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The Impact of Advanced Technology Adoption on Wage Structures: Evidence from Taiwan Manufacturing Firms

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We examine the impact of advanced technology adoption on wage and employment structures in Taiwan. Using a survey of manufacturing firms that provides direct information on the use of advanced technologies, we find that firms using more advanced technologies pay higher wages to both non-production and production workers and employ higher fractions of non-production workers. Controlling for the possible endogeneity of technology adoption suggests that the estimated impact of new technologies on wages is downward-biased and that the effect on production workers' wages may be minimal.

INTRODUCTION

Over the past several decades much evidence has been mustered to support the hypothesis that the introduction of advanced technologies to the workplace has changed wages and the structure of employment. The technology–skill complementarity hypothesis asserts that, as new technologies are installed, the relative demand for skilled workers increases and average wages tend to increase. Alternatively, the causation may be reversed: highly paid skilled workers are more likely to use advanced technologies. A number of recent papers have investigated the wage–technology relationship in the United States and other developed countries, but the issue has received little attention in developing and newly industrializing countries. The issue is of particular interest in Taiwan, where the government has adopted a number of policies to encourage the adoption of factory automation equipment during the 1980s and 1990s, including preferential taxation, financial subsidy, technical assistance and on-the-job training. According to the Taiwan Production Automation Survey, the ratio of automated equipment value to total machine equipment value increased substantially, from 25% in 1985 to 55% in 1991.

A number of recent papers using surveys of the labour force indicate that technological change is the main cause of increased wage dispersion between skilled and unskilled workers in the United States and other developed countries (e.g. Katz and Murphy 1992; Juhn *et al.* 1993; Berman *et al.* 1994; Krueger 1993; and Autor *et al.*1996). Similarly, recent studies using plant-level surveys also support the correlation between technology use and wages. For example, Dunne and Schmitz (1995), Doms *et al.* (1997), Siegel (1998) and Beede and Young (1998) use plant-level data to show that technologically advanced plants pay higher wages and employ a greater fraction of skilled workers in the United States. Haskel (1999) examines several demand-side and institutional factors on the skilled–unskilled wage differentials in UK manufacturing and finds that computer introduction explains about half of the increase.

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Other literature suggests that highly paid skilled workers are more likely to use advanced technologies. Chennells and Van Reenen (1997, 1998) find that the estimated impact of new technologies on wages in Great Britain is seriously upward-biased if one does not control for the endogeneity of technology adoption. They conclude that it is more likely that higher wages have a positive effect on the likelihood of introducing advanced technologies than vice versa. Haskel (1999) uses a panel of 80 industries over 1980–89 and finds that computer introduction explains about 50% of the skill premium rise. Also, using employer–employee matched data, DiNardo and Pischke (1997) and Entorf and Kramarz (1997) suggest that worker quality rather than productivity enhancement drives the technology–wage correlation in Germany and France. Bartel and Sicherman (1999) match a variety of industry-level measures of technological change to a panel of workers and reaffirm this evidence in the United States.

Previous studies of the technology–wage relationship in developing countries have not had access to data on specific technologies used, and so have relied on indirect measures such as participation in the export market, investment in new technology (through R&D expenditure or foreign licenses) and worker training. Using these indirect measures, Tan and Batra (1997) find that technology investments lead to large wage premiums for skilled workers but not for unskilled workers in Taiwan, Columbia and Mexico. Aw and Batra (1995) show that the average technology–wage premium is 14% in Taiwan.[1]

The purpose of this study is to address four main questions: (1) Do technologically advanced firms pay higher wages to both production and non-production workers in a developing country? (2) Does controlling for technology use reduce the observed positive correlation between firm size and wages? (3) Since non-production workers include engineering and managerial occupations, do technologically advanced firms have a larger share of non-production labour? (4) Does the technology–skill complementarity hypothesis still hold when we adjust for the endogeneity of new technology adoption decisions?

To analyse these issues, we utilize firm-level data from the 1991 Taiwan Manufacturing Survey. This survey provides direct information about the technology used at Taiwanese manufacturing firms. Specific technologies considered include three types of computer equipment, numerically controlled machines (NC), automatic machine systems, robots, flexible manufacturing systems and computer-aided design (CAD). Use of these machines should be a good indicator of adoption of advanced technology in the production process. Our measures of technology adoption are similar to those used by Dunne and Schmitz (1995), Doms *et al.* (1997), DiNardo and Pischke (1997) and Gale (1998). We analyse the impacts of technologies on firm wages and employment structures following the empirical model proposed by Dunne and Schmitz (1995). We then consider the determinants of technology adoption and wages for production workers and non-production workers simultaneously. We anticipate that wages provide useful information about worker productivity, because the Taiwanese labour market appears to be highly competitive. Compared with the United States and other industrialized countries, the Taiwanese labour market includes a larger proportion of small firms with little intervention by unions or government (Fields 1992; Hou 1993). Since we rely

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on cross-sectional data, we cannot further examine the relationship between changes in wages and measures of technology adoption.

Our empirical findings suggest that the use of advanced manufacturing technologies is strongly positively correlated with wages for both non-production and production workers. Controlling for the endogeneity of technology adoption, the correlation remains significant for non-production workers, although not for production workers. Firms that adopt a large number of advanced technologies appear to have a high share of non-production workers compared with firms that adopt a small number of new technologies. In addition, our evidence supports the claim that, once technology controls are included, the size–wage premium falls significantly. These results are largely consistent with US results (Dunne and Schmitz 1995; Doms *et al.* 1997).

The remainder of the paper is organized as follows. In Section I, we present descriptive evidence of technology adoption in two-digit manufacturing industries and the average wages for firms, by firm size and the number of technologies used by a firm. Section II describes the empirical model specification. Section III presents the empirical results. Conclusions and further discussion follow in Section IV.

I. Data and Descriptive Analysis

The data used in this study come from the 1991 Taiwan Manufacturing Sampling Survey conducted by the Statistical Bureau of Taiwan. This survey is a supplement to the 1991 manufacturing census.[2] The original data set consists of 13,330 firms. After excluding firms missing information on key variables (technology used, wage and firm size), 9296 firms remain for analysis.

Employment is reported as the number of non-production and production workers. These occupational categories have been broadly classified as ‘skilled’ and ‘unskilled’ respectively (Berman *et al.* 1994).[3] Each firm reports total yearly salaries and employment levels for each category. Working hours data are not collected.[4] The average wages of non-production and production workers are calculated as the ratios of total salary to total employment in each category.

Table 1 provides information on the percentage of firms using eight different technologies broken out by two-digit manufacturing industries. These advanced technologies include mainframes, work-stations, personal computers, numerically controlled machines, automatic machines, robots, flexible manufacturing cell/systems, and computer-aided design/computer-aided machines. Looking across the eight technologies, the most frequently adopted are personal computers and automatic machines on the factory floor; the least employed technologies are robots and flexible manufacturing cell/systems. Among industries, the wood and bamboo products industry (SIC 16) has the lowest percentage of firms using advanced technologies. In three industries—chemical matter manufacturing (SIC 21), petroleum and coal products (SIC 23) and electrical and electronic machinery (SIC 31)—over half of the firms utilize personal computers. Establishments in those industries also use mainframes, work-stations, and automatic machines to a great extent. In addition, computer-aided design/computer-aided machines are most prevalent

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TABLE 1

PERCENTAGES OF FIRMS USING SPECIFIED TECHNOLOGIES

Technology: 2-digit industry (SIC code)	Mainframe	Work station	Personal computer	Numerically controlled machines	Automatic machines	Robots	Flexible manufacturing cell/systems	Computer-aided design/ computer-aided machines	No. of firms
Food manufacturing (11)	3.7	17.3	33.0	6.4	36.4	0.9	0.4	3.2	561
Textile mill products (13)	1.9	16.3	38.1	3.6	32.8	1.1	0.2	5.6	522
Wearing apparel and accessories (14)	1.8	11.4	31.4	2.3	13.6	0	0	3.6	220
Leather and fur products (15)	3.8	11.4	29.7	2.2	22.0	0.5	1.6	1.1	182
Wood and bamboo products (16)	0	7.3	12.7	3.4	17.1	1.0	0	1.5	205
Furniture and fixtures manufacturing (17)	1.0	10.1	21.3	8.7	21.0	1.4	0.3	2.8	286
Pulp, paper and paper products (18)	2.5	14.3	29.0	8.1	24.3	0.2	0.7	4.7	407
Printing processing (19)	1.1	4.9	24.7	2.7	26.4	0.5	0	2.7	182
Chemical matter manufacturing (21)	6.2	21.5	50.4	10.4	33.5	1.5	2.3	10	260
Chemical products manufacturing (22)	1.7	17.3	45.4	4.9	32.4	8.5	8.5	5.5	469
Petroleum and coal products (23)	8.3	16.7	66.7	0	33.3	0	0	0	12
Rubber products manufacturing (24)	2.5	13.0	29.0	10.5	29.0	0.6	1.2	7.4	162
Plastic products manufacturing (25)	2.1	11.6	29.1	5.2	31.2	3.7	0.2	3.9	844
Non-metallic mineral products (26)	2.0	11.8	23.9	6.2	24.9	1.6	0.7	3.6	305
Basic metal industries (27)	3.1	17.3	37.5	9.7	33.4	1.2	0.6	6.4	485
Fabricated metal products (28)	1.9	9.6	27.4	12.1	26.5	1.7	0.5	7.5	942
Machinery and equipment (29)	2.7	15.6	35.5	17.5	28.7	2.1	1.2	9.8	674
Electrical and electronic machinery (31)	8.2	24.5	56.5	12.8	36.3	2.6	1.3	14.1	1285
Transport equipment (32)	3.7	14.8	42.1	17.4	30.3	8.8	2.1	11.3	432
Precision instruments (33)	1.2	13.9	33.9	14.7	21.9	2.0	0.8	8.0	251
Misc. industrial products (39)	1.0	11.1	28.9	3.9	20.2	0.8	0.7	4.9	610

Source: Manufacturing Sampling Survey in Taiwan, 1991.

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in electrical and electronic machinery (SIC 31) and transport equipment (SIC 32).

Table 2 presents the average annual wages (in thousands of New Taiwan dollars) for firms, by firm size (measured by total employment) and the number of technologies employed at a firm.[5] The first number in each cell is the average wage paid in the firms. The second number (in parentheses) is the standard deviation of the average firm wages, and the third number is the total number of firms in each cell. For example, there are 1480 firms that use none of the technologies and whose total employment is less than 10 employees; the average wage in these firms is NT$19,606,000 with a standard deviation of NT$83,560,000.

As shown by the third number in each cell, we find large firms tend to employ more technologies than smaller ones. The last column of Table 2 indicates that average wages are increasing with the size of firms. Average wages are also increasing with the number of technologies employed at the firm, as seen in the last row.

Table 3 presents a cross-tabulation of occupational mix of workers by the number of advanced technologies used in firms. The rows correspond to the number of technologies used in firms; the columns present the percentages of workers by occupational class in the firm. There is an increasing relationship between technology use and the share of workers in engineering, technical,

TABLE 2

AVERAGE WAGES BY FIRM SIZE AND NUMBER OF ADVANCED TECHNOLOGIES USED[a]

	0 techs. used	1–2 techs. used	3–4 techs. used	5–6 techs. used	7–8 techs. used	Sample mean
Below 10 employees	196.06	211.42	258.77			200.12
	(83.56)	(92.49)	(178.89)			(87.52)
	1480	423	21			1924
10–29 employees	208.77	239.30	259.21	606		222.32
	(83.39)	(96.35)	(96.16)	(–)		(90.75)
	1614	1105	74	1		2794
30–49 employees	232.98	258.10	289.24	369.24		250.38
	(100.40)	(104.05)	(129.87)	(116.66)		(105.97)
	524	655	83	7		1269
50–99 employees	230.75	272.30	302.06	319.24	851.18	264.80
	(89.75)	(97.15)	(117.58)	(89.23)	(–)	(101.34)
	417	885	164	16	1	1483
100–499 employees	239.76	288.07	324.31	336.02	461.34	295.40
	(90.11)	(108.50)	(116.50)	(113.58)	(36.44)	(112.48)
	190	813	424	89	4	1520
Above 500 employees	279.14	288.49	345.32	387.55	356.11	343.29
	(106.84)	(84.78)	(132.15)	(158.83)	(128.17)	(134.35)
	4	68	136	78	20	306
Sample mean	210.95	257.71	313.34	358.29	392.75	244.26
	(87.90)	(102.66)	(122.81	(135.26)	(154.37)	(106.11)
	4229	3749	902	191	25	9296

[a] The first number in a cell is the mean of average plant wages; the second number (in parentheses) is the standard deviation of average plant wages, and the third number is the number of plants in the cell. Wages are in thousands of New Taiwan dollars.

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TABLE 3

DISTRIBUTION OF OCCUPATIONAL CLASS BY TECHNOLOGY USE (%)

	Managers and supervisors (1)	Engineers and technicians (2)	Clerical and sales (3)	Non-production workers [(1), (2) and (3)] (4)	% of total wages paid to non-production workers (5)
Firms using no technologies (N = 4229)	13.5	3.8	11.0	28.3	33.1
Firms using 1 or 2 technologies (N = 3949)	12.9	5.3	12.6	30.8	37.6
Firms using 3 or 4 technologies (N = 902)	12.6	6.9	13.8	33.3	42.3
Firms using 5 or 6 technologies (N = 191)	11.6	9.4	12.6	33.7	42.2
Firms using 7 or 8 technologies (N = 25)	10.9	9.4	14.0	34.3	43.6
Full sample (N = 9296)	13.1	4.9	12.0	29.9	36.1

clerk and sales occupations (columns (2) and (3)), and a negative relationship between technology use and the share of workers in managerial and supervisory occupations (column (1)). Columns (4) and (5) show a consistent pattern of non-production workers and wages. Firms using more technologies employ a higher proportion of non-production workers and pay them a higher fraction of total wages.

II. THE EMPIRICAL MODEL

We estimate two models. The first is the conventional model, which treats technology adoption as an exogenous variable and estimates wage functions and employment structures using ordinary least squares (OLS). The second is a mixed model, which examines the determinants of technology adoption and the impact of technology use on wage structure simultaneously.

(a) The ordinary least squares (OLS) equation

A basic empirical model of firm wages and employment structure may be written as

(1) $Y_i = f$(technology, firm size, firm age, capital–labour ratio, proportion male, foreign ownership, industry).

Variable definitions and summary statistics are reported in Table 4. We use several alternative dependent variables (Y_i): the log of average worker wages (*LNW*), the log of average non-production workers' wages (*LNNPW*), the log of average production workers' wages (*LNPW*) and the non-production workers' share of total employment in firm i. The wage variables are defined as yearly average wages and salaries per full-time employee; fringe benefits and other nonwage payments are excluded. Following common practice in the

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TABLE 4
DEFINITION OF VARIABLES AND SUMMARY STATISTICS

Variables	Definition of variables	Mean (standard deviation)
LNW	Log (*Average worker wage*) (NT$'000)	5.408 (0.435)
LNNPW	Log (*Average non-production worker wage*) (NT$'000)	5.599 (0.488)
LNPW	Log (*Average production worker wage*) (NT$'000)	5.298 (0.466)
MANL	Percentage of managers and supervisors	0.131 (0.104)
TECHL	Percentage of engineers and technicians	0.049 (0.082)
CLERL	Percentage of clerical and sales	0.120 (0.111)
NPL	Percentage of non-production workers	0.299 (0.141)
NPS	Percentage of total wages paid to non-production workers	0.361 (0.164)
MAIN	Dummy variable for mainframes	0.031 (0.174)
WORK	Dummy variable for work-stations	0.150 (0.358)
PC	Dummy variable for personal computers	0.357 (0.479)
NC	Dummy variable for numerically controlled machines	0.091 (0.287)
AUTO	Dummy variable for automatic machines	0.286 (0.452)
ROBOT	Dummy variable for robots	0.020 (0.139)
FMC	Dummy variable for flexible manufacturing cell/systems	0.008 (0.089)
CAD	Dummy variable for computer-aided design/ computer-aided machines	0.070 (0.255)
TECH0	Dummy variable for no technologies	0.455 (0.498)
TECH1	Dummy variable for 1 or 2 technologies	0.425 (0.494)
TECH3	Dummy variable for 3 or 4 technologies	0.097 (0.296)
TECH5	Dummy variable for 5 or 6 technologies	0.021 (0.142)
TECH7	Dummy variable for 7 or 8 technologies	0.003 (0.052)
TECH	The number of different technologies	1.014 (1.269)
SIZE1	Dummy variable for fewer than 10 employees	0.207 (0.405)
SIZE2	Dummy variable for 10–29 employees	0.301 (0.459)
SIZE3	Dummy variable for 30–49 employees	0.137 (0.343)

(continued)

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TABLE 4 *Continued*

Variables	Definition of variables	Mean (standard deviation)
SIZE4	Dummy variable for 50–99 employees	0.160 (0.366)
SIZE5	Dummy variable for 100–499 employees	0.164 (0.370)
SIZE6	Dummy variable for 500 or more employees	0.033 (0.178)
SIZE	Total number of employees	103.645 (461.669)
LNKL	Log ratio of the book value of fixed capital stock to total number of employees (NT$'000/person)	6.093 (1.267)
AGE	Age of plant since establishment (years)	12.705 (8.701)
FOR	Dummy variable for foreign ownership	0.068 (0.252)
MALE	The proportion of employees who are male	0.613 (0.253)
PATL	Patent number/employment at the two-digit industry	0.011 (0.016)
RDS	R&D/sales at the three-digit industry	0.005 (0.018)

literature, non-production workers are identified as skilled labour and production workers are identified as unskilled labour.

We employ three measures of technology use: (1) a set of eight dummy variables to represent different technologies present in the firm; (2) a set of four dummy variables that measure the number of different technologies present in the firm; and (3) the number of technologies used in the firm. Throughout this study, we assume that firms using a larger number of technologies are more technologically advanced. Clearly, this is a crude measure of technology use. One potential problem with this measure is that, if capital and worker skill are complementary, we may find a positive relationship between technology use and worker wage simply because more technology-intensive plants are more capital-intensive. To control for this possibility, all the wage regressions include the log of plant-level capital–labour ratios.

The technology dummy variable groupings are: firms using one or two technologies (*TECH1*), firms using three or four technologies (*TECH3*), firms using five or six technologies (*TECH5*), and firms using seven or eight technologies (*TECH7*). The omitted group is firms using zero technologies (*TECH0*). Size is also included as a set of five dummy variables, based on total employment, with the smallest firms the omitted group (*SIZE1*).

With respect to the remaining characteristics of the firms in the regression, gender composition is measured by the proportion of workers who are male (*MALE*) and the foreign ownership dummy variable (*FOR*) is included to test for wage differences between foreign firms and local firms.[6] Firm age (*AGE*) is

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introduced as a proxy variable to represent the differences in worker characteristics such as education and experience.[7] To control for industry-specific factors that influence wages, we also include 67 three-digit industry dummies in the regressions.

(b) The mixed model

In the second part of the empirical analysis, we extend the previous literature to represent the decision to adopt new technology as endogenous. As noted by Chennells and Van Reenen (1997, 1998) and Siegel (1998), technology adoption may be endogenous for at least two reasons. First, a positive shock to the wage will induce firms to substitute machinery for labour as the relative factor price of capital is cheaper. Second, a firm's unobserved ability is likely to be associated with both higher wages and higher-quality capital.

The empirical model can be written as follows. The wage equation is

$$\ln W_i = \gamma_1 \; TECH_i^* + \alpha_1 \; MALE_i + \beta_1' X_{1i} + \varepsilon_{1i}. \tag{2}$$

The technology adoption equation is

$$TECH_i^* = \gamma_2 \ln W_i + \delta_1 PATL_i + \delta_2 RDS_i + \beta_2' X_{2i} + \varepsilon_{2i}. \tag{3}$$

The specification of (2) is similar to that of (1), except that $TECH^*$ is a latent variable for the technology intensity. We use the number of technologies employed at the firm (0–8) as a measure of overall technology use. This measure was also used by Gale (1998) and was endorsed as a proxy for technology intensity by Doms *et al.* (1997). Because male workers are often paid more than females, the proportion of workers who are male is also included. Other control variables represented by the vector X_1 include the logarithm of the capital–labour ratio, firm size (represented by a set of dummy variables), firm age and foreign ownership. The wage rate variable W_i alternatively represents firm average wage (*LNW*), wages of non-production labour (*LNNPW*) or wages of production labour (*LNPW*).

Equation (3) describes the determinants of technology adoption, which has been discussed by Dunne (1994) and Gale (1998).[8] Technology adoption is anticipated to depend on the wage rate, because advanced technologies may substitute for some types of labour and complement other types. The vector X_2 includes firm size, firm age and foreign ownership. Firm size, represented as a continuous variable, is included to control for the possibility that there may be fixed costs in the adoption of new technologies. If those costs can be spread across a larger production base, then large firms may be more likely to utilize these innovations. Based on vintage effects, young firms might be expected to use more advanced technologies than old firms. However, the relationship between firm age and technology use is an empirical issue. Dunne (1994) finds that plant age is not related to technology use among US manufacturing plants, but Gale (1998) finds a negative effect. The foreign ownership variable is included because foreign firms may have better access to advanced technologies than local firms.

A difficulty in estimating the simultaneous-equation model is in selecting identifying variables, i.e. variables that influence technology adoption but not

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wages in the technology equation, and variables that influence wages but not technology adoption in the wage equation. For the technology equation, we use the number of patents (normalized by employment) at the two-digit industry level (*PATL*) and R&D/sales intensity at the three-digit industry level (*RDS*). These two variables represent the technological sophistication of the industry's products and processes, and are anticipated to be correlated with technological opportunities in the production process. For the wage equation, we use the proportion of workers who are male, since male workers are likely to be better paid than are female workers.[9] Hellerstein *et al.* (1999) find that women are paid significantly less than men in US manufacturing. The wage differential between men and women is larger than the productivity differential, suggesting sex discrimination.

Equation (3) is estimated as an ordered probit. The dependent variable, $TECH_i$, is ordinal and has nine response categories, $R_0, \dots, R_8$, to which each of the N firms is assigned if the technology intensity, $TECH_i^*$, falls within given bounds. More formally,

$$(4) \qquad TECH_i = R_j \quad \text{if } \mu_j \leqslant TECH_i^* < \mu_{j+1} \qquad \text{for } 0 \leqslant j \leqslant 8,$$

where μ_j is a real number corresponding to a threshold parameter. The ordinal technology intensity variable is defined as

$$(5) \qquad TECH_{i,j} = 1 \quad \text{if } TECH_i = R_j;\ 0 \text{ otherwise}, \qquad \text{for } 1 \leqslant i \leqslant N,\ 1 \leqslant j \leqslant 9.$$

From (3), (4) and (5), and the assumption that the residuals in (3) are normally distributed, the probability that a firm's technology intensity belongs to the jth response group is

$$(6) \qquad \Pr[TECH_i = R_j] = \Phi[(\mu_j - \Pi'Z/\sigma)] - \Phi[(\mu_{j-1} - \Pi'Z/\sigma)],$$

where $\Pi'Z$ represents the right-hand side of the technology adoption equation (3), σ is a parameter to be estimated, and Φ is the standard normal distribution function. The resultant likelihood function that will be estimated is

$$(7) \qquad \operatorname{Log} L = \sum_{i=1}^{N} \sum_{j=1}^{9} TECH_{i,j} \log(\Phi_{i,j} - \Phi_{i,j-1}).$$

The two-stage procedure suggested by Maddala (1983) is used to estimate the mixed model in (2) and (3). The first stage is to estimate the reduced-form equations of wage and technology adoption, using OLS and ordered probit models, respectively. The second stage is to estimate (2) by OLS, after the *TECH* variable is replaced by the maximum likelihood estimate of the technology adoption probability for the reduced form *TECH* estimate of *LNW* (or *LNNPW*, *LNPW*) for the wage variable. We calculate the correct asymptotic covariance matrix for the two-stage estimate of (2) and (3) using LIMDEP econometric software (Murphy and Topel 1985; Greene 1995).[10]

III. Empirical Results

In this section we use two empirical models to explore the impacts of technology adoption on workers' wages and employment structures. Our

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TABLE 5
WAGE REGRESSIONS WITH SPECIFIED TECHNOLOGIES (OLS)[a]

	LNW	*LNNPW*	*LNPW*
Constant	4.508	4.788	4.423
	(171.29)***	(162.85)***	(149.03)***
MAIN	0.107	0.093	0.093
	(4.14)***	(3.21)***	(3.18)***
WORK	0.078	0.072	0.059
	(6.34)***	(5.24)***	(4.28)***
PC	0.089	0.080	0.068
	(9.39)***	(7.57)***	(6.44)***
NC	0.023	0.012	0.025
	(1.50)	(0.72)	(1.46)
AUTO	−0.008	−0.007	−0.017
	(−0.87)	(−0.68)	(−1.58)
ROBOT	−0.009	−0.024	−0.001
	(−0.30)	(−0.74)	(−0.04)
FMC	−0.116	−0.101	−0.113
	(−2.61)***	(−2.03)**	(−2.25)**
CAD	0.040	0.036	0.018
	(2.34)**	(1.88)*	(0.91)
SIZE2	0.108	0.184	0.090
	(9.61)***	(14.68)***	(7.14)***
SIZE3	0.175	0.295	0.153
	(12.49)***	(18.79)***	(9.66)***
SIZE4	0.220	0.382	0.181
	(15.59)***	(24.23)***	(11.37)***
SIZE5	0.241	0.418	0.219
	(15.09)***	(23.45)***	(12.13)***
SIZE6	0.183	0.391	0.198
	(6.11)***	(11.67)***	(5.84)***
LNKL	0.085	0.065	0.084
	(24.91)***	(17.18)***	(21.89)***
MALE	0.173	0.121	0.181
	(9.79)***	(6.15)***	(9.10)***
FOR	0.203	0.270	0.152
	(12.58)***	(14.98)***	(8.34)***
AGE	0.004	0.003	0.004
	(8.41)***	(5.70)***	(7.14)***
$\overline{R}^2$	0.288	0.292	0.212

[a] All regressions include dummy variables for 67 three-digit industries. Figures in parentheses are *t*-statistics. ***, **, and * represent statistical significance at 1%, 5% and 10% levels respectively.

approach is first to estimate a set of wage regressions and non-production worker share regressions by OLS and then to estimate the simultaneous model, controlling for the endogeneity of technology adoption.

(a) Ordinary least squares

Wage regressions. In order to investigate the influence of different technologies on wages, we include all eight technology dummy variables simultaneously in the regression. Table 5 shows the OLS regressions for the

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TABLE 6
WAGE REGRESSIONS WITH TECHNOLOGY CONTROLS (OLS)[a]

	LNW	*LNNPW*	*LNPW*
Constant	4.489	4.773	4.404
	(170.58)***	(162.73)***	(148.68)***
TECH1	0.065	0.067	0.044
	(7.16)***	(6.55)***	(4.27)***
TECH3	0.115	0.114	0.063
	(7.10)***	(6.28)***	(3.43)***
TECH5	0.157	0.122	0.114
	(5.09)***	(3.56)***	(3.30)***
TECH7	0.174	0.167	0.129
	(2.25)**	(1.93)**	(1.47)
SIZE2	0.109	0.183	0.092
	(9.66)***	(14.56)***	(7.25)***
SIZE3	0.182	0.297	0.160
	(12.86)***	(18.87)***	(10.03)***
SIZE4	0.231	0.388	0.192
	(16.28)***	(24.51)***	(12.03)***
SIZE5	0.272	0.441	0.247
	(17.40)***	(25.33)***	(14.07)***
SIZE6	0.259	0.455	0.264
	(9.22)***	(14.54)***	(8.36)***
LNKL	0.086	0.066	0.086
	(25.34)***	(17.39)***	(22.34)***
MALE	0.175	0.123	0.183
	(9.85)***	(6.21)***	(9.19)***
FOR	0.207	0.273	0.155
	(12.76)***	(15.10)***	(8.52)***
AGE	0.004	0.003	0.004
	(8.76)***	(6.00)***	(7.43)***
$\overline{R^2}$	0.282	0.289	0.208

[a] See Table 5 footnote.

log of average total worker wages, non-production worker wages and production worker wages. We find a wage differential of 9%–11% associated with mainframe use (*MAIN*). By contrast, the use of flexible manufacturing systems (*FMC*) is associated with an 11% lower wage. The estimated differentials for work stations (*WORK*), personal computers (*PC*) and computer-aided design/computer-aided machines (*CAD*) are larger for non-production than for production workers.

As an alternative measure of new technology, the eight dummy variables are replaced by four dummy variables representing the number of different technologies present in the firm. The results are reported in Table 6. Examining the first regression, we find an increasing relationship between technology use and wages: firms employing one or two of the advanced technologies pay on average 7% higher wages than those employing no technologies; those employing three or four, five or six and seven or eight technologies pay 12%, 16% and 17% higher wages, respectively. The firm size–wage effect is evident as well, with a nearly monotonic relationship between firm size and average

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wage. Compared with workers in the smallest firms, those in classes *SIZE2–SIZE6* earn a premium of 11%, 18%, 23%, 27% and 26%, respectively.

The second and third columns report the results of the non-production worker and production worker wage regressions. With the exception of the magnitudes of the technology and size coefficients, the results for non-production and production workers are very similar. Firms employing one or two, three or four, five or six and seven or eight technologies pay non-production workers about 7%, 11%, 12% and 17% more, respectively, than firms with no advanced technologies. The premiums for production workers in firms with advanced technologies range from 4% to 13%. These results are comparable to estimates for US manufacturing plants, where Dunne and Schmitz (1995) find that production workers in plants with the most technologies receive 14% higher wages than production workers in plants with the fewest technologies. Once worker quality controls are included, however, Doms *et al.* (1997) find that the technology premium drops to 8%. In a contrasting study of wage inequality, Hanson and Harrison (1995) find no evidence that industries or plants in Mexico that engage in technological upgrading have a higher skilled–unskilled wage gap. The technological upgrading is expressed by royalty payments for foreign technology, total factor productivity growth and the share of imported machinery in investment.

The coefficients on firm size, classes *SIZE2–SIZE4* in the non-production worker regression, are on average about twice those in the production worker regression. This finding is consistent with the size–wage profile suggested by Aw and Batra (1995), who find a higher wage premium associated with non-production labour than with production labour in Taiwan.

Among all three-digit industries, petroleum refining (SIC 211) and basic chemicals (SIC 321) have the highest wages on average. In contrast, the beverage (SIC 118), wood and bamboo (SIC 160) and other food manufacturing industries (SIC 119) have the lowest wages.[11]

Our results suggest that the effects of technology and firm size differ between the Taiwanese and US labour markets. Our finding that technology–wage premiums are larger for non-production workers than for production workers in Taiwan contrasts with the results of Brown and Medoff (1989), Dunne and Schmitz (1995) and Doms *et al.* (1997), who find a smaller effect of technology measures on non-production worker wages than on production worker wages in the United States. Furthermore, the estimated size–wage premiums for Taiwanese non-production labour exceed the magnitude of those for production labour, contrary to the size–wage pattern in the United States.

Next consider our other variables. The coefficients on the log of the capital–labour ratio are consistent with the findings of most previous empirical studies, showing that firms with greater capital intensity employ highly paid workers. Firm age is positively correlated with worker's wage. Wages are also positively and significantly associated with the fraction of employees in the firm who are male, and with foreign ownership.[12] All the other variables in the regressions are statistically significant at the 1% level.

We have seen that larger firms are more likely to use these technologies, perhaps because of large fixed costs. This suggests that the technology premiums may be viewed as part of a firm-size effect. To evaluate this possibility, we compare the size–wage premia in regressions that include the

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TABLE 7
WAGE REGRESSIONS WITHOUT TECHNOLOGY CONTROLS (OLS)[a]

	LNW	*LNNPW*	*LNPW*
Constant	4.461	4.747	4.387
	(170.55)***	(162.99)***	(149.45)***
SIZE2	0.123	0.197	0.101
	(11.01)***	(15.85)***	(8.07)***
SIZE3	0.208	0.324	0.177
	(15.05)***	(21.02)***	(11.38)***
SIZE4	0.269	0.425	0.216
	(19.84)***	(28.20)***	(14.22)***
SIZE5	0.329	0.497	0.283
	(23.16)***	(31.36)***	(17.71)***
SIZE6	0.347	0.533	0.321
	(13.75)***	(18.99)***	(11.32)***
LNKL	0.093	0.073	0.090
	(27.70)***	(19.39)***	(23.86)***
MALE	0.176	0.124	0.184
	(9.91)***	(6.24)***	(9.22)***
FOR	0.219	0.283	0.163
	(13.54)***	(15.74)***	(8.99)***
AGE	0.004	0.003	0.004
	(8.84)***	(6.06)***	(7.50)***
$\overline{R^2}$	0.276	0.285	0.206

[a] See Table 5 footnote.

technology controls with the premia in those that do not (Table 7). For all worker classes, a clear picture emerges. The size premium for each firm size class falls significantly when the technology controls are included.[13]

In the regression of average wage paid to all employees, for class *SIZE2* the premium falls by 11% ((0.109 – 0.123)/0.123) when the technology variables are included. For the classes *SIZE3–SIZE6* the premium falls by a larger amount—13%, 14%, 17% and 29%, respectively. For non-production workers, the premium falls by 7%, 8%, 9%, 11% and 15%, for classes *SIZE2–SIZE6*, respectively. For production workers, the size premium falls by 9%, 10%, 11%, 13% and 18% for *SIZE2–SIZE6*, respectively. Obviously, including technology controls substantially lowers the size–wage premium. Therefore, consistent with some of the US evidence, the wage premium to employer size appears to be closely linked with new technology in our data.

Non-production worker share in employment. The employment structure of firms, as measured by the fraction of non-production workers at the firm, is studied in Table 8. The coefficients on the technology dummies indicate that firms using more technologies employ more skilled employees, especially engineers and technicians (*TECHL*) (column (2)) and managers and supervisors (*MANL*) (column (1)). This finding is consistent with Doms *et al.* (1997). The other columns show a very similar pattern, in terms of both numbers (*NPL*) and wages (*NPS*); firms utilizing more technologies employ a higher percentage of non-production labour.

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TABLE 8
OCCUPATIONAL MIX OF WORKERS IN PLANTS (OLS)[a]

	MANL[b]	*TECHL*[c]	*CLERL*[d]	*NPL*[e]	*NPS*[f]
Constant	0.112	−0.002	0.076	0.186	0.247
	(15.63)***	(−0.37)	(9.51)***	(19.63)***	(22.16)***
TECH1	0.015	0.010	0.010	0.035	0.043
	(6.17)***	(4.98)***	(3.74)***	(10.88)***	(11.22)***
TECH3	0.029	0.019	0.021	0.069	0.088
	(6.76)***	(5.51)***	(4.26)***	(12.09)***	(12.98)***
TECH5	0.034	0.041	0.015	0.090	0.101
	(4.16)***	(6.18)***	(1.62)	(8.31)***	(7.89)***
TECH7	0.036	0.039	0.028	0.103	0.120
	(1.72)*	(2.34)**	(1.24)	(3.78)***	(3.74)***
SIZE2	−0.051	0.006	−0.001	−0.046	−0.032
	(−17.09)***	(2.38)**	(−0.09)	(−11.58)***	(−6.87)***
SIZE3	−0.072	0.003	0.001	−0.068	−0.048
	(−19.07)***	(0.93)	(0.18)	(−13.74)***	(−8.17)***
SIZE4	−0.084	0.005	−0.001	−0.080	−0.049
	(−22.14)***	(1.63)*	(−0.27)	(−16.03)***	(−8.26)***
SIZE5	−0.103	0.003	−0.006	−0.106	−0.079
	(−24.63)***	(0.78)	(−1.32)	(−19.31)***	(−12.18)***
SIZE6	−0.135	0.002	−0.018	−0.151	−0.130
	(−17.96)***	(0.26)	(−2.15)**	(−15.27)***	(−11.19)***
LNKL	0.008	0.002	0.007	0.017	0.015
	(7.78)***	(3.06)***	(7.10)***	(13.74)***	(10.51)***
MALE	0.023	0.030	−0.035	0.017	0.007
	(4.83)***	(7.71)***	(−6.66)***	(2.79)***	(0.95)
FOR	0.013	0.005	−0.005	0.013	0.041
	(3.03)***	(1.44)	(−1.00)	(2.34)**	(6.04)***
AGE	0.001	0.001	0.001	0.001	0.001
	(3.71)***	(1.35)	(2.82)***	(6.02)***	(5.37)***
$\overline{R}^2$	0.108	0.055	0.036	0.145	0.132

[a] See Table 5 footnote.
[b] *MANL*: percentage of managers and supervisors.
[c] *TECHL*: percentage of engineers and technicians.
[d] *CLERL*: percentage of clerical and sales workers.
[e] *NPL*: percentage of non-production workers.
[f] *NPS*: percentage of total wages paid to non-production workers.

Considering the remaining variables, the log of the capital–labour ratio is positive and significant, indicating that capital-intensive firms hire more skilled and non-production workers. Large firms employ a smaller share of managers and supervisors. The proportion of managers and supervisors, and that of clerical and sales workers, are higher among the older firms. Firms with a high proportion of male employees and those that are foreign-owned employ more non-production workers, especially managers and supervisors.

(b) The mixed model

To investigate the effect of treating technology adoption as endogenous, the mixed model was estimated separately across the different worker groups. The results are presented in Table 9. Turning to the *TECH* regressions first, we find

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TABLE 9

THE DETERMINANTS OF TECHNOLOGY ADOPTION AND THE IMPACT OF TECHNOLOGY ON WAGES (MIXED MODEL)[a]

	(1)		(2)		(3)	
	TECH	*LNW*	*TECH*	*LNNPW*	*TECH*	*LNPW*
Constant	−16.745 (−60.66)***	4.933 (50.26)***	−18.774 (−72.20)***	5.343 (46.96)***	−15.908 (−55.80)***	4.473 (48.19)***
TECH		0.214 (5.21)***		0.265 (5.56)***		0.048 (1.24)
LNW	3.129 (59.21)***					
LNNPW			3.405 (70.55)***			
LNPW					3.017 (54.43)***	
SIZE	0.001 (23.86)***		0.001 (13.23)***		0.001 (24.47)***	
SIZE2		0.006 (0.22)		0.051 (1.59)		0.079 (3.05)***
SIZE3		0.005 (0.10)		0.072 (1.41)		0.134 (3.21)***
SIZE4		−0.009 (−0.15)		0.084 (1.27)		0.155 (2.87)***
SIZE5		−0.081 (−0.98)		−0.004 (−0.04)		0.189 (2.43)**
SIZE6		−0.255 (−2.03)**		−0.205 (−1.40)		0.185 (1.56)
LNKL		0.045 (4.29)***		0.011 (0.92)		0.081 (8.25)***
MALE		0.187 (9.01)***		0.079 (3.29)***		0.250 (12.91)***
FOR	−0.113 (−2.72)***	0.132 (4.96)***	−0.501 (−11.51)***	0.183 (5.92)***	0.146 (3.64)***	0.134 (5.36)***
AGE	−0.007 (−5.67)***	0.004 (7.37)***	−0.010 (−7.88)***	0.003 (4.79)***	−0.003 (−2.37)***	0.004 (7.38)***
PATL	0.473 (0.48)		−0.050 (−0.07)		1.520 (2.23)**	
RDS	2.988 (5.48)***		1.257 (2.19)**		6.624 (12.15)***	

[a] Figures in parentheses are *t*-statistics. ***, ** and * represent statistical significance at 1%, 5% and 10% level, respectively.

that wages have a significantly positive effect on technology adoption. The estimated coefficients are all statistically significant at the 1% level. With respect to the other firm characteristics, we find that larger firms and younger firms employ more new technologies. The negative correlation between age and technology adoption is consistent with the vintage-effect hypothesis. This result is similar to that found by Gale (1998) in US manufacturing, but contrasts with the evidence reported by Dunne (1994) for a US sample and by Siegel (1998) for a Long Island sample. Surprisingly, the impact of foreign ownership on technology adoption is ambiguous. The coefficients of the R&D/sales variable are all significantly positive, suggesting that technology opportunity has a strong effect on technology use in our data.

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Treating the *TECH* variable as endogenous in the regressions yields a difference in the effect of technology use on production and non-production worker wages. For non-production workers the coefficient is significantly positive, but for production workers it is not significantly different from zero. Comparing these results with wage regressions that treat *TECH* as exogenous suggests that the estimated positive impact of technology on wages is downward-biased.[14] The Hausman tests show that the differences between the estimates of these two specifications are statistically significant. Thus, we reject the hypothesis that technology adoption is exogenous.

Examining the other coefficients, we again find a monotonically increasing relationship between firm size and wages for production workers. However, the firm-size wage premiums disappear for non-production workers. Both firm age and the log of the capital–labour ratio are positively correlated with wages. Firms with foreign ownership, or those that have a higher proportion of male employees, also tend to pay higher wages.

To summarize, the results presented here are somewhat at odds with evidence reported by Chennells and Van Reenen (1997, 1998) on British establishments. Those authors find that it is only the pay of skilled workers that increases the likelihood of introducing new technology, but that technical change *per se* has little direct influence on the earnings of skilled workers. In contrast, our findings suggest that higher pay in both skilled and unskilled groups increases the probability of adopting advanced technology and that the effect of technology on wages may be confined to skilled workers.

IV. Conclusion

This paper examines the impact of advanced technology adoption on wages and employment structures in Taiwan. Using manufacturing survey data for 1991, our cross-sectional results are consistent with existing empirical evidence that firms using more advanced technologies pay higher wages for production and non-production workers (Berndt *et al.* 1992; Krueger 1993; Dunne and Schmitz 1995; Autor *et al.* 1996; Doms *et al.* 1997). The share of non-production workers in firms that use advanced technologies is higher than that in firms that do not use these technologies.

Nevertheless, we find distinctive differences between the labour markets of Taiwan and the developed countries. First, neglecting any bias arising from the endogeneity of technology adoptions, we find that the magnitudes of technology premiums for non-production labour are larger than for production labour in Taiwan. In contrast, Dunne and Schmitz (1995) and Doms *et al.* (1997) showed that for the United States the correlation between technology measures and non-production workers' wages is weaker than that for production workers' wages. Second, in the United States, average size–wage premiums for production labour exceed those for non-production labour. The reverse pattern is found for Taiwan. Our OLS estimates are that the size–wage premiums associated with non-production labour are about twice those associated with production labour. This result appears consistent with the earlier size–wage profile in Taiwan reported by Aw and Batra (1995). However, the size–wage premiums disappear for non-production workers after controlling for the endogeneity of technology adoption.

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We find that the size–wage premium is smaller for all size classes when technology use variables are included. We examine the simultaneous relationship between technology and wages using the mixed model. These results suggest that higher wages of both non-production and production workers have a strong positive impact on technology adoption, but that technology adoption exerts a direct influence only on wages of non-production workers.

Our dataset has several limitations that should be noted. First, it contains only information on firms, and is not a matched employer–employee data set. We cannot investigate the influence of worker characteristics on wages directly. Second, these cross-sectional data do not allow us to assess the impact of technology controlling for firm fixed effects, which can be examined using panel data. Third, we use technology counts as a proxy for the intensity of technology use within a firm. This measure may disproportionately overstate the extent of technology use in larger firms, since not all of the workers may work with the machines. Finally, higher wages at the firms with advanced technology may be related to higher unobserved quality of the workers. Further research on this issue may be fruitful if data linking individual workers and firms are available.

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NOTES

1. These papers use 1985 Taiwan data.
2. For discussion of the Taiwan manufacturing census, see Aw *et al.* (1997).
3. This classification is imperfect (Leamer 1994) but has successfully tracked employment and wage by skill category (Berman *et al.* 1994; Feenstra and Hanson 1997). Haskel (1999) used a similar classification of workers as manual and non-manual and distinguished skilled and unskilled subgroups.
4. According to the Taiwanese labour force survey, the working hours across industries ranged from 45.7 to 48.3 hours per week in 1991.
5. The exchange rate was 1 US$ = 25.75 NT$ in 1991.
6. We use a broad definition of foreign ownership: those firms with any foreign capital share are defined as 'foreign'. Feenstra and Hanson (1997) find that wage inequality is linked to foreign direct investment.
7. One possible explanation for the size–wage premium is that employers who pay their workers higher wages are more likely to survive and grow (Brown and Medoff 1997; Troske 1999). The positive correlation between plant age and wages may reflect that plant age is a proxy for characteristics of the workforce.
8. The study of technology adoption using cross-sectional data is problematic because of the difficulty of incorporating the dynamic structure of the adoption decision, especially the learning and diffusion processes (Besley and Case 1993).
9. We assume that the *MALE* variable does not capture worker quality differences, since there are no strong reasons why women should be less capable than men in using new technologies after controlling for their skills and other characteristics.
10. We thank the anonymous referees and William H. Greene for their advice on this point.
11. To save space, we do not report the coefficients of the 67 three-digit industry dummy variables in the tables.
12. In developing countries, foreign firms tend to pay higher wages (e.g. Aitken *et al.* 1996).
13. We reject the hypothesis of no technology effect in each of the three wage regressions (*LNW*, *LNNPW* and *LNPW*). The *F*-statistics are 25.9, 19.8 and 8.5, respectively.

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14. The OLS estimated coefficients of the *TECH* variables in the wage regressions that treat *TECH* as exogenous (*LNW*, *LNNPW* and *LNPW*) are 0.037, 0.031 and 0.025, respectively. All the coefficients are significant at the 1% level. To save space, we do not report these regressions.

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