Doing, and Economic Growth', *Journal of Economic Theory,* 36:2, 346–369.

Polanyi, M., 1967, *The Tacit Dimension*. Routledge and Kegan Paul, London.

Porter, M., 1990, *The Competitive Advantage of Nations* (Macmillan, London).

Prentice, R. L. and Gloeckler, L. A., 1978, 'Regression Analysis of Grouped Survival Data with Application to Breast Cancer Data', *Biometrics*, v. 34, pp. 57–67.

Rose, N. and Joskow, P., 1990, 'The Diffusion of New Technologies: Evidence from the Electric Utility Industry', *RAND Journal of Economics*, v. 21, No. 3, pp. 354–373.