MEXICO:
IN-FIRM TRAINING FOR THE KNOWLEDGE ECONOMY

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Background paper for the 2002 LAC Flagship Report
"Knowledge in Latin America and the Caribbean:
Reconsidering Education, Training and Technology Policies"[♠]

World Bank Policy Research Working Paper 2957, January 2003

[♠] This background paper was completed as part of the 2002 Flagship Report "Knowledge in Latin America and the Caribbean: Reconsidering Education, Training and Technology Policies". We gratefully acknowledge the research assistance of Luis Chalico and Marcela Rubio Sanchez (consultants) and programming provided by Alex Cano (INEGI-Aquascalientes), and we extend special thanks to Abigail Duran (INEGI-Aguascalientes) for facilitating this study. Send comments to htan@worldbank.org or gacevedo@worldbank.org

ABSTRACT
Mexico: In-Firm Training for the Knowledge Economy

Hong Tan and Gladys Lopez-Acevedo

In this paper, we used panel firm-level data to study in-firm training in Mexican manufacturing in the 1990s, its determinants, and effects on productivity and wages. Over this decade, not only did the incidence of employer provided training become more widespread among manufacturing enterprises, but a higher proportion of the workforce received training within firms. Technological change, as proxied by R&D, was an important driver of these training trends. It contributed to increased training over time through a rising share of firms doing R&D, but more importantly, through a greater propensity over time to train conditional on conducting R&D. We investigated the productivity and wage effects of training in several ways: (1) estimating the wage and productivity effects of training treated as endogenous; (2) using training event histories to examine the impacts of changing training status over time; and (3) looking at how training (and technology) practices changed where firms were located in productivity and wage distributions over the 1990s. Together, these cross-sectional and panel analyses found evidence that training had large and statistically significant wage and productivity outcomes, that joint training and R&D yielded larger returns than investments in just one or the other, and that both training and technology investments enabled firms to improve their relative position in the wage and productivity distribution between 1993 and 1999.

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I. INTRODUCTION

One consistent thread running through the literature on the Knowledge Economy[1] is the central role that human capital plays in the creation and effective use of knowledge (World Bank 1999, ILO 1998, OECD 2000). Human capital, broadly defined to include formal schooling and job training, contributes to economic growth through raising the productivity of workers and firms, and facilitating the adoption and effective use of new technologies. This latter effect, which Welch (1970) calls the "allocative effect" and Schultz (1975) "the ability to deal with disequilibria", is thought to be more valuable in the rapidly-changing and information-rich environment that characterizes the Knowledge Economy, and is thus more highly rewarded.

The empirical evidence on the links between human capital, on the one hand, and technological change and productivity and wage growth on the other, is strong. Microeconomic studies in the technology literature have identified the critical role of educated and trained workers in the innovative process[2] (Setzer, 1974), and industry-level studies have found more recent vintages of capital (a proxy for new technology) to be complementary with the education of the workforce (Bartel and Lichtenberg, 1987). Numerous studies using worker-level data have also shown that more educated and/or trained individuals are also more productive in a rapidly changing environment in which cognitive abilities to decipher and process new information are most important, and thus earn higher incomes (Welch, 1970; Mincer, 1989; Lillard and Tan, 1992; Foster and Rosenzweig, 1996).[3] There is also cross-national evidence from OECD countries that technical change in the industrial sector has been skill-biased[4], that is, associated with increased use of a more highly educated and skilled workforce (Berman, Bound and Machin, 1998; Doms, Dunne and Troske, 1997) as has technology transfer to developing countries over the 1980s and 1990s (Berman and Machin, 2000; Pavcnik, 2000).

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[1] We use the term "Knowledge Economy" loosely to refer to an economy where the principal driver of economic growth is not increases in factor inputs, but the expanded flow and use of knowledge derived from trade opening and global flows of foreign capital and technology, and made possible by the introduction of a new class of information and communication technologies (ICT).

[2] Traced over the life-cycle of a process innovation, Setzer (1974) found that skill requirements were high in the initial phase of development, but that they declined over time as the characteristics of the new technology became better understood and production became routinized.

[3] This finding applies equally well to agriculture and to non-agriculture. The Welch (1970) and Foster and Rosenzweig (1996) studies pertain to farmers' adoption of new and improved seed, fertilizer and growing methods in U.S. and Indian farming, respectively; Mincer (1989) and Lillard and Tan (1992) find evidence of both increased likelihood of training and higher returns to training in industries characterized by higher rates of total factor productivity growth.

[4] Much of this cross-national evidence relies on a limited measure of skill, namely, the proportion of workers that are non-production. However, this finding continues to be supported in countries with more detailed data on occupations and on educational attainment of the workforce.

Evidence on the specific role of in-firm training in the Knowledge Economy is more limited. In contrast to education, which is readily measured, much of this skills development occurs out of sight within or between enterprises, and is rarely captured in official data sources. What firm-level data exists, however, show in-firm training to be a major component of a country's investment in the human capital of its workforce rivaling, in some middle or high-income countries, its investments in formal education (see Mincer, 1994; Tan and Batra, 1995). In-firm training also plays a key intermediating role between education and technology acquisition and use. It complements the broad general knowledge that formal education and pre-employment training provides with firm-specific skills required to productively operate existing production processes. Here, the evidence suggests that employers tend to train the more educated who, being better learners, are also more likely to benefit from training. And the evidence also shows that in-firm training usually accompanies introduction of new technologies, possibly because a highly-skilled workforce is better able to master and effectively use new technologies (Tan and Batra, 1995; Biggs, Shah and Srivastava, 1995; World Bank, 1997; Tan, 2000).

In this paper, we exploit the availability of unique enterprise-level surveys to look at in-firm training in the manufacturing sector of Mexico, and its links to the Knowledge Economy. The 1990s was a decade of dramatic changes for Mexico, including economic shocks from the peso depreciation of 1993/94, trade opening and growing integration into North America with the enactment of NAFTA, significant inflows of foreign direct investment (FDI) into the country, and diffusion of new information and communication technologies (ICT) into industry. We are interested in how manufacturing enterprises responded—in their training practices—to the challenges and opportunities presented by these trends in technology and trade, and to what effect. Several surveys—Encuesta Nacional de Empleo, Salarios, Tecnologia y Capacitacion (ENESTYC), and Encuesta Industrial Anual (EIA)—collectively provide a unique opportunity to address these issues. The ENESTYC surveys, fielded several times over the 1990s, provide a wealth of firm-level information on the key variables of interest—in-firm training, different measures of technology, export orientation, productivity and wages. A sample of ENESTYC firms linked to the EIA panel can also be used to examine dynamic changes in some of these key variables over the 1993-1999 period.

The paper begins in Section II with an overview of the principal trends in in-firm training over the 1992-1999 period, in terms of numbers of workers trained, as well as the incidence of formal training and its sources across enterprises varying by size, technology, and exports. A formal analysis of the key determinants of training, including education, export orientation, foreign ownership, and research and development (R&D) is provided in Section III. Section IV turns to the wage and productivity outcomes of training. These outcomes are investigated in several ways: estimating the wage and productivity effects of training treated as endogenous; using training event histories to examine the impacts of changing training status over time; and looking at how the firm-level transitions over time within productivity and wage distributions are shaped by training practices. Section V concludes with a summary of the main findings.

II. OVERVIEW OF IN-FIRM TRAINING IN MEXICO

We begin by using the 1992 and 1999 ENESTYC surveys to paint a broad picture of trends over the 1990s in enterprise training in the manufacturing sector of Mexico. The ENESTYC is a large stratified (by employment size) random sample of manufacturing establishments surveyed by INEGI, the national statistical agency, to elicit detailed qualitative and quantitative information on employment structure, wages, technology adoption and use, and worker training. The ENESTYC survey has been fielded four times—1992, 1995, 1999 and most recently 2001—though only data from the first three surveys are available. Here, we tabulate the 1992 and 1999 establishment data (with sampling weights) to highlight trends over time in post-school training received by workers and in the incidence of training across establishments.

The analysis here, and in the remainder of this paper, will focus on formal training. The ENESTYC surveys elicited information on both informal training provided on-the-job by co-workers and supervisors, as well as formal training which have both theoretical and practical course-work. Formal training can either be provided in-house in company training programs or from a variety of external sources, both public and private. These external training providers include technology institutes, universities, employer associations, training firms and external training consultants. Because virtually all employers report providing some kind of informal OJT to its workforce, especially the new-hires, this variable is not a useful discriminator of employer interests in training. We therefore focus on more formal kinds of training where the cross-national empirical evidence suggests that productivity payoffs to skills investments may be greater (see Tan and Batra, 1995).

Table 1 shows the number of workers who receive formal training, both in terms of absolute numbers and as a proportion of the employed workforce in firms, in two years—1992 and 1999. The figures are presented by four firm sizes—micro firms with less than 15 workers, small firms with 16-100 workers, medium firms with 101-250 workers, and large firms with over 250 workers—and by training source—whether in an in-house company training program or from external training providers. The first panel shows that the number of workers getting any formal training in a given year in enterprises almost doubled over the 1992-1999 period—from over 760 thousand to 1,327 thousand by 1999. As a proportion of the employed workforce in firms, these numbers rose from 25 percent in 1992 to 38 percent in 1999. These are dramatic trends, and in subsequent sections, we ask whether these trends are related to trade or to increased adoption of new technology.

The second and third panels show the corresponding trends by training sources. Two points emerge. First, most of the rising trend in training appears to be associated with external training. There was only a modest increase over this period in the proportion of the workforce receiving in-house training—from 17 to 19 percent—but a dramatic increase in the proportion getting training externally—from 8 to 19 percent. Second, these same trends—for any formal training, and by training source—are mirrored in all firm sizes. What is encouraging is that formal training in micro, small and medium-size firms rose (in some cases, doubled) over this period, both from in-house and from external training sources. Only in the largest firm size category has the proportion of the workforce getting in-house training stayed roughly the same over time.

Table 1
Workers With Formal Training By Source – 1992 and 1999

Firm Size	1992			1999		
	Total with formal training	Total size of Workforce	% with formal training	Total with formal training	Total size of Workforce	% with formal training
Any Formal Training						
Micro <15	22,665	471,869	4.8	85,342	759,107	11.2
Small <100	87,242	610,973	14.3	241,786	757,126	31.9
Medium < 250	125,242	459,100	27.3	245,618	561,220	43.8
Large > 250	525,318	1,447,606	36.3	755,007	1,395,914	54.1
Total	760,466	2,989,548	25.4	1,327,753	3,473,367	38.2
In-House Training						
Micro <15	13,119	471,869	2.8	35,052	759,107	4.6
Small <100	44,455	610,973	7.3	117,668	757,126	15.5
Medium < 250	76,658	459,100	16.7	117,660	561,220	21.0
Large > 250	390,469	1,447,606	27.0	390,947	1,395,914	28.0
Total	524,701	2,989,548	17.6	661,327	3,473,367	19.0
External Training						
Micro <15	9,546	471,869	2.0	50,290	759,107	6.6
Small <100	42,786	610,973	7.0	124,118	757,126	16.4
Medium < 250	48,585	459,100	10.6	127,958	561,220	22.8
Large > 250	134,849	1447,606	9.3	364,060	1,395,914	26.1
Total	235,765	2,989,548	7.9	666,426	3,473,367	19.2

Source: 1992 and 1999 ENESTYC Surveys, INEGI
Note: Estimates are weighted.

Table 2 presents the corresponding training trends with establishments as the unit of observation. For each year, the table shows the number of establishments (weighted) that reported training—any formal training, and training by source—as well as training incidence relative to the underlying size distribution of firms in the manufacturing sector. In each firm size category, incidence of training among firms—any training and by source—rose over time. The trends, aggregating across size, are less dramatic because of the greater relative number of micro enterprises in the population in 1999 as compared to 1992, and because micro enterprises are generally less likely to provide formal training to their employees as compared to their larger counterparts. Finally, using establishments as the unit of observation masks the dramatic rise over time in external training. Since the share of the workforce getting external training more than doubled between 1992 and 1999 (from 8 to 19 percent), while incidence of external training among firms only increased modestly over this period (from 8.4 to 8.9 percent), it follows that employers were providing external training to more of their workers, conditional on training.

Table 2. Establishments Providing Formal Training By Source – 1992 and 1999

	1992			1999		
Firm Size	Firms with formal training	Total number of firms	% with formal training	Firms with formal training	Total number of Firms	% with formal training
Any Formal Training						
Micro <15	6,725	120,843	5.6	18,180	283,164	6.4
Small <100	5,701	13,117	43.5	10,392	19,810	52.4
Medium < 250	1,842	2,720	67.7	2,812	3,336	84.3
Large > 250	1,606	2,094	76.7	2,063	2,202	93.7
Total	15,874	138,774	11.4	33,447	308,512	10.8
In-House Training						
Micro <15	3,035	120,843	2.5	10,940	283,164	3.9
Small <100	3,197	13,117	24.4	7,420	19,810	37.4
Medium < 250	1,287	2,720	47.3	2,082	3,336	62.4
Large > 250	1,316	2,094	62.8	1,700	2,202	77.2
Total	8,835	138,774	6.4	22,142	308,512	7.2
External Training						
Micro <15	4,512	120,843	3.7	14,034	283,164	5.0
Small <100	4,433	13,117	33.8	8,458	19,810	42.7
Medium < 250	1,433	2,720	52.7	2,582	3,336	77.4
Large > 250	1,318	2,094	62.9	1,873	2,202	85.1
Total	11,696	138,774	8.4	26,947	308,512	8.7

Source: 1992 and 1999 ENESTYC Surveys, INEGI
Note: Estimates are weighted using sampling weights.

Who were these external training providers? Table 3 reports the principal sources of external training cited by firm respondents in the 1992 and 1999 ENESTYC surveys, separately by firm size. In addition to an open-ended "other" category, they included public and private universities and technology centers, public training centers, private companies, industry associations and chambers of commerce, and private training consultants. Particularly noteworthy is the high frequency with which respondents—both small and large—identified private companies, industry associations and to a lesser degree public centers for worker training as the principal providers of external training. Also noteworthy is the growing role, between 1992 and 1999, of private training consultants and equipment suppliers. In both years, public and private universities and technology centers only played a small role as providers of external training for firms.

Table 3. Providers of External Training for Employers—1992 and 1999 (Percent)

	Large	Medium	Small	Micro	Total
1992					
Public centers for worker training	11.7	11.1	13.9	14.5	13.5
Public universities & technology centers	7.2	4.6	2.9	5.4	4.5
Private universities & technology centers	3.6	3.0	2.0	6.1	3.7
Private companies	45.1	39.9	35.1	35.7	37.2
Training centers of industry associations	17.1	25.7	32.8	35.7	30.9
Private training consultants	12.1	13.8	11.5	1.8	8.6
1999					
Public centers for worker training	9.0	10.3	12.4	11.2	11.3
Public universities & technology centers	3.1	2.3	1.3	2.3	2.0
Private universities & technology centers	5.1	3.1	3.4	1.9	2.8
Private companies	57.1	51.1	40.7	27.0	36.4
Training centers of industry associations	8.0	17.3	16.7	22.4	18.8
Private training consultants	10.0	10.0	12.5	12.4	12.0
Equipment suppliers	6.0	4.3	6.3	10.0	7.9

Source: Authors' calculations from the 1992 and 1999 ENESTYC surveys.

What was driving these rising trends in training over the 1990s? Two hypotheses have been advanced in the literature—first, the effect of globalization and, in particular, the post-1994 growing integration of Mexico into the North American market under NAFTA; and second, the effect of technological change and adoption of new information and communication technologies (ICT), both of which are believed to be relatively skill-intensive (or skill-biased)—as possible explanations for the growing demand for training.

Table 4 provides some initial insights into the postulated relationships between training and crude measures of technology and trade for 1992 and 1999. In the first panel, the incidence of formal training is reported for firms cross-classified by size and by whether or not they did any research and development (R&D).[5] In the second panel, training incidence is reported by size and the export status of firms. The table provides casual evidence that both forces may have contributed to the rising trend in training incidence. In each year for any given size category, firms that conduct R&D or that export are invariably more likely to provide formal training than those that do not. Over

[5] Our use of R&D as a technology measure recognizes that firms can access or create technology through many other routes—through licensing, imported machinery, use of new information and communication technologies (ICT), joint-ventures, and inter-firm linkages. Because our focus here is on in-firm training, we use R&D as convenient proxy for a firm's technological capability.

time, training incidence trends upwards irrespective of technology or trade status, but these trends are especially pronounced for firms conducting R&D or exporting. It is unclear, however, which one of these forces is driving rising skill trends since both are correlated over time. In the following section, we analyze these trends more formally using a regression framework.

Table 4. Incidence of Training by R&D and Export Status – 1992 and 1999

	% Firms Training by R&D Status				% Firms Training by Export Status			
	1992		1999		1992		1999	
Firm Size	Do not do R&D	Do R&D	Do not do R&D	Do R&D	No Exports	Exports	No Exports	Exports
Micro <15	4.5	20.7	5.1	30.5	5.4	16.4	6.2	21.5
Small <100	41.0	49.7	46.0	71.7	42.3	50.3	47.7	70.2
Medium < 250	66.0	70.7	78.9	92.7	65.5	72.8	82.0	86.4
Large > 250	75.7	78.2	91.4	96.1	75.5	78.5	89.7	95.5
Total	8.8	36.1	8.1	46.6	10.0	49.4	9.0	58.7

Source: 1992 and 1999 ENESTYC Surveys, INEGI
Note: Estimates are weighted using sampling weights.

III. DETERMINANTS OF TRAINING TRENDS: 1992-1999

To gain insights into the proximate factors that have contributed to these training trends, we estimate probabilistic regression models relating the incidence and intensity of training to measures of technology, trade, and education, and controls for a variety of other factors. For training incidence, a 0,1 indicator variable for whether or not the employer provided any formal training to its employees in the past year, we estimate a probabilistic probit model. For training intensity, or the fraction of the workforce that received formal training, we rely on a tobit model where training intensity is censored (from below) for those firms that do not train.

We consider several sets of explanatory variables for firm attributes, worker characteristics, industry and location. These include:

- Firm attributes—indicator variables for firm size, foreign equity, use of automated and computerized machinery, R&D, exports, and union representation.
- Worker characteristics—percent of workforce that is female, and their schooling by level of education completed (secondary, college, post-graduate/professional certification).
- Industry—indicator variables for nine two-digit industries including food, textiles, wood products, paper, chemicals, non-metallic minerals, basic metals, metal products and machinery, and other industries.
- Location—indicator variables for nine broad geographic regions.

Table 5 reports the probit results for any formal training, separately for 1992 and 1999. Since probit coefficients are not readily interpreted, we report the marginal effects of a change in the explanatory variables on the probability of employer-provided formal training. Several results stand out. First, consistent with the previous cross-tabulations, firm size is a statistically significant predictor of training incidence with larger firms being more likely to provide formal training than smaller firms; significantly, this size effect becomes more pronounced over time. Second, foreign equity is associated with an increased likelihood of training, though this relationship is not monotonic with percent foreign ownership; by 1999, only joint-ventures with less than 50 percent foreign equity are more likely to train than local employers. Third, the probability of training is positively and significantly related to R&D, and the impact of R&D on training more than doubles between 1992 and 1999. The other technology measures—the share of computerized machinery—fared less well, and is not significantly associated with increased skill requirements.[6] Fourth, union representation is associated with a greater likelihood of training, a result that is echoed in other developing country training studies. Finally, trade—as represented by indicator variables for degree of export orientation—is positively associated with training in both years but this relationship is not robust. Trade may indirectly influence training through other means, such as through improved access to foreign technology, a question we return to later.

[6] This result stands in contrast to the OECD literature, and U.S. studies in particular, that show the strong positive association between use of advanced manufacturing technologies and computers on skill needs.

Table 5. Probit Estimates of Training Incidence – 1992 and 1999 Marginal Effects of Explanatory Variables (dF/dx)				
	1992		1999	
Explanatory Variables	dF/dX	z-stat	dF/dX	z-stat
% Female	-0.0134	-0.50	0.0069	0.45
% High school	0.0490	1.81	0.0242	1.61
% College	0.0139	0.44	0.0310	1.37
% Post-graduate	0.1847	2.90	0.1133	4.04
% Computer equipment	-0.0003	-0.77	0.0001	0.18
Do R&D	0.0895	4.32	0.1784	6.22
Indicator for Exports	0.0195	0.98	0.0064	0.36
Union representation	0.1405	4.48	0.1298	5.22
Foreign Equity <50 percent	0.0635	1.27	0.2291	2.80
Foreign Equity >=50 percent	0.0598	2.48	0.0665	1.73
Small 16-100 workers	0.1571	5.65	0.2143	9.28
Medium 101-250 workers	0.3223	7.89	0.4608	11.24
Large >250 workers	0.3869	8.23	0.5963	13.03
Textiles, clothing and leather	-0.0123	-0.62	0.0137	0.84
Wood products	-0.0036	-0.10	0.0228	1.07
Paper products	0.0068	0.21	0.0321	0.87
Chemical and oil derivatives	0.0363	1.13	0.0931	2.49
Non-metallic minerals	-0.0233	-0.75	0.0021	0.10
Basic metals	0.0115	0.29	0.0721	1.91
Metal products and machinery	-0.0096	-0.40	0.0393	1.97
Other industries	-0.0531	-3.25	0.0023	0.08
Pacific North	-0.0369	-1.58	0.0504	1.53
Pacific Central	-0.0112	-0.37	-0.0040	-0.20
Pacific South	-0.0489	-1.78	0.0575	1.54
Central North	-0.0212	-0.63	0.0097	0.39
Central	-0.0259	-0.97	0.0466	1.70
Central South	-0.0085	-0.32	0.0302	1.56
Gulf	0.0020	0.04	0.0668	1.68
South East	0.0544	0.91	0.0569	1.48
Number observations		5,066		6,620
Uncensored observations		0.348		0.307

Source: 1992 and 1999 ENESTYC surveys

Notes: 1) weighted regressions

2) Omitted groups: micro domestic firms, non-exporters in food, beverage and tobacco industries in the northern region.

Simulations suggest that the observed rising training trend over the 1990s is attributable principally to the changing relationships between training and its covariates, rather than the covariates themselves. Changes over time in the means of these covariates—for example, changing industrial structure, size distribution of firms and geographic location, R&D, and exports—are less important. In Table 6 we forecast what incidence of training would have been if (i) the estimated probit coefficients for 1992 were applied to the covariates prevailing in 1999 (effects of changing covariate means), and (ii) the probit coefficients for 1999 were applied to the covariates prevailing in 1992 (effects of changing relationships). Compared to the (predicted) incidence in 1992, the forecast incidence under (i) is barely changed, with only modest increases of training predicted among medium and large firms, and an overall decline in training (from 11.3 to 8.7 percent) because of the increased weight of micro and small firms in the 1999 population. In contrast, under (ii) when the 1999 coefficients are used for 1992, the forecast incidence of training in 1992 rises dramatically for all firm sizes, as well as overall.

Table 6. Simulations of Training Incidence (percent)

Firm Size	Predicted 1992 1992 Xs and 1992 βs	Predicted 1992 1999 Xs and 1992 βs	Predicted 1992 1992 Xs and 1999 βs
Micro	5.4	5.4	6.1
Small	43.7	37.4	52.7
Medium	66.9	69.0	80.0
Large	76.5	78.5	89.4
Overall	11.3	8.7	13.2

Source: authors' calculations

These results are essentially unchanged when tobit models are estimated for training intensity in 1992 and 1999.[7] In this model, training intensity is defined as the proportion of the establishment's workforce that received training, conditional on receiving training whether from in-house or external training providers. Most probit results carry over in this model specification, in particular, the key roles of education, R&D, firm size, foreign equity, and union representation. In each case, the statistical significance of these empirical relationships became stronger by taking into account, in addition to the probability of training, information on the share of the workforce receiving training. Export status, while positive, never assumed statistical significance as a determinant of training. Furthermore, for the uncensored sample (that is, firms that train), the tobit results indicate that the marginal effects of the key covariates—R&D, education, and firm size—on the share of workers trained are larger in 1999 as compared to 1992. In other words, not only do these covariates increase the likelihood of training over time, they are also associated with an increase in the proportion of workers trained within the firm.

Training by Skill Groups and Source

Did these training trends over the 1990s vary across skill groups and by source of training? Are the more skilled workers the principal beneficiaries of training, which would exacerbate skill gaps, or do trends favor less-skilled workers and so reduce skill differences? These questions can be addressed using training details elicited by the

[7] The tobit regression results for training intensity are available upon request from the authors, for the aggregate "any formal training" models, for in-firm and external training, and separately by occupation.

ENESTYC surveys separately for each skill group—managers, professional and technical employees, skilled production workers, and unskilled production workers. To fully exploit this detail, we "stack" the data treating each skill group in the firm as one observation, so there are multiple observations (up to 4) for each firm. In the analysis, we include indicator variables for skill groups so the likelihood of training is measured relative to unskilled production workers (the omitted group).[8] Additional information on the schooling and gender composition of each skill group allow us to compute and include in the regression model group-specific measures of years of schooling and share of female employees.

Table 7. Probit Estimates of Any Formal Training Pooled Across Occupations—1992 and 1999 Marginal Effects of Explanatory Variables (dF/dx)

Dep: Any formal training	1992		1999	
	dF/dx	z-stat	dF/dx	z-stat
Explanatory Variables				
Managers	-0.0188	-1.67	-0.0646	-5.76
Profesional & technical	0.0762	4.80	-0.0199	-1.91
Skilled production	0.0501	2.92	-0.0098	-1.06
Mean Years S (occupation)	0.0030	2.78	0.0055	4.47
% Female (occupation)	0.0076	0.45	-0.0220	-1.74
% secondary school	0.0075	0.38	0.0009	0.05
% college	-0.0300	-0.94	-0.0078	-0.23
% post-graduate	0.1056	2.17	0.1133	3.42
% machinery computerized	-0.0000	-0.03	0.0003	0.79
Do R&D	0.0586	4.18	0.1330	5.99
Export indicator variable	0.0054	0.44	0.0085	0.65
Unionized	0.0956	5.33	0.0802	4.80
Small firm size	0.0749	3.99	0.1350	7.64
Medium firm size	0.1973	7.40	0.3208	10.96
Large firm size	0.2690	8.45	0.4212	12.93
Foreign equity <50	0.0807	2.25	0.1201	2.49
Foreign equity >=50	0.0691	4.17	0.0057	0.30
Number of Observations	17,368		20,412	
Pseudo R-2	0.3021		0.2948	

Source: 1992 and 1999 ENESTYC surveys

Notes: 1) weighted regressions
2) Industry and region indicator variables included but not reported.
3) dF/dx reported instead of probit coefficients, and represent change in the the probability of training with a change in the explanatory variable
4) corrected for common error term across occupations from the same firm.

[8] The regressions also control for the correlated errors of all observations drawn from the same firm ("the so-called family effect")

Table 7 shows the 1992 and 1999 probit results for any formal training, pooling across skill groups. Most of the training results for firm size, R&D, foreign equity, and exporting carry over, and will not be repeated here so as to focus on the results by occupation or skill groups. For ease of interpretation, the table reports the marginal effects on training of small changes in the covariates. First, consider the occupation-specific results. For a given occupation, an increase in average years of schooling raises the likelihood of training, a relationship that persists and becomes quantitatively more important over the 1990s. In both years, there is no relationship between training and the share of females in that occupation. Holding education and proportion female constant, the results suggest that over time, the likelihood of in-firm training increased for the less skilled groups. In 1992, professional, technical and skilled production occupations (but not managers) were more likely to receive training than unskilled production workers. By 1999, the likelihood of training for unskilled production workers was no different from the other occupations, and was significantly greater than for managers.

In addition to the occupation-specific measures, the model included measures of schooling distribution in the firm as a whole to investigate whether a given skill group's likelihood of training might be influenced by the educational mix of the whole workforce. For example, there is interest in knowing whether unskilled workers benefit—in terms of skill acquisition—from working alongside more educated co-workers. Table 6 suggests that they do. Holding constant group-specific attributes, each skill group's likelihood of training is positively influenced by the post-graduate share of employees in the firm, but not by the shares of secondary school and college-educated workers. Highly-educated employees—professionals, engineers, scientists and technicians—have been shown to play a pivotal role in early adoption and use of new information and communications technologies (Tan, 2000). Use of ICT is likely to require complementary investments in training at all skill levels if the new technologies are to be used effectively.[9]

Table 8 reports the corresponding probit results for training incidence by source of training—whether from in-house training programs, or provided by external training institutions or consultants. Like Table 7, these results highlight several changes over the 1992 to 1999 period: (i) an increased likelihood of training for unskilled production workers relative to other more skilled groups; (ii) the continued and increased importance of years of schooling on training; and (iii) highly-educated professional and technical staff and their role in increasing training for all skill groups.

Distinguishing between sources of training yields several additional insights. First, R&D has a much greater impact on the likelihood of external training than on in-house training programs. In 1992, the marginal effects of R&D on in-house training is 1.6 percent, while the effect on external training is 3.1 percent. By 1992, both marginal

[9] The "O-ring hypothesis" may provide one explanation for the presence of such neighborhood effects. In essence, it argues that firms will pay wage premiums to all workers, skilled or unskilled, when complex technologies are used. To function effectively, all components—both high-tech components and low-tech ones made by unskilled workers—must meet high standards of reliability, with catastrophic consequences when a low-tech component such as an "O-ring" fails. This might explain why firms employing a high proportion of highly-skilled workers (a proxy for the use of new and complex technologies) are also more likely to train their unskilled production workers.

effects more than double—to 3.7 and 7.8 percent, respectively—but keep their relative importance by training source. Second, computerization becomes marginally significant as a determinant of training by 1999, but only for in-house training. Third, union representation in both years raises the likelihood of training, but the marginal effects of union status is more important for in-house provision of training (4-5 percent) than for external training (about 2.5 percent), possibly unions are more effective getting in-house company training programs included in collective bargaining. Fourth, there is some evidence that training differentials between domestic companies and firms with foreign equity narrowed over the 1990s. Finally, consistent with overall trends reported previously in Section II, training from both sources rise with firm size, but only external training shows signs of increasing over time with size. Thus, compared to micro and small firms, larger firms are increasingly sourcing their training from external sources over the 1990s.

Table 8. Probit Estimates of In-House and External Training Pooled Across Occupations—1992 and 1999 Marginal Effects of Explanatory Variables (dF/dx)

Dep: In-house or external training	1992		1999	
	In-House	External	In-House	External
Explanatory Variables				
Managers	-0.3033**	0.0233**	-0.0331**	-0.0294**
Profesional & technical	0.0075	0.0952**	-0.0139**	-0.0023
Skilled production	0.0046	0.0504**	-0.0071	-0.0031
Mean Years S (occupation)	0.0004	0.0022**	0.0017**	0.0039**
% Female (occupation)	0.0059	-0.0031	-0.0083	-0.0127
% secondary school	0.0139	-0.0088	0.0092	-0.0153
% college	-0.0002	-0.0145	0.0283	-0.0460**
% post-graduate	0.0243	0.0584**	0.0341*	0.0626**
% machinery computerized	-0.0000	0.0001	0.0003*	-0.0000
Do R&D	0.0164**	0.0311**	0.0369**	0.0780**
Export indicator variable	0.0050	-0.0002	0.0065	0.0025
Unionized	0.0561**	0.0264**	0.0429**	0.0271**
Small firm size	0.0246**	0.0546**	0.0614**	0.0773**
Medium firm size	0.0875**	0.1226**	0.0997**	0.2649**
Large firm size	0.1547**	0.1457**	0.1555**	0.2822**
Foreign equity <50	0.0016	0.0565**	0.0110	0.0662*
Foreign equity >=50	0.0281**	0.0265**	-0.0058	0.0041
Number of Observations	17,368	17,368	20,412	20,412
Pseudo R-2	0.3045	0.2775	0.2565	0.2609

Source: 1992 and 1999 ENESTYC surveys

Notes: 1) weighted regressions
2) Industry and region indicator variables included but not reported.
3) dF/dx reported instead of probit coefficients, and represent change in the the probability of training with a change in the explanatory variable
4) corrected for common error term across occupations from the same firm
5) ** and * denote statistical significance at the 1% and 5% levels.

Joint Investments in Training and R&D

Thus far, we have treated R&D as being an exogenous determinant of training propensities by employers even though the causality could run the other way, that is, from skills development and training to R&D. In the technology literature, the typical argument is that a skilled and trained workforce facilitates employer investments in new technology and R&D. New technology is seldom adopted as is—its attributes are uncertain and often unknown—and a complex process of experimentation and adaptation by engineers and highly skilled workers is usually required to realize its full productive potential (see Schultz, 1975; Bartel and Lichtenberg, 1987).

While causality in the Granger-sense is impossible to ascertain without long panel data, some insights may be gained by looking at the joint realization of training and R&D investments. We estimate a bivariate probit model of training and R&D, first to test if the two outcomes are jointly determined (from the correlation, ρ, in the two equations) and secondly, to ascertain whether one outcome is more or less likely without the other. For example, what is the likelihood that employers engage in R&D without complementary investments in worker training or, conversely, is training likely without R&D. Table 9 report selected results of estimating the bivariate probit models for 1992 and 1999. Wald tests that $\rho = 0$ yield chi-squared statistics that reject the null hypothesis that training and R&D decisions are independently determined in 1992 as well as in 1999.

Table 9. Bivariate Probit Models of Training and R&D – 1992 and 1999

	1992				1999			
Explanatory	Train		Do-R&D		Train		Do-R&D	
Variables	Coeff.	Z	Coeff.	Z	Coeff.	Z	Coeff.	Z
% Female	-0.1021	-0.45	0.0741	0.23	0.0133	0.10	-0.3456	-1.93
% Secondary Ed	0.3746	1.62	-0.3730	-1.63	0.1721	1.36	-0.1831	-1.15
% College Ed	0.1996	0.72	0.7172	1.94	0.3172	1.66	0.4116	1.92
% Post-graduate	1.6840	3.12	1.3537	3.13	1.1037	4.50	0.9305	3.70
% Computers	-0.0014	-0.51	0.0043	1.80	0.0024	0.65	0.0047	1.64
Export indicator	0.1770	1.11	0.1310	1.00	0.2230	1.80	0.6328	4.35
Unionization	0.8279	4.76	0.3814	2.89	0.7261	5.26	0.2710	2.03
Foreign equity <50	0.3570	1.19	-0.2212	-1.25	0.8786	2.63	-0.2940	-1.38
Foreign equity >50	0.3163	2.08	-0.4235	-2.83	0.3348	1.59	-0.2712	-1.64
Small firm	0.8884	6.11	0.6015	4.72	1.0769	9.62	0.6444	4.75
Medium	1.3540	8.44	0.7556	5.90	1.6896	12.29	0.7823	5.18
Large	1.5262	8.76	0.8082	5.91	2.0520	14.33	0.9176	5.50
Constant	-1.7952	-5.31	-1.7717	-8.08	-2.1850	-11.5	-1.8181	-7.71
No. observations	5,066				6,620			
Rho	0.3039				0.4691			
Chi2-test that rho=0	20.268				42.576			

Source: 1992 and 1999 ENESTYC surveys

Notes: 1) dummy variables for 9 two-digit industries and 8 regions included but not reported. Omitted groups: micro domestic firms, non-exporters in food, beverage and tobacco industries in the northern region.

The bivariate probit estimates of training and R&D are not without interest. Several factors shaping these two decisions are apparent in Table 9. First, both training and R&D propensities rise strongly with firm size. Second, as compared to local firms, companies with foreign equity are more likely to train but less likely to report R&D, possibly because foreign partners bring in technology whose attributes are already well-known. This relationship, however, is not statistically robust. Third, the impact of exports on either decision is negligible is 1992, but this changes by 1999 especially for the R&D decision. The impact of exporting on training is small, but the impact on R&D is large and statistically significant. NAFTA may have created competitive pressures for exporting firms to improve their technology through R&D, and indirectly through R&D to upgrade worker skills. Union representation or collective bargaining is associated with increased training and R&D in both years. Finally, the educational distribution of the workforce plays a key role in <u>both</u> decisions. As before, the share of the workforce with a college education, post-graduate in particular, appears to drive training by employers; here, the results suggest that a highly educated workforce also independently increases the likelihood of employer investments in new technology through R&D.

Table 10. Predicted Joint Probabilities of Training and R&D – 1992 and 1999

	Predicted Probabilities (%)				Conditional Probabilities (%)	
1992	TR=1 R&D=1	TR=0 R&D=1	TR=1 R&D=0	TR=0 R&D=0	TR=1 given R&D=1	R&D=1 Given TR=1
Micro	1.00	5.32	4.38	89.30	14.20	16.92
Small	17.37	11.82	26.43	44.37	57.39	38.21
Medium	29.30	7.83	37.78	25.09	77.45	42.78
Large	34.20	5.98	41.63	18.18	84.28	44.54
1999						
Micro	1.35	3.74	4.16	90.75	24.00	20.76
Small	18.77	7.12	27.33	46.78	69.46	38.06
Medium	37.08	2.96	41.71	18.25	91.34	45.35
Large	46.59	1.42	43.81	8.19	96.69	50.78

Source: authors' calculations based on results from 1992 and 1999 ENESTYC surveys
Notes: TR=training, R&D=do R&D.

The joint probabilities of training and R&D predicted by this model are tabulated above in Table 10. First, consider the left panel which reports the predicted probabilities of the four realizations of training and R&D: (1) both train and do R&D; (2) train but no R&D; (3) R&D but do not train; and (4) neither train nor do R&D. In both years, the probability of (1)—both training and doing R&D—rises with size while the probability of (2)—neither training nor doing R&D—falls with size. Of greater interest are the predicted probabilities of (2) and (3), that is, of investments in one activity but not the other. They show that while a substantial number of (especially large) firms train but report no R&D, the likelihood that firms do R&D without training is extremely low. In 1999, no more than 7 percent of firms in any given size category are ever predicted to report R&D without training. In short, while firms may train for a variety of reasons, they seldom engage in R&D without complementary investments in worker skills.

IV. WAGE AND PRODUCTIVITY OUTCOMES OF TRAINING

In this section, we turn our focus on the wage and productivity outcomes of infirm training. Training outcomes are linked to its determinants—the focus of the previous section—by the underlying behavioral model of training as an investment. That is, that profit maximizing employers will invest in training only when the discounted present value of the returns from training exceed or equal training costs; no training investments take place when costs exceed expected future returns. If training takes place, we should expect its realization to be associated with higher productivity, holding constant other productivity-augmenting factors, as well as higher wages, that is, provided employers share some part of the higher productivity with its employees.[10]

We look at three dimensions of the postulated relationship between training and its wage and productivity outcomes. First, we examine the cross-sectional association between outcomes and training treated as an endogenous choice variable. When training is endogenous, simply regressing wages or productivity on a training indicator variable could potentially result in biased estimates of training effects. Second, we exploit firm-level panel data—for 1993-1996—in the Annual Survey of Manufacturing (EIA) to estimate the impacts on wages and productivity of changes over time in training. We ask: compared to firms that do not train, are the wage and productivity outcomes larger for firms that train continuously, start training, or stop training; if so, are the relative rankings of the size of these effects ordered in a way consistent with these changes in training over time? Finally, we explore the evolution over time of firm-level productivity and wages, and how firms change their relative positions in the productivity and wage distributions between 1993 and 1999. Specifically, we ask whether these transitions—up or down these distributions—are shaped by training event histories, and by other investments in technology and trade.

Two different data sources are used to address these issues. The cross-sectional analyses relating outcomes to endogenous training relies on the same 1992 and 1999 ENESTYC surveys used in the previous section. Because of concerns about the quality of production data, this first analysis focuses only on the wage effects of training.[11] For the panel analyses, we rely on linked EIA-ENESTY surveys. The EIA, available annually from 1993 to 1999, contains detailed and comparable information on the productivity and wage outcomes of interest, but not in-firm training; training information elicited in the ENESTYC survey can be brought to bear at three points in time—1993,

[10] In his seminal study, Becker (1964) notes that when human capital is firm-specific, employers and workers will have an incentive to share both the costs and the resulting returns to training because of the bilateral monopoly issue that arises from its firm-specific nature; without cost-sharing, no investments are made in these idiosyncratic skills. Using linked worker-firm data from Mexico, both Tan (1995) and Lopez-Acevedo and Chalico (2002) find evidence that training effects are larger for productivity than for wages, suggesting that employers and workers share in the costs and returns to training.

[11] Using the multivariate outlier detection procedure suggested by Hadi (1992), a number of wage outliers were identified in ENESTYC, the 1999 survey in particular, and cleaned. Time limitations precluded a similar data cleaning exercise for the productivity data, which in any case was not reported consistently in the two surveys. These concerns suggested an initial focus on wages using the ENESTYC, turning to the EIA surveys which collected comparable production data over time.

1995, and 1996—for a sub-sample of EIA firms. We caution that this sub-sample of firms differs from the population at large in two important respects: they tend to be larger, and as survivors over the 1993-1996 period, are probably more productive on average than the typical firm. [12]

Outcomes with Endogenous Training

We are interested in estimating the effects δ of a binary (0,1) training variable, T_i on two outcomes Y_i—hourly wages and total factor productivity (TFP)—controlling for other observable and unobservable (to us) factors X_i that also affect Y_i. In the previous section, we noted that the training decision is systematically related to observable factors such as trade, technology and other firm and industry attributes. If so, these systematic differences between training and non-training firms need to accounted for so as not to confound the δ effects of interest. More problematic is when the training decision is endogenously determined together with the outcome variables Y_i by common, unobserved factors.

The solution is to estimate the probabilistic training decision along with the productivity or wage equation using maximum likelihood methods. Following Heckman (1979), Barnow, Cain and Goldberger (1981), and Bjorklund and Moffitt (1987), we can write the outcome and training equations as a system of equations:

$$
\begin{aligned}
Y_i &= \beta . X_i + \delta . T_i + \varepsilon_i \\
T_i^* &= \phi . Z_i + \mu_i \\
T_i &= 1, \quad \text{if } T_i^* > 0 \\
&= 0, \quad \text{otherwise}
\end{aligned}
$$

where outcome Y_i is a function of explanatory variables $X_{i,}$ the realization of training $T_{i,}$ and an error term $\varepsilon_{I;}$ and T_i^* is a latent (unobserved) variable representing the net expected present value of returns to training. T_i^* is assumed to be a function of Z_i, which may include a subset of variables in $X_{i,}$[13] and an error term μ_i. In the training equation, the employer provides training—T_i=1—if the net present value of training returns T_i^* are positive; otherwise, T_i=0 and the employer does not train. The estimation problem arises when there is a non-zero correlation between ε_i and $\mu_{i,}$ the error terms in the outcome and training equations, since estimates of δ are biased upwards (overstated) if the correlation ρ is positive, or biased downward if ρ is negative. [14] In this case, joint estimation of the system of equations via maximum likelihood methods is required; when ρ is zero, unbiased estimates of δ can be obtained by ordinary least-squares (OLS) regression methods.

[12] There is a theoretical and empirical literature on industry evolution and patterns of productivity growth among entrants, exits, and surviving firms. Compared to surviving firms, firms that exit the industry tend to have both lower initial levels of productivity, and productivity levels that decline as they approach the exit point. For example, see Jovanovic (1982), Olley and Pakes (1996), Roberts and Tybout (1996).

[13] Two exclusionary restrictions are required to identify the training equation. These are described in the text accompanying the results.

[14] See Greene (2000) for an extended discussion of this point.

In the analysis that follows, we report estimates of the wage effects of training, δ using several specifications of the training indicator variable. We defer analysis of productivity to a subsequent section using the annual industrial survey (EIA). Here, the focus is on the logarithm of monthly wages per worker, including base wages, overtime and bonuses, as the outcome measure. This wage variable, created by dividing total monthly wage bill by the number of paid employees, was extensively cleaned for outliers with exceedingly high or low wage rates.[15]

Table 11 reports selected wage regression results from different specifications of the training indicator variable, separately by year—1992 and 1999—to test for differences in outcomes over time. In the first two model specifications, which provide a useful baseline, training is treated as being exogenously determined and the models are estimated by OLS. One considers an indicator variable for any formal in-firm training; the other considers training by source, either provided in-house in company training programs, or provided by external training providers and institutions. The third model treats the binary training variable as being endogenously determined, and the training and wage equations are jointly estimated by maximum likelihood methods. Because the training probit results resemble those presented earlier, they are not reported in Table 11. The fourth model treats both training and R&D as being jointly determined by a bivariate probit model. We estimate this wage model by OLS[16], including as regressors predicted values of the joint training and R&D binary indicators—both train and do R&D, train only, and conduct R&D only—with neither train nor do R&D as the omitted category.

Compare the wage effects of training, δ, estimated by the different model specifications. In the first two columns of Table 11, when training is treated as being exogenous, OLS yields baseline estimates of the wage effects of training that range from 8.8 percent in 1992 to 13.4 percent in 1999. When disaggregated by source of training (column 2), estimates of δ range from 5-6 percent in 1992 to 7-8 percent in 1999. Both sets of results suggest that the returns to training have risen modestly over time. In the third column, the MLE estimates of δ are about 43 percent in both years, significantly larger—by a factor of five—than those estimated by OLS. OLS understates the wage effects of training, δ by ignoring the large, negative correlation ρ between the error terms in the wage and training equations.[17] One possible explanation for the negative correlation is that firms are more likely to train when demand (and the opportunity cost of

[15] Most of the outliers were concentrated among micro enterprises, especially in the 1999 survey, and this suggested the dropping of all micro enterprises (less than 15 employees) from the analysis, at least for the analysis that pooled wage information across the four occupational/skill groups; they are included in the analysis by occupation.

[16] Maximum likelihood routines to estimate this trivariate normal model are not readily available. Inclusion of the training and R&D predicted values yields consistent estimates of the parameters of interest, but their standard errors are incorrect. In future research, an attempt will be made to correct the standard errors using the procedure suggested by Greene (2002).

[17] In 1992 and 1999, ρ varies between –0.5 and -0.4, and Wald tests of the null hypothesis that $\rho=0$ are decisively rejected in both years.

Table 11. Wage Regressions with Different Training Specifications								
1992 ENESTYC (4,356 obs)	OLS – Exogenous Training		OLS – Exogenous Training		MLE Endogenous Training		OLS – Bivariate Training & R&D	
	Coef.	t	Coef.	t	Coef.	z	Coef.	t
Constant	6.5027	**	6.5131	**	6.4332	**	6.3615	**
Mean Schooling	0.0155	*	0.0147		0.0144		0.0077	
% Female	-0.3642	**	-0.3696	**	-0.4125	**	-0.3565	**
% Managers	2.0306	**	2.0029	**	1.9578	**	2.1216	**
% Prof. & Tech.	1.0598	**	1.0706	**	0.9551	**	1.0330	**
% Skilled Prod.	0.2055	**	0.2025	**	0.1748	**	0.1982	**
Foreign K <50%	0.0771		0.0741		0.0787		0.0629	
Foreign K>50%	0.2152	**	0.2126	**	0.2084	**	0.2327	**
Export <50%	0.0518		0.0514		0.0425		0.0141	
Export >50%	0.0418		0.0462		0.0281		0.0209	
Training Indicator	0.0882	**			0.4359	**		
In-house Training			0.0553	*				
External Training			0.0648	**				
TR=1 R&D=1							0.5362	**
TR=1 R&D=0							0.4174	**
TR=0 R&D=1							0.4163	
Rho ρ					-0.5365			
Wald-test χ^2					15.33	**		
1999 ENESTYC (4,653 obs)								
Constant	6.3215	**	6.3424	**	6.2309	**	6.2077	**
Mean Schooling	0.0245	*	0.0245	*	0.0213	*	0.0157	
% Female	-0.2709	**	-0.2692	**	-0.2345	**	-0.1359	
% Managers	2.0776	**	2.0310	**	2.3894	**	1.9470	**
% Prof. & Tech.	0.5564	**	0.5726	**	0.4401	**	0.5290	**
% Skilled Prod.	0.0095		0.0080		-0.0078		0.0275	
Foreign K <50%	0.0064		0.0167		-0.0490		0.0980	
Foreign K>50%	0.3350	**	0.3395	**	0.3017	**	0.4073	**
Export <50%	0.1395	**	0.1380	**	0.1115	**	-0.1507	
Export >50%	0.0894		0.0919		0.0532		-0.1720	*
Training Indicator	0.1345	**			0.4274	**		
In-house Training			0.0841	**				
External Training			0.0774	*				
TR=1 R&D=1							1.4061	**
TR=1 R&D=0							0.1957	
TR=0 R&D=1							1.3235	
Rho ρ					-0.4109			
Wald-test χ^2					14.13	**		

Source: 1992 and 1999 ENESTYC Surveys

Notes: 1. Regressions also included firm size, industry and region dummy variables.
2. Instruments for MLE training equation included years in operation, R&D, computerization, and union representation.

labor's time) is low.[18] We are not convinced by this explanation but are unable to offer an alternative. We note, however, that several other studies have reported similar findings with endogenized training for a variety of countries at different stages of development, e.g. Dearden, Reed, and Van Reneen (2000) on British industry, Tan and Batra (1995) on manufacturing in five middle-income countries in East Asia and Latin America, and Nielsen and Rosholm (2002) on three African countries.

The fourth column of Table 11 reports OLS estimates of the wage effects of predicted joint training and R&D decisions. Recall that these are the predicted joint probabilities from a bivariate probit model (Tables 10 and 11) that, by construction, are uncorrelated with the error terms in the training and R&D equations. They are thus also uncorrelated with the error term in the wage equation, and yield unbiased parameter estimates of δ. Like the endogenous training specification, this model yields wage effects δ that are large and positive, especially for the predicted joint probability of both training and doing R&D.[19] For this group, δ is estimated to be 54 percent, rising over time to 140 percent. For the other groups—training only or doing R&D alone—the estimated δ's are also positive, but they are not consistently significant.

The wage results for the other variables are also of interest. First, mean years of schooling are associated with wage returns of between 1.5 and 2.5 percent, with an apparent rise in schooling returns over time. Second, controls for gender indicate that employers tend to pay women employees lower wages, about 35-40 percent less in 1992 but declining to between 14-27 percent less by 1999. Third, compared to unskilled production workers, managers appear to maintain their relative wage position over the 1990s, while the wage relativities of skilled production workers and professional and technical workers fell over this period. Fourth, majority foreign-owned firms appear to pay a wage premium of 20-23 percent in 1992, rising to 30-40 percent by 1999. Finally, while exporting is not related to wages in 1992, it becomes positive and statistically significant by 1999.

Tables 12 and 13 report the corresponding OLS and MLE estimates of δ by four occupation groups, separately for 1992 and 1999. Three main findings emerge from these analyses disaggregated by occupation. First, echoing the previous findings for the wage effects of training at the level of the firm, the OLS estimates of δ are understated by treating training as exogenous. The OLS estimates of δ range from 5-24 percent in 1992, but are only statistically significant for some occupations; in 1999, estimates of δ range between 3 and 10 percent, but these never attain statistical significance. Second, MLE estimates of δ are positive, large and statistically significant in both years, ranging between 39 and 107 percent in 1992 and between 19 and 72 percent in 1999. Thus, it appears that the returns to training may have declined over the 1990s. Finally, the results are consistent with higher relative returns to training for more skilled workers—72 to 107 percent for managers, and 24 to 39 percent for unskilled production workers.

[18] Dearden, Reed and Van Reneen (2000) make this argument to explain the tripling of productivity and wage impacts of training when training is endogenized.

[19] The standard errors of these predicted training-R&D variables have not been adjusted and, as such, should be treated with caution.

Table 12. OLS and MLE Wage Regressions with Training Indicator Variable 1992 ENESTYC by Occupation

	Unskilled Production		Skilled Production		Professional & Technical		Managers	
OLS-Exogenous Training Variable	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Mean S in Occ.	0.0316	**	-0.0040		0.0330	**	0.0420	**
% female in Occ.	-0.2321	**	-0.5400	**	-0.2537	**	-0.3721	
Foreign equity <50 %	0.1067	*	0.0515		0.1065		0.5629	*
Foreign equity >=50%	0.0580		0.1304	*	0.2932	**	0.2438	**
Small firm	0.1344	**	0.3439	**	0.3098	**	0.4441	**
Medium firm	0.2453	**	0.4353	**	0.5106	**	0.8805	**
Large firm	0.3581	**	0.4682	**	0.5870	**	1.0366	**
Export <50%	0.0485		-0.0006		0.0466		-0.1067	
Export > 50%	0.2216	**	0.1027		-0.1061		0.1767	
Training indicator	0.0574		0.2355	**	0.0525		0.2414	**
Constant	6.1527	**	6.5454	**	6.6665	**	7.3379	**
Sample size	4,594		3,567		4,635		4,125	
R-squared	0.2011		0.2725		0.3647		0.4802	
MLE - Endogenous Training Choice	Coef.	z	Coef.	z	Coef.	z	Coef.	Z
Mean education	0.0310	**	0.0097		0.0329	**	0.0372	**
Proportion female	-0.2388	*	-0.3619	**	-0.2840	**	-0.3929	
Foreign equity <50 %	0.0913		-0.0107		0.0193		0.3016	
Foreign equity >=50%	0.0375		0.0960		0.2462	**	0.1492	
Small firm	0.0839		0.0986		0.2518	**	0.3197	*
Medium firm	0.1287	*	0.1014		0.3683	**	0.6083	**
Large firm	0.1983	**	0.0932	*	0.4229	**	0.6845	**
Export <50%	0.0448		0.0201		0.0113		-0.1324	
Export > 50%	0.2185	**	0.1282	*	-0.1465		0.1380	
MLE Training indicator	0.3963	**	0.5982	**	0.4085	*	1.0716	**
Constant	6.1329	**	6.4858	**	6.6230	**	7.3617	**
Sample size	4,594		3,316		4,635		4,125	
Rho	-0.4226		-0.6316		-0.4492		-0.6419	
Wald Test (rho=0) χ^2 statistic	6.63	**	9.45	**	5.09	**	7.65	**

Source: 1992 ENESTYC Survey

Notes: 1. Regressions included industry and region dummy variables

2. Instruments for MLE training equation included years in operation, R&D, computerization, and union representation.

Table 13. OLS and MLE Wage Regressions with Training Indicator Variable 1999 ENESTYC by Occupation								
	Unskilled Production		Skilled Production		Professional & Technical		Managers	
OLS Exogenous Training								
Mean S in Occ.	-0.0013		0.0106		0.0285	*	0.0552	**
% female in Occ.	-0.1703	**	-0.2217	*	-0.2752	**	-0.2354	*
Foreign equity <50 %	-0.1429		0.0401		0.1923	**	0.2388	*
Foreign equity >=50%	0.1888	**	0.0300		0.3473	**	0.3915	**
Small firm	0.1648	**	0.2901	**	0.3051	**	0.6530	**
Medium firm	0.2016	**	0.3303	**	0.4636	**	1.0823	**
Large firm	0.3753	**	0.4704	**	0.6060	**	1.4104	**
Export <50%	0.0853		0.0638		0.1696	**	0.1701	
Export > 50%	0.0815		0.3182	**	0.3696	**	0.2539	**
Training indicator	0.0270		0.0984		0.0924		0.0735	
Constant	6.2157	**	6.2340	**	6.3483	**	6.7121	**
Sample size	4,767		4,481		5,053		4,760	
R-squared	0.1205		0.1799		0.2501		0.4191	
1999 ENESTYC	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Mean education	-0.0024		0.0174		0.0260	*	0.0505	**
Proportion female	-0.1632	**	-0.3991	**	-0.2406	*	-0.2275	
Foreign equity <50 %	-0.1927		-0.0277		0.0937		0.0373	
Foreign equity >=50%	0.2021	**	0.2264	**	0.2830	**	0.2548	**
Small firm	0.1182	*	0.2464	**	0.1728	*	0.5291	**
Medium firm	0.1021		0.2082	*	0.1729		0.7849	**
Large firm	0.2486	**	0.3369	**	0.2621		1.0365	**
Export <50%	0.0650		0.0262		0.1455	**	0.1124	
Export > 50%	0.0653		0.1473		0.3551	**	0.2142	*
MLE Training indicator	0.2436	*	0.1861		0.6080	**	0.7179	**
Constant	6.2112	**	6.1105	**	6.3324	**	6.7351	**
Sample size	4,767		3,644		5,053		4,760	
Rho	-0.2630		-0.1806		-0.4552		-0.5083	
Wald test (rho=0) χ^2 statistic	3.66	**	2.13		7.16	**	18.52	**

Source: 1999 ENESTYC Survey

Notes: 1. Regressions included industry and region dummy variables
2. Instruments for MLE training equation included R&D, computerization, union.

Findings using Linked EIA-ENESTYC Data

The wage and productivity outcomes of in-firm training can also be looked at using panel data from the *Encuesta Industrial Anual* (EIA) linked to ENESTYC. The EIA is an annual survey of firms that together account for roughly 80 percent of output of the manufacturing sector, and is available continuously from 1993 to 1999. It contains detailed firm-level information on production (inputs and outputs), wage bill and hours of work, exports, foreign equity, and expenditures on different measures of technology, including R&D, technology licensing, use of patents and trademarks, and imported equipment and machinery. While EIA does not elicit information on in-firm training, a sub-sample of EIA firms (between 2,058 and 3,266) can be linked to the firms in the three ENESTYC surveys of 1992, 1995, and 1999 that do.

We use the linked EIA-ENESTYC panel to investigate how employer decisions to begin, stop or continue investing in worker training affect firm-level changes in wages and productivity over time. Training information is only available for three points in time—in 1992, 1995 and 1999—and this motivates us to split the 1993-1999 EIA panel into two sub-periods: 1993-1996, which includes the 1994 peso devaluation and recession, and 1996-1999 which roughly corresponds to the post-NAFTA period. We use reported training information (TRN) at the beginning and the end of each sub-period to define four training change decisions—begin, stop, continue, and do no training—to characterize firms. Using the 1993-1996 sub-period as an example, firms:

- begin training if TRN92=0 and TRN95=1
- stop training if TRN92=1 and TRN95=0
- continue training if TRN92=1 and TRN95=1, and
- do no training if TRN92=0 and TRN95=0

The corresponding training change variable for the 1996-1999 sub-period is readily defined using TRN95 and TRN99 from the 1995 and 1999 ENESTYC surveys. We are interested in testing the maintained hypothesis that training firms are more productive and pay higher wages than non-training firms; furthermore, that firms training continuously over time are more productive (and pay higher wages) than those that either begin training or stop training.

Before turning to the model specification, it is useful to describe the two outcome variables of interest. TFP is calculated as the residual from a constant returns-to-scale Cobb-Douglas production function estimated on pooled cross-section time-series data from the 1993-1999 EIA panel. In the specification reported here, the logarithm of value-added is regressed on the logarithms of total hours, fixed capital assets, and two-digit industry and year dummy variables; data are deflated to real 1994 prices using industry-specific PPIs.[20] For the sample as a whole, the residual log-TFP measure has zero mean. In a given year, each firm may have a TFP value different from (either greater or less

[20] We also tested alternative TFP measures, including ones allowing each industry to have its own input coefficients. Because the results are robust to the different TFP measures used, we focus on the simplest measure of TFP described above.

than) zero; over time, its TFP level may change, rising or falling relative to the sample mean of that year.[21] The second outcome measure—the logarithm of hourly wages—is calculated by dividing total wage bill (base wage, bonuses, overtime and mandatory social security contributions) by total hours worked, and deflating hourly wages into 1994 real prices using the CPI.[22]

In each sub-period, we regress measures of TFP and hourly wages on the training change variables, on the wealth of time-varying information on technology-inputs and exposure to international trade, as well as control variables for firm size, two-digit industry, and region. Table 14 reports the random-effects GLS estimates for these panel models, separately for each sub-period. For brevity, only the key estimated parameters for training, technology and trade are shown.

Table 14. Wage and Productivity Effects of Training, Technology and Trade
Linked EIA-ENESTYC 1993-1999 Panel – Random Effects GLS Estimates

	Log-Hourly Wage Regressions				Log-TFP Regressions			
RHS Variables	1993-96		1996-99		1993-96		1996-99	
	Coef.	z	Coef.	Z	Coef.	z	Coef.	z
Training Status								
Started training	0.1941	5.41	0.1185	2.35	0.1924	3.16	0.0916	1.20
Stopped training	0.1683	5.02	0.1095	1.59	0.1430	2.51	0.0583	0.56
Continued training	0.2984	10.03	0.2749	5.73	0.2397	4.73	0.1848	2.53
Technology Measures								
Foreign K <50 %	0.0311	1.54	0.0101	0.68	-0.0667	-1.35	-0.0545	-1.58
Foreign K >=50 %	0.1282	7.38	0.0432	3.96	0.1162	2.73	0.0370	1.46
Have R&D spending	0.0263	2.67	0.0206	2.96	-0.0228	-0.95	-0.0033	-0.21
Buy/use patents	0.0931	8.10	0.0639	7.54	0.0441	1.69	0.0306	1.62
Imported machinery	0.0208	2.32	0.0203	3.26	0.0573	2.69	0.0175	1.23
Exports	0.0363	3.28	0.0203	2.34	0.0912	3.69	0.0526	2.77
Constant	1.7772	9.47	1.5671	9.74	-0.4741	-1.12	0.2829	0.96
Sample size	6,025		7,674		5,851		7,557	
Overall R2	0.2871		0.2009		0.0361		0.0359	

Source: 1993-1999 EIA panel.
Notes: 1. Log-hourly wage in real 1994 new pesos, with outliers removed (see text)
2. Log-TFP is the residual estimated from a Cobb-Douglas production function (see text).
3. Indicator variables for firm size, two-digit industry, and region were included in regressions but parameter estimates are not reported here. Omitted groups include non-training firms that do not export and that have 100 percent national ownership.

[21] Other studies have used a multilateral index of TFP attributed to Caves, Christensen and Diewert (1982). In a given year, each firm's productivity (and hence TFP) is calculated relative to that of a hypothetical firm which is assigned the mean values of the production function in that year. Overall and firm-specific TFP can grow over time by chain-linking these reference points from year to year.

[22] The analysis using hourly wages was restricted to the sample with reasonable wage figures, after screening for and excluding outliers.

The results in Table 14 provide strong support for the hypothesis that wages and productivity are higher in firms that train. Relative to the omitted group—firms that did not train—the wage and productivity effects of training are invariably positive for the firms that reported either starting or stopping training during the sub-period. These wage and productivity effects are statistically significant at the 1 percent level in the 1993-1996 sub-period; in the second sub-period, only the wage effects of training are statistically significant for the group that started training. However, firms that trained continuously have both wage and productivity effects that are positive and statistically significant at the 1 percent level in both sub-periods.

Also noteworthy is the size (ranking) of the effects for the three training change groups, relative to firms that do not train. Both wage and productivity effects are largest for firms that trained continuously, second largest for firms that started training, and smallest for those that stopped training. For example, in the 1993-1996 sub-period, the wage effects for these three groups were 0.29, 0.19, and 0.16 respectively; the corresponding TFP effects were 0.23, 0.19 and 0.14. This relative ranking holds in the 1996-1999 sub-period as well. Like the ENESTYC results reported earlier, the size of these wage and productivity effects falls in the second sub-period. Studies in East Asia using similar panel data report results that echo these findings for Mexico (Tan, 2000).

These training effects are all the stronger by being conditioned on inclusion of a wide range of control variables for technology, FDI, and trade that arguably also affect firm-level productivity (and possibly wages). Their effects on TFP and wages are not without interest. Together, they proxy many of the ways in which firms access new technology and knowledge—through FDI and joint-ventures, through own R&D spending, through technology licensing and patents, through investments in imported equipment that embody new technology, and through exporting. Table 14 suggests that all these different sources of knowledge have a positive and statistically significant impact on log hourly wages in both sub-periods. However, using the yardstick of the second productivity measure—log-TFP—it is evident that their effects are not precisely measured. When the effects of these different knowledge sources are statistically significant—foreign equity greater than 50 percent, purchases of imported equipment, and exporting—they are only significant during the 1993-1996 sub-period.

We also experimented, without success, using a "within" model specification in which each outcome variable is measured relative to its own (in sample) mean while in the 1993-1999 panel.[23] By subtracting out each firm's mean, we convert the model to one of regressing changes in log-hourly wages and log-TFP on the vector of training, technology, trade and other control variables. As many empirical studies have found, the noise-to-signal ratio of these change outcome measures is too great, and none of the right-hand side regressors were statistically significant.

[23] A "fixed-effects" model specification would have been more appropriate if the training variables were time-varying. However, since the training change variable is constant for each firm within sub-periods, first-differencing would have eliminated the training variables of interest, though not the other time-varying technology and trade variables.

Long Term Evolution of Productivity and Wages

Finally, we ask whether firms are able to improve their relative position in the productivity and wage distribution over the long term through in-firm training. The empirical evidence presented thus far is that training has a positive impact on contemporaneous TFP and wage levels, and furthermore, that initiating training or continuing training increases TFP and wage levels over short periods of time. Here, the test conditions upon initial levels of TFP (or hourly wages) in 1993, and examines whether in-firm training facilitates its movement up (or correspondingly, inhibits declines down) the productivity or wage distribution over a seven-year period.[24] Training event histories permit a further refinement to this test, by distinguishing between firms that reported training just once, twice, or in all three years of the 1992, 1995 and 1999 ENESTYC surveys.

We address this issue graphically, and then within a regression framework. Our focus will be on TFP, though as will be evident, the results are virtually identical when analyzing hourly wages. Using the 1993-1999 firm-level TFP estimates reported previously, we first assign firms to a productivity quartile j in each year t, where j=1 to 4. We are particularly interested in 1993 and 1999, the first and last years in the EIA-ENESTY panel. The empirical distributions of TFP in 1999, that is, its cumulative distribution function (or CDF), can then be graphed separately for each 1993 TFP quartiles. Let this conditional CDF be represented by $F(\phi_{1999} \mid \phi_{j1993})$, where as before, j represents initial-year TFP quartile 1 through 4. To test the hypothesis that in-firm training facilitates movement up the TFP distribution over time, we graph the CDF's of 1999 TFP for four groups of firms defined by their training event histories.

Figure 1 shows the cumulative distributions of 1999 TFP conditional on initial year (1993) TFP levels, separately by training group. Consider the top left graph for the group of firms that reported no training in any of the three ENESTYC years. The horizontal axis represents the level of TFP in 1999, which can be either negative or positive since the sample mean of TFP is, by construction, 0. The vertical axis goes from 0 to 1, and measures the proportion of firms below the CDF at any given TFP level. To illustrate, we have depicted a vertical line corresponding to the sample mean of TFP. At the point where each CDF intersects the 0 vertical line, reading across to the vertical axis tells you the proportion of firms in that sample with 1999 TFP levels less than the sample mean of TFP.

Two principal points emerge from these four sets of graphs. First, moving from left to right, each CDF corresponds to the TFP distribution for the next higher, initial-year quartile of TFP. This strict ordering, plus the observation that CDFs do not overlap or cross-over, is suggestive of persistence; that is, that firms with high (low) levels of TFP

[24] We condition on initial position in the TFP distribution because there is evidence in the literature of persistence in firm-specific (and unexplained) effects over time. For example, see Roberts and Tybout (1996), and Aw, Chung and Roberts (2002) for empirical details on how productivity evolves over time in surviving firms, new entrants, and plant exits in several developing countries.

in one year also tend to have high (low) TFP levels in future years. Second, and most importantly, the CDFs are shifted over to the left (to lower TFP levels) for the sample of firms that do not train, while CDFs are increasingly shifted over to the right (to higher TFP levels) for the groups of firms that had repeated episodes of training. Thus, for any given initial-year TFP quartile, there is evidence that training, and repeated training episodes in particular, facilitates movements up the distribution of future TFP.

Figure 1
CDF of 1999 TFP Conditional on Initial 1993 TFP Quartile
By Training History over the 1993-1999 Period

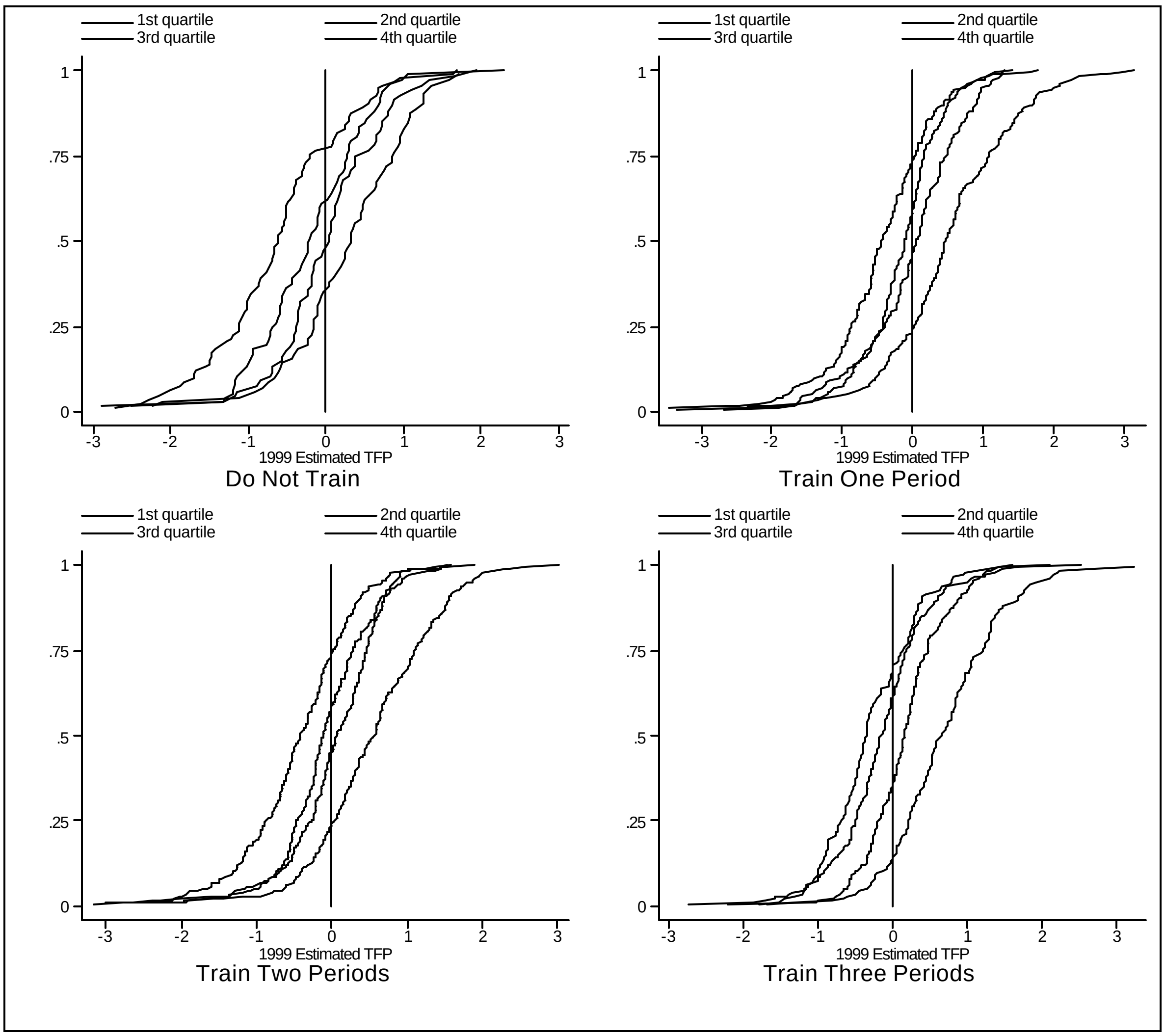


Table 15 makes these same points by reporting the value of the CDFs for each initial-year TFP quartile at the sample mean of TFP, or 0. This value, $F(\phi_{1999} = 0 \mid \phi_{j1993})$, is interpreted as the probability that firms, in initial-year quartile j, will have TFP levels in 1999 less than the sample mean. For the overall sample, F(.) for the 1st quartile is 73.5

percent, so three-quarters of the firms in the lowest TFP quartile in 1993 will still have TFP levels in 1999 less than the sample mean. In contrast, F(.) for the 4th quartile is 22.9 percent, so less than a quarter of the highest productivity firms in 1993 will have TFP levels in 1999 below the mean. This is suggestive of persistence over time in firm-level productivity levels.

Table 15. Cumulative Distribution of 1999 TFP Conditional on 1993 TFP

$F(\phi_{1999} = 0 \mid \phi_{j1993})$

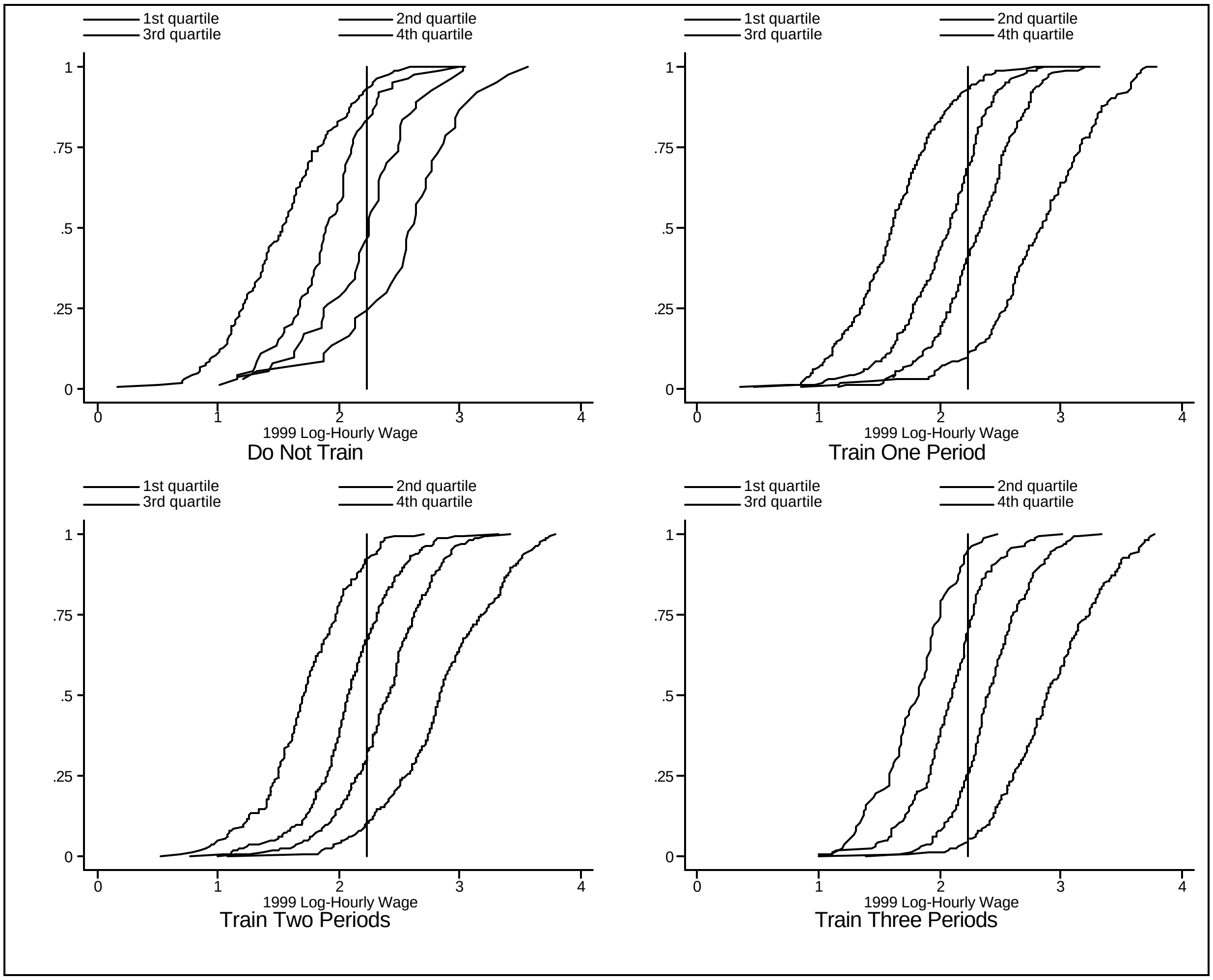
Training Histories 1993-1999	Quartiles of 1993 TFP			
	1st	2nd	3rd	4th
Overall sample	73.5	59.8	42.8	22.9
Did not train any year	76.4	61.1	47.1	35.2
Train one year	73.5	59.4	46.5	24.2
Train two years	74.3	58.5	44.9	24.1
Train all three years	70.0	57.1	35.9	13.8

Note: $F(\phi_{1999} = 0 \mid \phi_{1993})$ represents the probability that firms in the 1993 TFP quartile j, where j=1,2, 3 and 4, have 1999 TFP levels less than the sample mean of TFP in 1999.

This persistence notwithstanding, training is associated with a lower probability of having future TFP levels below the sample mean. To see this, note that the probability of future TFP being below the mean is invariably lower for those that train than for those that do not. For example, the difference in probabilities between non-trainers and continuous trainers is -6.4 percent (70.0 - 76.4) for firms in the 1st quartile of 1993 TFP, increasing to –21.4 percent (13.8 - 35.2) for firms in the 4th quartile. Among firms that train, those that train continuously usually have lower probabilities of being below the mean than those that train intermittently; these differences, however, are only pronounced for firms that have higher initial productivity in 1993—that is, those in the 3rd and 4th TFP quartiles. It bears repeating that the converse is also true, namely, that conditional on initial-year TFP levels, training is associated with a higher probability of future TFP levels being above the mean.

Figure 2 presents the corresponding CDFs for log-hourly wages in 1999 conditional on initial year (1993) wage quartile rank. For reference, the vertical line is drawn at 2.233—the 1999 mean log-hourly wage—and its intersection with the CDF shows the proportion of firms in each initial year quartile with hourly wages less than the sample mean. The wage distribution results mirror those for TFP, both in terms of persistence of wage levels over time, and in the manner in which training—continuous training in particular—shifts future wage distributions to the right. This similarity in the results reinforce the previous conclusion that training has been responsible, at least in part, for the dynamic evolution over time of firm-level productivity.

Figure 2
CDF of 1999 Log-Hourly Wages Conditional on Initial 1993 Wage Quartile
By Training History over the 1993-1999 Period



The test—for whether firms can improve their future position in the productivity and wage distribution through training—can also be formalized within a regression framework. Let the firm's position in the 1999 TFP (or wage) distribution be represented by its quartile rank which, being an ordinal variable, can be estimated by an ordered probit model.[25] The test, then, is to determine whether the probability of being in a higher TFP (wage) quartile in 1999 is greater when firms train than when they do not, and whether continuous training increases the probability of moving into a higher TFP (wage) quartile. Given strong evidence of persistence, this test of the effects of training will condition on initial-year quartile rank, and include joint tests with the competing

[25] The ordered probit model is a generalization of the simple probit model with two outcomes. In this case, the probability of observing outcome i, where i=1 to 4, corresponds to the probability that a linear function of the explanatory variables, plus an error term, falls within the range of the cut-off points estimated for that outcome i by the model.

determinants of productivity and wages. These include technology as measured by the number of R&D and technology transfer episodes over this 7 year period, and trade as represented by an export indicator variable, and years of exporting experience.

Table 16. Ordered Probit Estimates of 1999 TFP and Hourly Wage Quartile Conditional on 1993 Quartile Position – EIA-ENESTYC Linked Panel

	1999 TFP				1999 Hourly Wage			
	Model 1		Model 2		Model 1		Model 2	
Explanatory variables	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
1993 Quartile Position	0.4613	23.3	0.4399	21.96	0.9346	37.91	0.8912	35.4
Training 1 period	0.1077	1.41	0.0913	1.18	0.1482	1.83	0.1349	1.66
Training 2 periods	0.1553	2.01	0.1083	1.39	0.2200	2.71	0.1620	1.98
Training all 3 periods	0.2407	2.91	0.1725	2.06	0.2537	2.91	0.1799	2.05
R&D 1 period			-0.0112	-0.21			0.1100	1.98
R&D 2 periods			-0.0051	-0.07			0.1115	1.50
R&D 3+ periods			0.2436	3.64			0.2127	2.93
Tech transfer 1 period			-0.0191	-0.31			0.0267	0.43
Tech transfer 2-3 periods			0.1326	1.92			0.1279	1.81
Tech transfer 4-5 periods			0.2730	3.37			0.4661	5.33
Tech transfer 6+ periods			0.4443	6.01			0.5952	7.16
Exports			0.0032	0.04			0.0647	0.82
Years exporting			0.0199	1.49			0.0407	2.91
_cut1	0.8524		0.6661		2.1904		2.0234	
_cut2	1.6315		1.4615		3.3095		3.1699	
_cut3	2.4073		2.2530		4.4384		4.3500	
Observations	2,831		2,381		2,909		2,909	
Pseudo R^2	0.0832		0.0941		0.2793		0.2973	

Source: 1993-1999 EIA panel.
Notes: 1. Log-TFP is the residual estimated from a Cobb-Douglas production function (see text).
2. Log-Hourly Wage is the total wage bill (basic pay, overtime plus bonuses) divided by hours
3. Indicator variables for firm size, two-digit industry, and region were included in regressions but parameter estimates are not reported here.

Table 16 reports the results of estimating several specifications of this ordered probit model for 1999 TFP and hourly wage. Consider the results for TFP, shown in the first two columns of the table. Consistent with the graphical analysis, initial-year TFP quartile is a very good predictor of future TFP quartile rank. It is positive and statistically significant in all model specifications. Nonetheless, controlling for persistent firm productivity effects, training in model 1 is associated with positive movements up the TFP productivity distribution, effects that are larger for firms that train continuously as compared to those that do so intermittently. In model 2, the continuous training variable remains statistically significant at the 5 percent level when other competing technology and trade determinants are included. While the trade variables are not significant, the results for the technology variables mirror those for training, namely, that sustained investments in technology are needed to move up the TFP distribution. R&D, and technology transfer through licensing and patents, are statistically significant only for the firms that reported investing in these innovative activities for at least half of the intervening 7 years.

The corresponding results for the 1999 log-hourly wage quartile rankings are shown in the right-most two columns of Table 16. They are virtually identical to the results for log-TFP outcomes. Both continuous training, and repeated investments in technology through R&D and technology transfer, are significantly associated with movements up the hourly wage distribution. The only difference between the wage and TFP results is in the export variable: here, in the wage quartile rankings, the estimated linear parameter for years of exporting experience is positive and statistically significant at the 1 percent level. Conditional upon initial year (1993) wage levels, each year that a firm exports is associated with a 4 percent increased likelihood of moving up to the next wage quartile rank.

V. SUMMARY OF FINDINGS

In this paper, we have used unique time-series and panel firm-level data to investigate in-firm training in the manufacturing sector of Mexico, its wage and productivity outcomes, and its links to the Knowledge Economy. The analyses revealed that over the decade of the 1990s, not only did the incidence of employer provided training become more widespread among manufacturing enterprises, but a higher proportion of the workforce, including less skilled production workers, received training within firms. External training delivered by private sector providers—including private companies, industry associations and chambers of commerce, consultants and equipment suppliers—accounted for much of this increase, with public training institutions and technology centers playing a relatively smaller role.

Which was the principal driver of training trends: technology or trade? The answer appears to be technology. Technology, proxied by whether or not firms conducted R&D, was a consistently important determinant of in-firm training in both 1992 and 1999. R&D contributed to increased training over time not only through a rising share of firms doing R&D but also, more importantly, through a greater propensity to train conditional on doing R&D. Some part of this latter finding may reflect contemporaneous increases over time in other technology inputs correlated with R&D that were not controlled for, such as use of imported equipment that embody new technology, adoption of computerized technologies[26], or purchases of foreign patents and technology licenses. In Section IV, several of these other technology inputs, together with R&D, were shown to be important correlates of wage and total factor productivity growth over the 1990s.

Trade—hypothesized to provide exporting firms with access to new technologies and know-how from foreign markets—did not appear to have created strong derived-demand for in-firm training. The effects of exporting on firms' training propensity, though positive, were seldom statistically significant. However, trade could have affected training <u>indirectly</u>, thorough technology. Recall the bivariate probit estimates in Section III which showed no effect of exporting on training but a strong exporting impact on the likelihood of R&D in 1999. One interpretation of this result is that competition from expanded trade under NAFTA led firms to begin or do more R&D, and indirectly through R&D, to begin or increase provision of in-firm training.

Consistent with the literature, schooling is shown to play a major role in shaping post-school skills development in firms. Even controlling for occupation—which is correlated with schooling—a rise in years of schooling of the workforce is usually associated with an increased propensity for in-firm training, in 1992 as well as in 1999. Distinct from mean years of schooling, the <u>distribution of schooling</u> in the workforce also affects in-firm training. The proportion of the workforce with tertiary education, the post-graduate group in particular, has a statistically significant positive effect on training

[26] See World Bank (2001) for a firm-level study of technology adoption using the 1992, 1995, and 1999 ENESTYC surveys. That study estimated probit and multinomial probit models of adoption of a wide range of new technologies, including CNC machine-tools, robots, and computerized machinery.

for all occupational groups, both low-skilled as well as high skilled. This is suggestive of "neighborhood" effects, where low skilled workers benefit (in terms of training) from working alongside more highly-educated colleagues. One interpretation of this findings is that effective use of new and complex technologies requires high reliability in all steps of the production process so that all workers, even the low-skilled occupations, need to be provided in-firm training. This result, coupled with increased investments over time in new technologies and R&D, may explain the trend in the latter half of the 1990s of providing more training for the least skilled workers relative to other occupation groups.

The evidence is consistent with employer training investments having large positive effects on firm-level wages. OLS estimates using a binary training indicator variable—treated as exogenously determined—understate substantially the wage effects of training and, in the analysis by occupation, yield wage effects that are often not different from zero (in 1999). When training is endogenized, and its wage effects estimated jointly with the training choice equation, the results for all workers as a whole and by occupation are invariably positive, large and statistically significant in both 1992 and 1999.[27] They indicate that returns to in-firm training are largest for the most highly skilled groups, and that these returns declined modestly over the 1990s. When training and R&D are jointly determined, as suggested by the bivariate probit model (see Section III and IV), the tentative results are that combined investments in training and technology yield the largest wage returns, larger than investments in just one or the other, returns that are statistically significant in both 1992 and 1999.

Investments in training and in technology also impact wages and total factor productivity over time. For a panel of firms followed over two sub-periods (1993-96 and 1996-99), the group of firms that reported either starting or stopping training during the sub-period invariably had higher wage and TFP levels that the group that did no training. Firms that trained continuously had the largest wage and TFP effects, impacts that were statistically significant in both sub-periods. These estimated effects are over and above those from contemporaneous employer investments in new technology—R&D, purchases of imported equipment, and technology transfer through technology licensing—and from exporting. These latter activities also tend to have positive impacts on wages and TFP, though their statistical significance varies by year and by outcome measure.

Finally, the evidence—graphical and from regressions—indicates that both training and technology investments enable firms to improve their relative position in the productivity and wage distribution between 1993 and 1999. While there is considerable persistence over time in firms' TFP ranking by quartile, training inhibits the probability of having future TFP (and wage) fall below the sample mean; furthermore, among firms that train, continuous training reduces this probability even more. Event histories for R&D and for technology transfer tell a similar story, namely, that more frequent technology investments—in half or more of the intervening 7 years—enable firms to move up the TPF (and wage) distribution.

[27] The size of these training wage effects—resulting from the negative correlation between the wage and training equations—are large enough to give us pause, and will need to be investigated further in future research.

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