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TECHNOLOGICAL CHANGE AND SKILLS DEMAND:

Panel Evidence from Malaysian Manufacturing

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ABSTRACT

There is a body of literature in industrialized countries that the growing demand for skilled labor is being driven by skill-biased technological change, fueled in large part by the adoption and use of new information and communications technologies (IT). This paper investigates the hypothesis for a developing country—Malaysia—using panel establishment data from the manufacturing sector for the 1985-1995 period. In the first section, the relationship between TFP growth and skills demand is investigated for insights into whether technological change is skill-biased, and if so, towards which skill groups. The second section turns to a direct technology measure—adoption of different types of IT, and its timing—to examine how workforce skills vary as employers adopt and use new information technologies. It finds evidence that employers move to a higher skill-mix in anticipation of IT adoption, and that these dynamic changes in skill-mix, both pre- and post-IT adoption, are associated with systematic changes in labor productivity and wages. Estimates of panel production function models find evidence that IT use leads to productivity gains—on the order of 4-6 percent per annum—with accumulated experience using the new technology. These gains (or "learning effects") are significantly larger when accompanied by worker training. Together, these results lend strong support for the skill-biased technological change hypothesis and for the critical intermediary role of skilled labor in IT adoption and use in Malaysia.

TECHNOLOGICAL CHANGE AND SKILLS DEMAND:

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I. INTRODUCTION

There is a recent body of literature in industrialized countries that the growing demand for skilled labor is being driven by skill-biased technological change, fueled in large part by the adoption and use of new information and communications technologies (IT). This growing trend in employment of skilled labor despite stable or even rising relative pay[1] is well-documented in many OECD countries. In the U.S. and U.K., the non-production share of employment in manufacturing—a crude measure of the skilled workforce—rose 7 to 10 percentage points over the 1970-1990 period to levels of about 43 percent. When available, more refined skill measures—by occupation or educational attainment—also showed similar rising trends over time. While many competing hypotheses have been put forward, including trade, global production and changing industrial structure, there is a growing consensus that skill-biased technological change has been the principal driving force behind these changes.[2] Studies show that only a small part of the rise in non-production employment shares comes from changing industrial composition; most of it is attributable to within-industry (and within-firm) increases in the share of non-production employment. The rise in non-production employment is also concentrated in the same industrial sectors across OECD countries with differing macro-economic and trade patterns, which tends to support a technology-driven explanation.

Additional support for this hypothesis comes from a body of research on the links between different measures of technology—research and development (R&D) intensity, age of capital, total factor productivity (TFP), computers, and use of information technology (IT)—and worker skills and wages (see OECD, 1996). Firm-level surveys in the U.S., U.K., Canada and Denmark show that establishments using advanced manufacturing technologies tend to employ more highly educated workers, scientists and engineers than those that do not.[3] Studies based on worker-level micro data find that use of computer technologies at work is higher among more educated workers, and that over time, the proportion of white-collar workers who used computers in the workplace grew much faster than did blue-collar workers.[4] They also show that workers who use

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[1] Simple theory would suggest that employers will respond to rising relative pay for skilled workers by substituting away from this more-expensive labor, and hiring "less expensive" unskilled labor.

[2] For example, see Machin, Ryan and Van Reenan, 1996; Berman, Bound and Griliches, 1994.

[3] See Doms, Dunne and Troske (1995), Siegel (1995), and Dunne, Haltiwanger and Troske (1997) for empirical evidence for the U.S.; for the U.K., see Machin (1995); for Canada, see Baldwin, Diverty and Johnson (1995); for Denmark, see Nyholm (1995).

[4] Studies include Krueger (1993) and Murnane and Terrell (1996) for the U.S., and Card, Kramarz and Lemieux (1995) for comparisons of the U.S., Canada and France.

computers receive a wage premium, even controlling for measurable attributes such as education, age and sex, and that the reward to these (unmeasured) cognitive skills rises over time with computer use in the workplace. There is also empirical evidence from the training literature that, holding constant the effects of education and skill level, workers are more likely to get training the higher is the rate of technical change in the workplace, and be paid a wage premium.[5]

This paper investigates the skill-biased technological change hypothesis for a developing country—Malaysia—using panel establishment data from manufacturing covering the period between 1985 and 1995. It does this in three ways. First, following the approach used in OECD studies, it estimates the relationship between TFP growth and skills demand for insights into the issue of whether technological change is skill-biased, and if so, towards which skill groups. Second, it uses a direct technology measure—adoption of different types of information and communications technology (IT), and its timing—to examine how the mix of workforce skills vary as employers adopt and use new information technologies. It finds evidence that employers move to a higher skill-mix in anticipation of IT adoption, and that these dynamic changes in skill-mix, both pre- and post-IT adoption, are associated with systematic changes in labor productivity and wages. Finally, it estimates panel production function models to identify the time-path of productivity gains from IT adoption and use. It finds evidence that IT use is associated with productivity gains on the order of 4-6 percent per annum with accumulated experience using the new technology, and that these "learning effects" are significantly larger when accompanied by worker training.

Research on this issue in developing countries is sparse at best. The findings reported in this paper lend strong support for the skill-biased technological change hypothesis and for the intermediary role of skilled labor in IT adoption and use. While the empirical results are specific to Malaysia, the analytic methodology should be of interest to policy makers in other developing countries interested in identifying skills demand as they address policy concerns over skill shortages and inadequate vocational training and in-service training needs, and especially as they embark on national IT strategies to promote use of new information and communications technologies.

II. BACKGROUND AND DATA

Over the past two decades, the Malaysian economy has been transformed from one reliant on agriculture and natural resources to one where the manufacturing sector has become the main driver of growth in the economy. With the exception of two contractions, in the mid-1980s and in the recent crisis, the economy has expanded at a rapid pace, growing in excess of 8 percent per annum since 1987. These macro trends have been accompanied by dramatic changes in the industrial and skill composition of the workforce and, until the recent crisis, by increasingly tight labor market conditions,

[5] See Lillard and Tan (1992) and Bartel and Sicherman (1998) for U.S. evidence; Tan and Batra (1996) for evidence on Mexico, Taiwan and Colombia; and Tan and Batra (1997) for Malaysia.

growing labor and skills shortages, and wage pressures driving up unit labor costs. And while labor retrenchments rose sharply during the recent crisis, unemployment rates remained moderate and some sectors of the economy continued to face labor shortages. As the economy recovers, these underlying trends are likely to resurface, and with them, policy concerns about future labor and skill shortages, and the adequacy of private and public sector responses to address them.

What kinds of skills will the Malaysian economy require in the future, especially as it embarks on the national goal of attaining developed country status by 2020 through, among other strategies, policies to promote technological change and IT diffusion and use?[6] Simply extrapolating from past trends (a fixed-coefficient planning approach) is unlikely to provide robust forecasts of future skill needs, especially if skill-biased technological change is important and if growing adoption and use of new information technologies by employers alters workforce skill requirements. To gain insights into future skill needs, and to identify what types of skills will be demanded by technological change, information is required on employers' production activities and technology used, factors that shape demand for different skill groups.

This information is available, at least in part, from the Department of Statistics' annual <u>Survey of Manufacturing Industries</u>. These surveys elicit a wealth of information on the attributes of employers and on production—value of output and sales, use of intermediate inputs, and fixed capital assets—that can be used to describe the demand characteristics of different groups of employers, and in less detail, the skill composition and wages of their workforce. A continuous panel of establishments from these surveys was constructed covering the period between 1985 and 1995, and will be the primary data set used in the paper. This panel data is used to estimate production functions to derive the first technology measure—total factor productivity (TFP) growth. For the second, and more direct, measure of technology, we rely on a specialized survey—the <u>Inter-Firm Linkages and Technology Development</u> (ILTD) Survey—fielded in 1997 to 2,300 establishments drawn from the sampling frame of DOS's annual survey of manufacturing. Firms provided data on the use and date of adoption of different types of IT, information that can be linked to a sub-set of firms in the 1985-1995 panel data.

<u>Trends in Skill Mix 1997-1995</u>

It is useful to start by documenting the broad trends in skills composition to be investigated in this paper. Since skill mix changes slowly over time, a long time-series is needed; as such, we assemble a panel from the <u>Industrial Survey</u> covering the 1977 and 1995 period using data from every other year in this time series. The survey provides information on several distinct occupations, separately for males and females: (1) <u>non-production occupations</u>, including professionals, managers, technicians, clerical staff, and

[6] The growing policy interest world-wide on "The Knowledge Economy" and the potential contribution of IT to development is mirrored in Malaysia. Recognizing that IT and multimedia will be critical enabling tools for increasing productivity and competitiveness of the economy, the Malaysian Government has invested heavily in the Multimedia Super Corridor (MSC), sought to diffuse IT widely across industry, and expanded education and training in IT skills.

general workers; and (2) production workers, including skilled production, semi-skilled production workers, and unskilled production workers. We refer to occupations as "skills" even though the term is often associated with education level; however, while there is not a one-to-one correspondence, these two skill measures are highly correlated.[7] This occupational detail allows flexibility in categorizing workers either as production or non-production (as the developed country literature has done), or by level of skill, which is our focus. One natural classification scheme, ranked in descending skill level, is: (i) professionals, technicians, and managers; (ii) skilled production workers; (iii) semi-skilled production workers; and (iv) unskilled employees, including clerical and general workers, and unskilled production workers.

Figure 1 shows skill trends in the manufacturing sector using the two alternative measures—percent of workforce in non-production jobs, and percent in highly-skilled non-production occupations—professionals, technicians and managers (henceforth, referred to as PTM). First, consider the non-production share in employment. Between 1977 and 1985, this rises from 23.3 percent to 27.7 percent, declines to 22.5 percent by 1991, and thereafter rises slowly to the 25 percent level by 1995. This dip reflects the pronounced downturn in economic activity during the second half of the 1980s when unemployment rates soared to levels in excess of 8 percent before declining in 1989. Employers laid off a higher proportion of non-production staff during the recession, but then returned to the trend line after 1989. The second measure reveals a similar, but much stronger secularly rising trend. The share of highly skilled PTM employees rises from 9.6 percent to 14.8 percent over the 1977 to 1995 period. Like non-production staff, a slight drop in PTM employment share is apparent between 1985 and 1989, though it recovers and continues to rise after 1989, ending the period at levels higher than those observed at the start. Thus, only a more refined skills-based measure reveals a rising secular trend in the highly skilled occupations in Malaysian manufacturing.

In tabulations not reported here, several other trends are noteworthy. First, except for the 1985-1989 period, which reflects cyclical factors, the employment shares of the other two skill groups—skilled production and unskilled production and general workers—decline secularly over time. Second, there are dramatic changes in the gender composition—females accounted for 42.5 percent of the workforce in 1977 and 46.5 percent by 1995—reflecting rising female labor force participation rates. In the highly skilled PTM category, there is nearly a three-fold increase of female professionals from 5.6 percent in 1977 to 14.8 percent by 1995; a doubling in the female share of managers to 19.7 percent, and a 50 percent gain in the proportion of technicians. Though smaller in size, significant gains in the proportion of females are also apparent among the other skilled and unskilled groups of production workers. In terms of actual numbers, these

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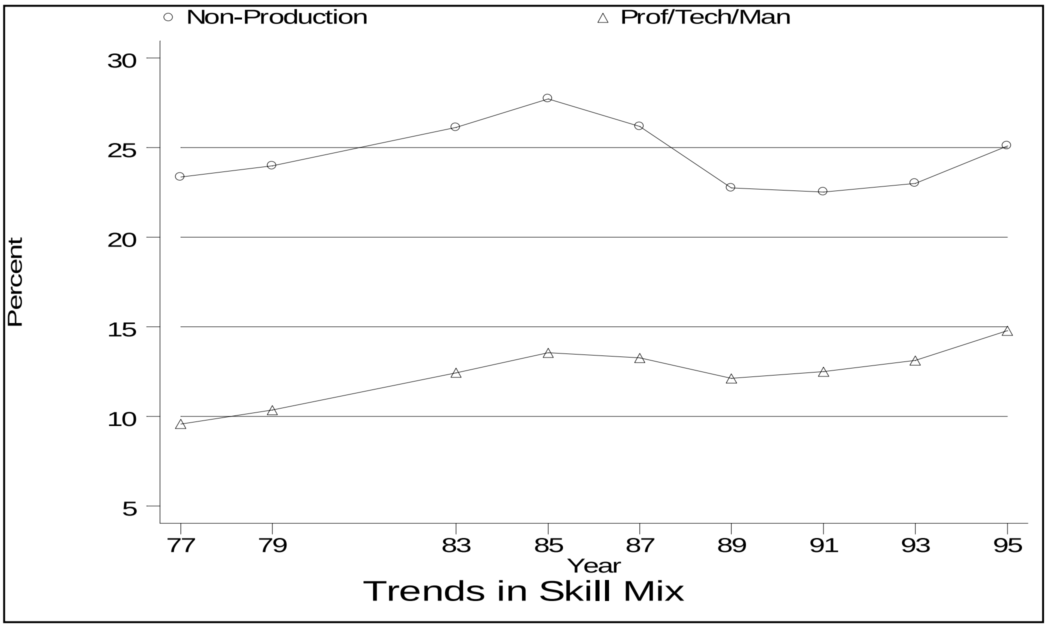
[7] Occupations can be mapped into educational categories using labor force surveys which elicit information on **both** educational attainment and occupation. For example, those in professional, technical and managerial occupations are predominantly individuals with university diploma or degree; production related occupations, on the other hand, tend to span the entire educational spectrum, with the majority concentrated at the lower and middle secondary school level.

latter gains translate into large increases in female employment since these skill groups together account for about 85 percent of total manufacturing employment.

Figure 1. Trends in Skill Mix in Manufacturing—1977 to 1995



III. SKILL-BIAS OF TECHNOLOGICAL CHANGE

To what extent has technological change been responsible for these trends in skill mix? To address this question, we adopt the empirical methodology used by a number of U.S. and U.K. studies (see Berman, Bound and Griliches, 1993; Machin, 1995; Dunne, Haltiwanger and Troske, 1997). Firms are assumed to minimize costs, which are a function of variable input prices (wage rates w_1 and w_2 of skill groups L_1 and L_2), output Y, and quasi-fixed factor inputs such as capital stock, K. If this cost function has a translog form, the following equation (in logarithms) of the wage share of the first skill group, L_1, in total wages can be derived:[8]

$$SHARE_{1it} = \beta_0 + \beta_1 t + \beta_2 \ln(w_1/w_2)_{it} + \beta_3 \ln K_{it} + \beta_4 \ln Y_{it} + \beta_5 \ln TFP_{it} \qquad (1)$$

where $SHARE_1$ is the wage share of the first skill group in total wages of firm i, t is a time-trend to allow wage shares to change over time, w_1/w_2 is the relative price (wage) of the first skill group L_1 relative to the wage of the omitted skill group L_2, and Y is output. For our analysis, we also include a measure of technological change, the level of TFP. Taking first differences of equation (1) and adding an error term ε_{it}, yields an equation of changes in wage shares:

[8] See E. Berndt (1990), The Practice of Econometrics, Chapter 9 for a derivation of this estimating equation.

$$\Delta SHARE_{1it} = \beta_1 + \beta_2 \Delta \ln(w_1/w_2)_{it} + \beta_3 \Delta \ln K_{it} + \beta_4 \Delta \ln Y_{it} + \beta_5 \Delta \ln TFP_{it} + \varepsilon_{it} \quad (2)$$

where the symbol Δ denotes change over time. We also experiment with an alternative dependent variable that is used in several OECD studies—the skill group's share of total employment–which, while not explicitly derived from the cost function framework, is similar in spirit to the first wage share dependent variable.

Equation (2) is a useful framework for analyzing changes over time in skill mix. Since (relative) wages are given and wage share is the wage rate of a given skill group multiplied by employment as a fraction of total wage bill, changes in wage shares reflect changes in the employment of different skill groups over time. The β_2 parameter provides an indication of how the shares of different skill groups are affected by changing relative wages. Theory would suggest that this parameter is negative ($\beta_2 < 0$) since a rise in relative wages for one skill group would lead cost-minimizing employers to substitute away from them, other things equal.[9] The β_3 parameter indicates whether capital and skills are complementary inputs ($\beta_3 > 0$) or substitutes ($\beta_3 < 0$) in the production process. The β_4 parameter indicates whether growing industries are more likely ($\beta_4 > 0$) or less likely ($\beta_4 < 0$) to increase employment of a particular skill group. Finally, the β_5 parameter of TFP shows the extent to which technological change is skill-biased. If TFP is skills-neutral, we would expect it to have no impact on skill mix ($\beta_5 = 0$), controlling for other factors. A positive β_5 parameter would imply that technological change is skill-using or "skill-biased", while a negative β_5 would indicate that technological change substitutes for skilled labor.

Deriving TFP Estimates

To test these hypotheses, we first estimate pooled cross-section time-series production functions to get a measure of TFP for each establishment over time. We use the panel establishment data from DOS's annual Industrial Survey covering the period between 1985 and 1995. The analysis is restricted to a sample of 57,612 firm-year observations covering 11,988 unique establishments, without missing information on the key production variables needed to estimate TFP. We use a simple Cobb-Douglas production function specification which (in natural logarithms) takes the following form:

$$\ln Q = \alpha \ln SL + \beta_1 \ln UL + \beta_2 \ln K + \varepsilon \quad (3)$$

where Q is value added, SL is skilled labor, UL is unskilled labor and K is capital. Value added is calculated as the difference between the value of the firm's output and its expenditures on materials, water, energy and electricity. Value added is expressed in real terms by deflating it using the producer price index for each two-digit industry. Skilled

[9] In practice, most empirical studies have argued against including the relative wage variable because of concerns about potential biases introduced by including a variable correlated with the dependent wage share variable which itself includes components of wages.

labor is measured as the total number of managerial and professional, technical and supervisory and other skilled workers employed in the firm. Unskilled labor includes clerical staff, other general workers and unskilled production workers. This breakdown by skilled and unskilled labor is a simple control for differences in labor quality; the subsequent analysis focuses on finer skill breakdowns. Capital is measured as the total year-end value of fixed assets and is deflated by the capital stock deflator available for each year.

The residual from this regression, ε, is used as a measure of the firm's level of technology, TFP. It is calculated by taking the difference between actual value added and that predicted using the estimated production function parameters. Since the production function measures the average output that can be produced using different mixes of capital and labor, a positive (negative) value of the residual ε indicates that the specific establishment is more (less) productive than the average firm operating with similar capital and labor inputs in a given year. When a common production function is estimated on a pooled cross-section time-series of year-firm observations, the residual ε_{ft} provides a measure of how TFP changes over time *t* for a given firm *f* relative to other firms in the sample. For the labor demand analysis, pooled cross-section time-series production functions were also estimated separately for each one of twelve two-digit industries to allow the production function parameters to vary across industries.[10] Individual firm-level ε_{ft} for each year-firm observation is calculated and appended to the panel data as our first measure of technological change, TFP. Industry-level aggregates of these TFP estimates are reported in Annex 1.

Estimating Skills Demand

With estimates of firm-level TFP in hand, we now turn to investigating the relationship between technology and changes over time in the skill composition. We consider four skill groups for all workers combined, and separately for males and females. In each case, we define wages relative to the least skilled group; in the gender-specific regressions, wages are defined relative to the wages of unskilled male workers. We also experiment with the alternative measure of skill mix—the employment share of a given skill group relative to total employment. Finally, we include the logarithm of the unemployment rate, ΔlnUR, as a control for macroeconomic changes, specifically to capture the effects of recession and recovery in the late 1980s and the tight labor market environment in the 1990s.

[10] The regression results are not reported here but are available on request. Across all industries, labor and capital shares are roughly two-thirds and one-thirds respectively and all three inputs are positive and statistically significant. In addition, the coefficient on skilled labor is typically higher than that of unskilled labor, indicating that skilled labor has a higher impact on productivity than unskilled labor.
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Table 1. Labor Demand Estimates by Skill Level 1985-1995
(Skill shares of Wage Bill)

Dependent Variable: Labor share of wage-bill	Professionals, Technicians, & Managers		Skilled Production Workers		Semi-Skilled Production Workers		Unskilled & General Workers	
All Employees	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
ΔlnVA	-.0161	-9.74	.0137	5.81	.0124	5.10	.0004	0.12
ΔlnK	.0073	8.39	-.0062	-4.98	-.0055	-4.28	.0018	1.48
$\Delta\ln(W_s/W_{us})$	-.0071	-1.28	.0045	0.53	.0088	1.51	n.a.	n.a.
ΔlnTFP	.0059	3.78	-.0056	-2.54	-.0102	-4.46	.0036	1.59
ΔUR	-.0025	-10.42	-.0001	-0.40	-.0016	-4.58	.0034	9.94
Male Employees								
ΔlnVA	-.0183	-11.80	.0082	4.25	.0100	5.34	.0020	1.16
ΔlnK	.0066	8.05	-.0040	-3.98	-.0040	-4.10	.0022	2.44
$\Delta\ln(W_s/W_{us})$	-.001	-0.39	.0108	1.71	.0090	2.08	n.a.	n.a.
ΔlnTFP	.0076	5.22	-.0027	-1.51	-.0093	-5.27	.0016	1.01
ΔUR	-.0003	-1.31	-.0000	-0.06	-.0011	-3.96	.0002	0.87
Female Employees								
ΔlnVA	.0024	4.42	.0056	4.70	.0024	1.80	-.0015	-1.09
ΔlnK	.0006	2.34	-.0021	-3.44	-.0014	-2.05	-.0003	-0.43
$\Delta\ln(W_s/W_{us})$	.0049	3.27	-.0060	-2.05	.0010	0.40	-.0323	-5.80
ΔlnTFP	-.0018	-3.62	-.0029	-2.63	-.0009	-0.72	.0017	1.29
ΔUR	-.0020	-22.41	-.0002	-1.12	-.0003	-1.73	.0023	9.41

Note: 1. Number of observations=57,612 and number of establishments=11,988
2. Regressions included indicator variables for 12 broad industrial sectors.

Equation (2) was estimated on the panel of 57,612 firm-year observations using a "fixed-effects" model.[11] The parameter estimates for the manufacturing sector as a whole are reported in Table 1. Before turning to the key variables of interest, two findings may be noted. First, relative wage effects on labor demand are mixed—sometimes negative as predicted by theory, sometimes positive—and be due to the correlation between the relative wage variables and the dependent variable since wage components are included in both.[12] Second, the control for macroeconomic conditions, ΔlnUR, is generally positive for unskilled production and general workers, and negative or neutral for the other more skilled groups—PTM employees, and skilled and semi-skilled production workers. On the surface, this result suggests (counter-intuitively) that employers reduce

[11] The fixed-effects model implements the first differencing approach that generates parameter estimates measured in terms of changes over time and, at the same time, eliminates any potential biases from unmeasured firm-level factors that may be correlated with included variables.

[12] . Similar mixed results are reported in other OECD studies, and have prompted many researchers to argue against including relative wages in labor demand models.

the share of skilled workers in favor of unskilled workers as unemployment rises. A more appealing interpretation is that unemployment—high in the 1980s and low in the 1990s—is picking up the secular decline over time in the unskilled wage (labor) share and an upward trend in the share of more skilled workers.

The evidence indicates that capital and highly skilled workers are complements while capital and less-skilled workers are substitutes. The estimated parameters for ΔlnK are generally positive and significant for the most highly skilled PTM group, in both wage and employment share specifications. The estimates range between 0.006 and 0.007 for all workers combined and for male PTM workers; for female PTM employees, the estimated parameters are much smaller (0.0004 to 0.0006) and do not attain statistical significance in the employment share specification. In contrast, the ΔlnK parameters are negative and statistically significant for less-skilled groups, suggesting that capital is a substitute for skilled and semi-skilled production workers. However, the evidence is mixed for the least skilled group of unskilled production and general workers—positive in some cases, negative in others (for females in particular).

The effects of output growth vary systematically by skill group. The estimated parameters of ΔlnVA are positive and significant for skilled production and semi-skilled production workers in both wage and employment share specifications. In contrast, the ΔlnVA parameters are negative and significant for the most highly skilled PTM group, for all workers combined and for males; the exception—female PTM workers—suggests that growing firms tend to increase the share of female professionals, technicians and managers. The evidence on output growth is mixed for unskilled production and general workers. In other words, controlling for the effects of technical change and capital, output growth has been sustained by expanded employment of both skilled and semi-skilled production workers and highly skilled female PTM workers, and reductions in the proportion of male PTM workers.

Finally, the results indicate that technological change is skill-biased towards the use of professionals, technicians and managers (the PTM group). Consider the top panel of Table 1 for male and female workers combined. The estimated parameter of TFP is positive and statistically significant (.0059) for the most highly skilled PTM group; for the other skill groups, the TFP parameters are either negative and significant, or are not different statistically from zero. This implies that technological change is skill-using for the PMT group but skill-replacing or skill-neutral for the less-skilled groups of workers. The second and third panels—by gender—reveal that within the PTM group, technical change is skill-using only for male workers—the estimated TFP parameter (.0076) is positive and statistically significant for males and negative and significant (-.0018) for females. It is worth noting that these results for Malaysia broadly parallel those reported in OECD studies either using research and development (R&D) expenditures or indicators of computer-use as proxy variables for technology to explain changes over time in the share of non-production workers.

How robust are these technology results, and do they vary across industries? To address these questions, equation (2) was estimated separately by two-digit industries using TFP measures estimated from industry-specific production functions, and focusing on professionals, technicians and managers—the group where the demand effects of technological change appear to be concentrated. The ΔlnTFP parameters estimated for the PTM group in each industry using two alternative skill share model specifications, are summarized in Table 2 separately by gender. Several points stand out. First, technological change is skill-biased in the use of professionals, technicians and managers, but only for male PTM workers; for female PTM workers, technological change is generally either neutral or skill-replacing. This result reinforces the earlier results for all manufacturing. Second, the effects of TFP are positive and significant for male PTM workers in several industries—wood products, glass and clay, basic metals, electronics and electrical machinery—when the wage share measure is used. Using the alternative model specification—skill shares of employment—adds food and beverages, paper and printing, general machinery and transportation equipment to the list of industries with a skill-bias to highly skilled workers. These are the same sectors that exhibited relatively higher rates of TFP growth over this period (see Annex 1).

Table 2. TFP and Skill-Bias in Demand for PTM Staff by Industry
Using alternative specifications of skill shares

INDUSTRY	Males		Females	
Dependent variable: labor share of employment	Skill share of Wage Bill	Skill share of Employment	Skill share of Wage Bill	Skill share of Employment
	Coefficient of lnTFP		Coefficient of lnTFP	
Food & beverages	.0002	.0097*	-.0017	-.0003
Textiles & apparel	.0051	.0056	-.0083*	-.0023
Wood products	.0107*	.0187*	-.0002	-.0004
Furniture	-.0082	-.0016	-.0011	-.0010
Paper & printing	.0052	.0235*	.0007	.0065*
Chemicals & rubber	.0035	.0070	-.0035*	-.0016
Glass & clay	.0224*	.0383*	-.0008	.0016
Basic metals	.0262*	.0254*	.0009	-.0012
Fabricated metals	.0103	.0090	-.0017	-.0019
General machinery	.0119	.0259*	-.0015	.0014
Elec. Mach. & electronics	.0231*	.0131*	-.0022	.0010
Transport equipment	.0032	.0182*	-.0025	.0009
Other industry n.e.c.	-.0056	.0118	.0018	.0007

Notes: 1. regressions estimated separately by broad industry sectors.
2. other included variables are log(value added), log(capital assets), log(relative wages), and a control for aggregate unemployment rates.
3. * denotes statistical significance at the 1 percent level.

IV. IT USE AND WORKFORCE SKILLS

In this section, we turn to a direct measure of technology—new information and communications technology (IT) and investigate the role of skills in the adoption and use of IT by manufacturing firms. Information on several key categories of IT was elicited in the 1997 Inter-Firm Linkages and Technology Development (ILTD) Survey, a survey of 2,300 establishments drawn from the sampling frame of DOS's annual survey of manufacturing. Firms provided data on the use and date of adoption of IT, information that can be linked to a sub-set of firms in the 1985-1995 panel data. These linked data allow us to investigate several questions about the nature of skill-bias in technological change: do higher-level skills play a role in employers' decisions to adopt IT, and the timing of that adoption; what are the dynamics of skills use—do employers using IT increase skills mix before or after adoption of IT, or are they always intensive in their use of higher-level skills as compared to non-adopters; and finally, what are the productivity outcomes of IT use, and do the productivity gains from IT adoption increase with experience using IT?

The ILTD Survey elicited information on 15 detailed types of IT which we group into four categories: (i) IT for administration, such as payroll and finance; (ii) IT for communications, including internal and external communications, and electronic data interchange (EDI); (iii) IT for control functions, including logistics, transportation and testing; and (iv) IT for production processes such as computer-aided design (2-D and 3-D CAD), CAM (computer-assisted manufacturing), industrial robots, CNC (computerized numerical control) machine tools, FMS (flexible manufacturing systems), and CIM (computer-integrated manufacturing). In addition, companies also reported the problems they faced in implementing IT.

Table 3 shows the incidence in 1996 of the four broad IT categories by industry and local or foreign ownership, weighted so as to be representative of the universe of firms in manufacturing. First, use of IT for administration, payroll and finance functions is most prevalent, followed next by IT for communications; least common is IT for control and production processes. Second, there are striking differences in IT use between local firms and firms with some foreign equity. In administration and finance, 28 percent of local firms and 67 percent of foreign firms use IT. This type of IT typically involves use of stand-alone PCs in smaller companies, and integrated IT systems in larger ones. The gap in IT use by ownership becomes larger in the other IT categories. Among local firms, 10 percent use IT for communications, and 6-7 percent use IT for control functions and for different production processes. The corresponding figures among foreign firms are 42, 26, and 33 percent for communications, control and production processes. Finally, variations in IT use across sectors are apparent, possibly reflecting inter-industry differences in technology level and the size distribution of firms. For example, IT use is especially high in electronics and electrical machinery, chemicals, transportation equipment, and metals—sectors that are more technology and capital-intensive—as compared to the SME-dominated, and more labor-intensive sectors such as textiles, apparel, wood and furniture.

Table 3. Proportion of Firms Using Each Broad Type of IT by Sector and Ownership

Industry	Administration & Finance IT		Communications IT		Control Technology IT		Process Technology IT	
	Local	Foreign	Local	Foreign	Local	Foreign	Local	Foreign
Food, beverages	0.39	0.51	0.15	0.23	0.09	0.19	0.08	0.09
Textile, apparel	0.11	0.57	0.03	0.37	0.02	0.18	0.01	0.16
Wood products	0.42	0.43	0.14	0.11	0.01	0.05	0.05	0.12
Furniture	0.24	0.69	0.14	0.37	0.02	0.32	0.06	0.21
Paper & printing	0.56	0.90	0.22	0.38	0.14	0.32	0.10	0.27
Chemicals	0.58	0.75	0.22	0.47	0.12	0.27	0.21	0.33
Glass, ceramics	0.42	0.60	0.15	0.28	0.07	0.35	0.08	0.28
Basic metals	0.49	0.68	0.08	0.38	0.13	0.11	0.07	0.60
Machinery	0.26	0.67	0.10	0.41	0.08	0.14	0.10	0.31
Elec. Machinery	0.83	0.81	0.44	0.72	0.30	0.65	0.44	0.74
Trans. Equipment	0.57	0.80	0.35	0.25	0.20	0.34	0.25	0.43
Other n.e.c.	0.24	0.55	0.05	0.13	0.10	0.02	0.00	0.30
Total	0.28	0.67	0.10	0.42	0.06	0.26	0.07	0.33

Note: Tables are weighted to reflect the universe of firms in the manufacturing sector in 1996.

What accounts for these distributions in IT use across firms? Table 4 lists the major impediments to introduction of IT reported by ILTD respondents. Companies were asked to rank each one of five possible impediments on a scale of 1 to 5, where 1 is "not important" and 5 is "critically important". We treat rankings of 4 and 5 as serious impediments, and tabulate responses by firm size and ownership to show the proportion of firms reporting each reason as being a "serious" impediment.

Table 4. Ranking of Serious Impediments to the Introduction of IT by Firm Size and Ownership

Serious Impediments to Introducing IT	Local Firms				Foreign Firms			
	Small	Medium	large	Total	Small	medium	large	Total
High cost of IT	0.20	0.42	0.30	0.20	0.38	0.40	0.39	0.38
Lack trained IT staff	0.23	0.45	0.31	0.24	0.38	0.46	0.43	0.39
Low returns to IT	0.15	0.27	0.13	0.15	0.26	0.30	0.30	0.27
Lack IT help	0.21	0.34	0.37	0.21	0.27	0.31	0.36	0.29
Little IT impact	0.12	0.22	0.05	0.12	0.21	0.25	0.26	0.22

Note: Tables are weighted to reflect the universe of firms in the manufacturing sector in 1996.

<u>The inadequate supply of IT personnel emerges as the key constraint to introduction of IT.</u> Most local and foreign firms in common ranked the lack of trained IT staff as the most important impediment, followed by the high cost of introducing IT-based technologies, and the paucity of external IT consultants. These responses, coupled

with the fact that they rank "low returns to IT investments" and "little impact from introducing IT" as not being serious impediments, suggest first—that many firms are probably familiar with the benefits of IT, and second—that many would have introduced IT if the costs were lower and trained IT personnel and consultants were more widely available.

<u>Patterns of IT Diffusion 1985-1995</u>

The patterns of IT diffusion over time can be deduced from the dates of adoption reported by firms. Here, we focus on the sample of 1,648 firms in the ILTD Survey that can be linked to panel data from the Industrial Survey, yielding a total of 14,845 year-establishment observations over the 1985-1995 period. In each year, we code an indicator variable for IT use as 0 if that year precedes the reported date of IT introduction, and as 1 if that year equals or post-dates the date of introduction. The cumulative proportion of firms that adopted a specific type of IT by any given date (termed the "rate of diffusion"), can be calculated as the mean of this indicator variable at any point in time.

Figure 2. Diffusion of IT For Communications, Control, Computer-Aided Design (CAD), and Production Processes by Ownership

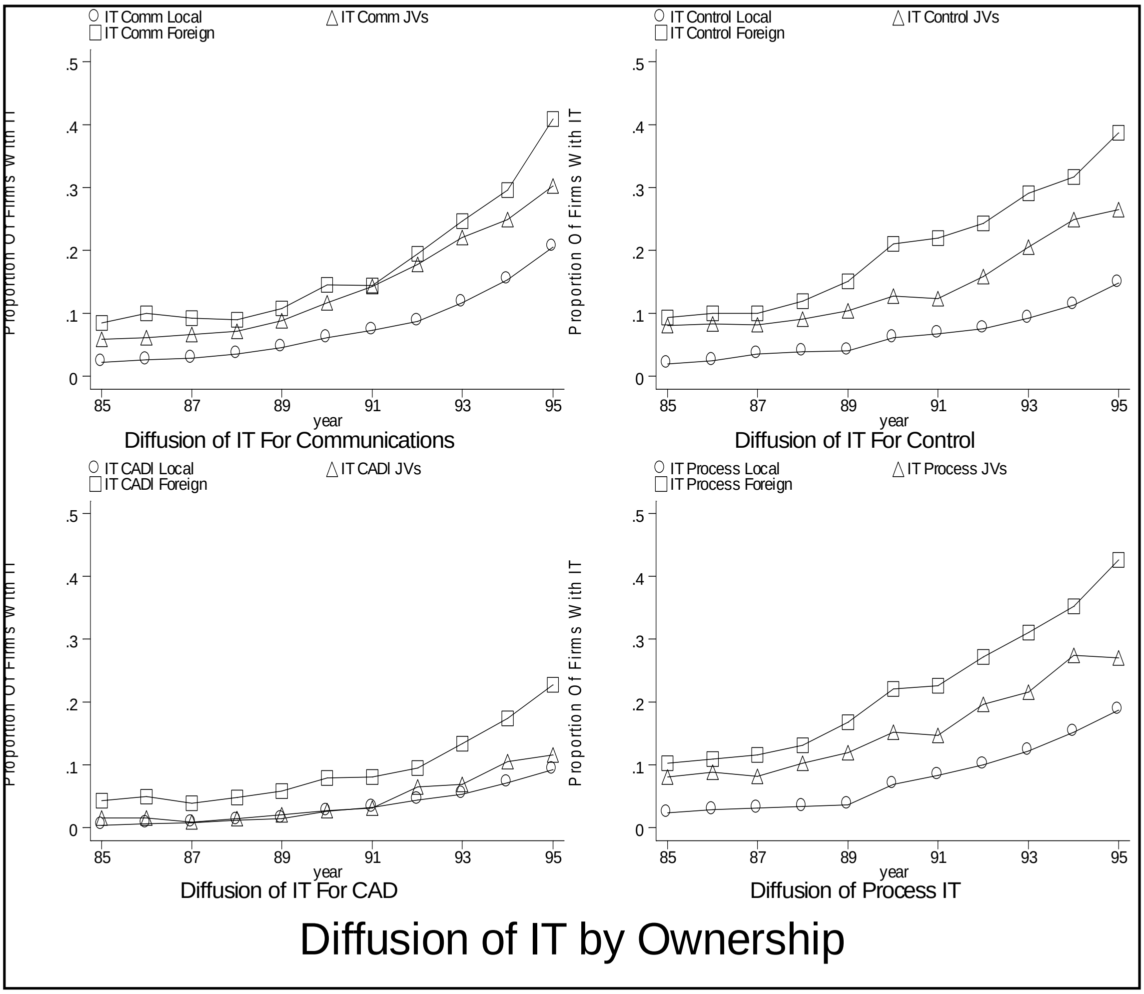


Figure 2 graphs the rates of diffusion over time of four technologically-complex types of IT, separately by ownership: (i) internal and external communications (including EDI), (ii) control and logistics, (iii) computer-aided design (both 2-D and 3-D CAD), and (iv) production processes including robots, CNC machine tools, and FMS. Each broad IT category includes several types of IT and, for convenience, we use the earliest date among them to represent the adoption date of that broad IT category.[13] In any given year, foreign firms are more likely to be using most types of IT, followed by joint-ventures, then by local firms. Of the four categories, the overall diffusion of IT for computer-aided design (CAD) is lowest, and is in use by only 9-11 percent of local firms and joint-ventures in 1995—bearing out policy concerns about the low level of design capabilities in local firms—as compared to 23 percent of foreign firms. Malaysian firms also lag behind in the use of IT for production—including automation, robots, computer-aided manufacturing (CAM), CNC machine tools, and flexible manufacturing systems—that are believed to have high productivity payoffs. By 1995, only 19 percent of local companies used any type of IT in their production processes as compared to 43 percent of foreign firms; this figure is only slightly higher (27 percent) among joint-ventures.

What role did skills play in IT adoption? To address this question, we estimated a panel probit model to investigate the effects of different skill mixes on the probability of IT adoption, holding constant the effects of other factors that are correlated with IT use. These other factors include firm attributes such as employment size, industry, local or foreign ownership, but also time in the sense that IT diffusion rates rise over time as individual firms learn from the experiences of other early IT adopters. Such a probit model may be written as:

$$\Pr(ADOPT)_{it} = \beta_0 + \beta_1 \Sigma_j\, SKILL_{ijt} + \beta_2 X_{it} + \beta_3\, DIFFUSION_t + \varepsilon_{it} \qquad (4)$$

where $ADOPT_{it}$, a 1,0 indicator variable denoting IT adoption in year t for the i^{th} firm, is related to X_{it}, a vector of company attributes such as firm size, industry and ownership; $SKILL_j$, the employment share of the j^{th} category of skills; and $DIFFUSION_t$, the rate of diffusion of IT at time t. In the empirical specification of the model, we allow different rates of IT diffusion by industry and, as such, drop industry from vector X. Finally, ε_{it} is an error term, and β's are parameters to be estimated by the probit model.

The probit results are reported in Table 5 for five types of IT—administration, computer-aided design (CAD), control and logistic functions, communications, and production processes. For each IT category, only firms that are at risk of adoption in a given year are included in the regression sample; firms that have already adopted that specific type of IT in previous years are dropped from the sample. The IT diffusion rate variable is calculated separately by year for each one of 13 industries so no industry dummy variables are required. Skill shares are lagged one year (to previous year levels)

[13] This turns out to be a good approximation since there is a tendency for reported dates of introduction of IT in each broad IT category to "cluster" around a particular year for a given firm. This is less likely for the most advanced types of process IT—such as FMS and CIM—many of which are fairly recent (post-1995) innovations, and as such, are not reflected in the diffusion figures which end in 1995.

to preclude any confounding effects that may arise from contemporaneous skill changes that occur during the year of IT adoption .[14]

Table 5. Probit Estimates of IT Adoption by Type of IT Technology

Explanatory Variables	IT for Administration		IT for Control & Logistics		IT for CAD		IT for Communications		IT for Production	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
Constant	-2.307	-27.51	-2.942	-23.08	-2.713	-24.46	-2.698	-26.89	-2.794	-25.81
Medium firms	0.426	9.06	0.320	4.04	0.470	6.79	0.374	6.23	0.503	7.94
Large firms	0.591	7.11	0.638	6.01	0.574	5.49	0.725	8.41	0.656	6.84
Joint-venture	0.037	0.60	0.027	0.27	0.069	0.81	-0.004	-0.06	-0.012	-0.15
Foreign firm	-0.044	-0.75	0.061	0.70	0.130	1.67	0.036	0.52	0.057	0.80
IT Diffusion Rate										
By industry/year	1.782	13.17	4.825	10.04	1.998	8.10	3.085	10.98	2.480	10.67
Employment share										
PTM	0.402	2.85	0.638	3.05	0.518	2.63	0.475	2.69	0.501	2.62
Skilled production	-0.078	-0.80	0.143	0.92	-0.140	-0.96	0.079	0.64	0.120	0.91
Unskilled workers	0.034	0.39	-0.137	-0.91	-0.031	-0.25	-0.010	-0.09	0.052	0.43
No. Observations	9,180		12,351		11,620		11,651		11,451	
Pseudo R^2	0.0764		0.1216		0.0987		0.0967		0.1129	

Table 5 makes several points. First, firm size is an important predictor of adoption for all types of IT. For example, compared to small firms (the omitted group), medium and large firms are 42 and 59 percent more likely to adopt IT for administrative purposes. Second, once firm size is controlled for, ownership does not appear to have an independent effect on IT adoption; the indicator variables for joint-ventures and foreign owned or controlled firms never attain statistical significance. Third, the industry rate of IT diffusion is positive and statistically significant, suggesting that companies are more likely to adopt IT the more firms there are in the industry that already use this type of IT. Finally, the evidence is strong that <u>IT adoption is shaped by the employment share of professionals, technical and managerial (PTM) employees, but not by shares of other skill groups</u>. The estimated PTM parameter falls in the 0.4-0.5 range, and among skill groups, is the only parameter that is statistically significant.

<u>IT Use and Changing Skill Mix</u>

The probit model, while informative, is not well suited to studying dynamic processes such as, for example, whether employers change their skill-mix over time in anticipation of introducing IT, or post-adoption how they vary skill-mix to more fully exploit the productive potential of IT after it is adopted. We may also want to know whether changes over time in the firms' skill-mix are accompanied by changes in the

[14] The use of lagged skill share measures also restricts the sample to firms adopting IT sometime between 1985 and 1995. Because some firms report adoption of IT prior to 1985 when our panel data begin, their 1985 skill share measures may reflect levels prevailing many years after the IT adoption date. Their lagged skill measures for 1985 are thus undefined, and they drop out of the regression sample.

labor productivity, capital intensity or wages by different skill categories. To do that, we use what is termed "event analysis".

The key to studying these dynamic changes is the date of IT adoption. Let the year of IT adoption be indexed $\tau = 0$, the years preceding adoption as τ = -1, -2 to –10, and the years following adoption as τ = 1, 2 to 10. Obviously, $\tau = 0$ will be different for each firm; depending upon when IT was adopted—as early as 1985 or as recently as 1995—τ may range from –10 to +10. No one firm will ever have values of τ spanning the entire range from –10 to +10 (a 20 year panel data set is needed for that), but we can estimate (using regression methods) the τ-profile of skill shares (and other variables) by using information on τ from all IT adopting firms. This τ-profile of skill shares and other variables is measured relative to $\tau = 0$, which includes firms that adopted IT that same year, but principally firms that never adopted IT anytime over this period. For the latter, τ by definition always equals 0, and these companies provide the "control group" against which τ-profiles of IT firms can be compared.

For example, suppose that we are interested in how employers vary their skill-mix in the years before and after IT adoption. A regression model relating skill shares to τ may be written as follows:

$$SKILL_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 \Sigma_{\tau} Z_{ijt} + \beta_3 YEAR_t + \varepsilon_{it} \qquad (5)$$

where $SKILL_{ijt}$ refers to the skill share j of the i^{th} firm in year t , X is a vector of firm and industry attributes, Z is a set of (1,0) indicator variables for each τ between –10 and +10, and $YEAR_t$ is a time trend. In this regression model, the estimated β_2 coefficients of Z trace out the τ-profile of skill share j relative to $\tau = 0$, with t-statistics for whether each of the β_2 coefficients are statistically different from zero. The same model can be used to examine how productivity, capital-intensity or wages vary with τ. Before turning to the regressions results, note that we treat the earliest adoption date of any of the five types of IT as representing the start date for all types of IT, and define τ accordingly.[15]

Table 6 reports selected results of this exercise. The first column shows the distribution of firm observations by τ : note that samples decline for extreme values (both positive and negative) of τ ; and that the sample size for $\tau = 0$ is large since this includes the group of firms that never adopted IT anytime over the whole period. The second through fourth columns report the estimated parameters of τ from skill-share regressions similar to (2); the fifth and sixth columns report estimates of τ for regressions on the logarithm of value added and capital assets per worker. To facilitate analysis, these τ-profiles of skill shares, value added and capital-per-worker are presented graphically as Figures 3 and 4, respectively. These graphs are fitted with a cubic spline to better reveal the underlying trends in these variables over τ .

[15] Including τ for multiple types of IT would make the regression model intractable, and introduce biases because of collinearity between multiple measures of τ. Using the earliest adoption date τ captures the dynamic effects not only of the first IT adoption but of subsequent IT investments as well.

Consider the τ-profiles of skill shares prior to and following adoption of IT. Ignoring extreme τ-values (greater than +7 and –7), where small sample sizes make parameter estimates suspect, Table 6 and Figure 3 show that prior to IT adoption, the PTM share of IT-using firms is generally indistinguishable from that of non-IT firms; a perceptible rise in the PTM share is observed in the two years prior to adoption, becoming larger and more statistically significant in the years following the first IT adoption. The employment share of skilled and semi-skilled production workers is usually lower than non-IT firms, both before and after IT adoption. However, there is a tendency for their shares to rise 6-7 years after IT is introduced, possibly because employers begin substituting them for PTM staff once the attributes of the new technology becomes known and routinized. For the least skilled group, shares are actually larger (and significantly so) pre-IT adoption as compared to non-IT firms, though they start falling about 2-3 years prior to adoption, continuing post-adoption to levels lower than those in non-IT firms. Together, these results suggest that the decision to introduce IT is a deliberate one, with firms changing their skill mix—more PTM staff and fewer unskilled workers—in the years just prior to IT introduction, continuing these trends post-adoption so as to more fully exploit the productivity potential of IT.

Table 6. Estimated Coefficients of Skill Shares and Key Variables

Pre- &	Sample Size	Skill Shares of IT Firms			Co-variates of IT Firms	
post-IT τ years	Firm-year observations	Professionals technicians & Managers	Skilled & Semi-skilled production	Unskilled & General Workers	Log (value added per worker)	Log (Capital per Worker)
-10	28	0.069**	0.006	-0.075	-0.285	-0.038
-9	63	0.042*	-0.020	-0.023	0.002	0.003
-8	98	0.012	-0.052	0.040	-0.124	0.149
-7	135	0.013	-0.028	0.015	-0.023	0.071
-6	173	-0.001	-0.015	0.016	-0.098	0.143
-5	237	0.001	-0.010	0.009	0.004	0.152
-4	278	-0.003	-0.027	0.030	0.074	0.154
-3	328	-0.004	-0.045**	0.049**	0.082	0.154*
-2	377	-0.001	-0.044**	0.045**	0.099	0.160*
-1	437	0.009	-0.047**	0.038**	0.108*	0.226**
0	10,261	n.a.	n.a.	n.a.	n.a.	n.a.
1	547	0.013	-0.041**	0.028*	0.147**	0.356**
2	485	0.017**	-0.041**	0.024	0.175**	0.355**
3	401	0.016*	-0.024	0.008	0.080	0.327**
4	312	0.017	-0.034	0.017	0.225**	0.362**
5	246	0.021*	-0.023	0.002	0.269**	0.322**
6	149	0.030**	-0.026	-0.004	0.284**	0.373**
7	112	0.042**	-0.029	-0.013	0.431	0.522**
8	82	0.037*	-0.002	-0.036	0.189	0.389**
9	60	0.020	0.010	-0.030	0.254*	0.432**
10	36	0.024	0.019	-0.043	0.531**	0.390

Note: 1. regressions include 12 industry dummy variables, indicators for medium and large firms, dummy variables for joint-ventures and foreign firms, and a time trend.
2. ** and * denote statistical significance at the 1 percent and 5 percent, respectively.

Figure 3. (Fit with Cubic Spline)
Skill Shares Pre- and Post-IT Adoption Relative to Non-IT Firms

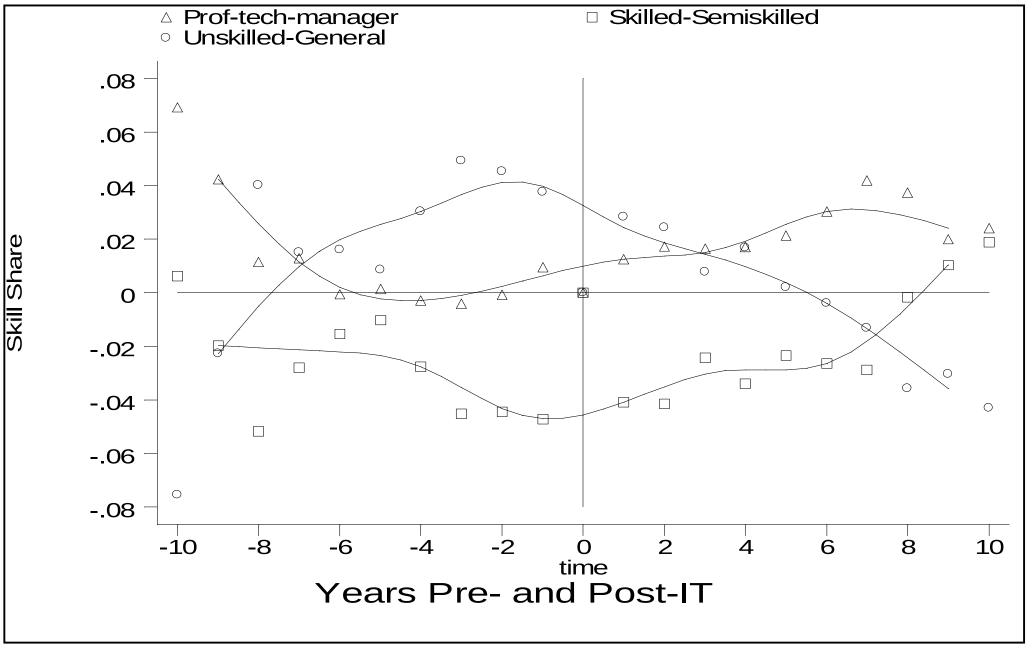
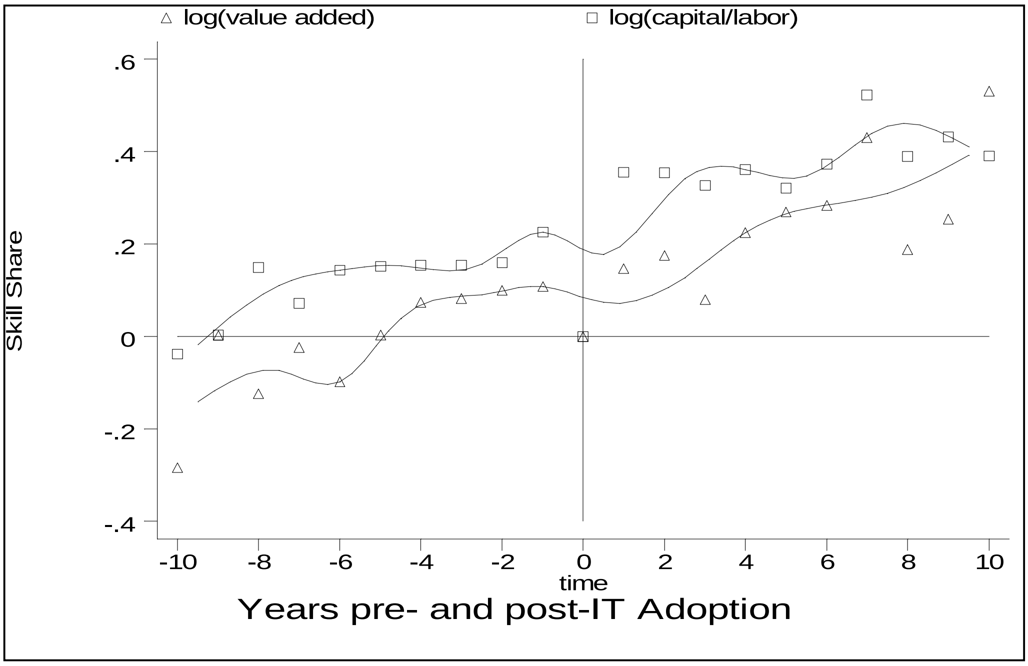


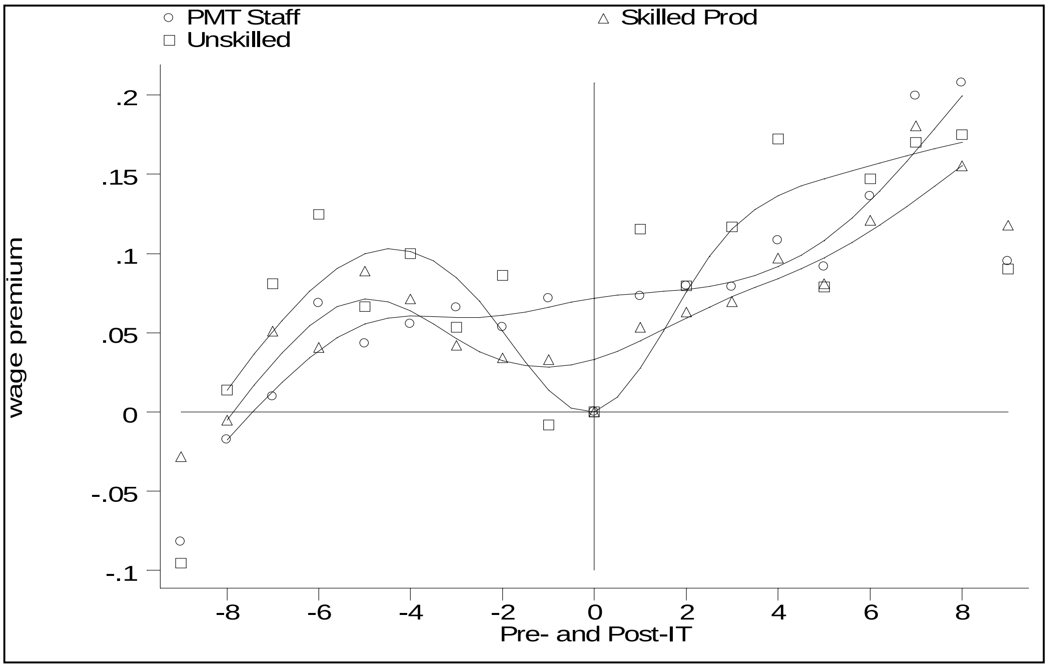
Figure 4. (Fit with Cubic Spline)
Value Added and Capital-Per-Worker Relative to Non-IT Firms



The τ-profiles for value added per worker and capital-intensity correspond to those observed for skill shares. In fact, as shown in Figure 4, they are even more clear-cut than the skill share trends. Firms that adopt IT typically have higher levels of productivity and capital-intensity than non-IT firms both before and after IT adoption, though these differences are usually only significant in the post-IT period. Like PTM staff, both value-added and capital per worker begin to rise in the years immediately preceding adoption, and the gaps between the IT and non-IT firms continue to grow (and become statistically significant) in the years following adoption of IT.

If the adoption and use of IT gives rise to productivity gains, is there any evidence that firms share some of these gains with their employees in the form of higher wages? To address this issue, equation (5) is estimated separately for each skill group, this time with the logarithm of mean wages of that skill as the dependent variable. The resulting τ-profiles of three skill groups—PTM staff, skilled production workers, and unskilled production and general workers—are depicted graphically in Figure 5 where, as before, the graph is fit with a cubic spline to better reveal the underlying wage trends. Recall that the τ-profile is interpreted as the wage premium (or discount) from years of experience using IT after its adoption, relative to wages paid to the same skill group in otherwise similar firms that do not use IT.

Figure 5. Wage Premiums by Skill Group (Fit by Cubic Spline)
Pre- and Post-IT Adoption Relative to Non-IT Firms



It appears from Figure 5 that employers share productivity gains from IT adoption with all groups of workers. Wage premiums start to grow and become statistically significant after $\tau = 0$ for all groups of workers, not just the PTM staff that were so critical in the decision to adopt IT. However, Figure 5 also suggests that there are some differences across groups in the τ -profiles of wages. For the least skilled group (represented by squares), there is a sharp decline in wage premiums in the 3-4 years preceding IT adoption, a recovery and leveling-off after $\tau = 0$. For skilled production workers (represented by triangles), the same pre- and post-IT trend in wage premiums are observed, but they are less pronounced. In contrast, for the most skilled PTM group (represented by circles), there is no dip pre-IT adoption and post-adoption wage premiums grow faster than that of other skill groups.

V. IT USE AND PRODUCTIVITY GROWTH

In this final section, we turn to a production function framework to investigate formally the productivity gains from introduction of IT, and the hypothesis that there are learning effects (productivity gains) from experience using IT. Trends in value-added and wages are suggestive, but not conclusive evidence, that IT adoption is associated with productivity gains. Some part of the gains are attributable simply to increases in capital intensity deriving, no doubt, from investments in IT equipment. The production function approach, augmented to include IT indicator variables and a measure of years of experience using IT, allows us to estimate not only the joint effects of capital and skill mix on productivity but also the productivity gains from learning by experience using IT. And we can test for whether learning effects are amplified in those companies that combine IT with a more skilled workforce, and with skills training. A value-added specification of a Cobb-Douglas production function, augmented to include measures of IT use as well as IT experience, may be written as follows:

$$\ln(VA)_{it} = \beta_0 + \beta_1 \ln(K)_{it} + \beta_2 \ln(L)_{it} + \beta_3 \Sigma_j IT_{it} + \beta_4 \Sigma \tau_{it} + \beta_5 Z_{it} + \nu_i + \varepsilon_{it} \quad (6)$$

where VA is value-added, K is capital assets, L refers to labor inputs of different skill groups of workers, Σ IT is a vector of indicator variables for j types of IT, $\Sigma \tau$ is a vector of indicator variables for IT experience, and Z_{it} refers to firm and industry attributes. The subscripts i refers to the firm, and t refers to years between 1985 and 1995, while ν_i is a time-invariant error term specific to the firm, and ε_{it} is the normal regression error. We estimate these panel production functions using a fixed effects model specification.[16]

Table 7 reports the production function results using IT indicator variables, for five types of IT—administration, communications, control functions, CAD, and production processes—and τ indicator variables for 1 to 10 years of IT experience. The regression also included a set of dummy variables for 12 industries and 2 ownership categories—joint-ventures and foreign-owned firms; these are omitted from the table for simplicity. Before turning to the IT-related results, note that increased capital assets (of

[16] The fixed effects specification eliminates the firm-specific ν_i error term—which captures unmeasured productivity attributes such as managerial ability—through first differencing. As an experiment, we also estimated random effects model specifications: the results were broadly similar, though the fixed effects specification tended to yield more robust estimates of the IT parameters of interest.

which IT investments are part) raise productivity, as do inputs of all types of labor (their coefficients are all positive and significant). However, the estimated labor parameters are larger for the most highly skilled PTM group than for the other skill categories, which suggests that the contribution to productivity of adding an additional PTM staff is greater than that for other types of labor.

Table 7. Production Function Estimates (Fixed Effects Model)
IT Learning Effects for All Firms and by Training Status

Dependent variable: Log(value-added)	Overall Sample		Firms Not Providing Formal Training		Firms Providing Formal Training	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Production Function						
Constant	10.211	44.09	10.988	26.70	11.138	26.23
Log(capital)	0.174	19.17	0.174	13.27	0.153	6.92
Log(PTM)	0.356	26.37	0.271	14.04	0.390	13.62
Log(Skilled Prod)	0.101	16.79	0.079	9.06	0.084	7.52
Log(Semi-skilled)	0.063	13.11	0.070	9.69	0.032	3.85
Log(Unskilled)	0.076	15.23	0.072	9.75	0.048	5.43
IT Indicator Variables						
IT for administration	0.129	5.19	0.079	2.11	0.064	1.45
IT for CAD	0.135	3.12	0.351	3.61	0.026	0.42
IT for communications	0.075	2.26	0.017	0.30	0.046	0.86
IT for control/logistics	0.086	2.16	0.074	0.98	0.059	0.93
IT for production	0.099	2.78	0.094	1.42	0.109	1.91
IT Experience τ years						
1	0.089	2.66	0.083	1.73	0.062	1.16
2	0.121	3.44	0.138	2.65	0.141	2.46
3	0.089	2.30	0.103	1.76	0.119	1.89
4	0.213	4.97	0.141	2.02	0.309	4.44
5	0.223	4.69	0.220	2.82	0.297	3.90
6	0.239	4.06	0.265	2.58	0.335	3.71
7	0.376	5.58	0.369	3.13	0.431	4.24
8	0.269	3.42	0.224	1.59	0.284	2.46
9	0.346	3.85	0.143	0.87	0.421	3.32
10	0.704	6.13	0.495	2.31	0.711	4.55
Sample size	13,559		7,066		4,163	
Overall R^2	0.6911		0.6358		0.6354	

Note: regressions include 12 industry dummy variables, and indicator variables for joint-ventures and foreign owned firms.

Consider the IT results for the overall sample of firms. First, all types of IT are associated with higher productivity, as is evident from the positive and statistically significant parameters of all five types of IT. Both IT for administration—which is the most common type of IT in use—and for computer-aided design (CAD) appear to have the largest productivity effects, followed by IT for production, control and logistics, and communications. Second, there is strong evidence of productivity gains from experience using IT. The parameters of the τ indicator variables are all positive and statistically significant at the 1 percent level, and more importantly, they become larger with years of

IT experience. Compared to $\tau = 0$, the omitted category[17], the coefficient at $\tau = 1$ is about 9 percent, rising to 37 percent by $\tau = 7$, and to 70 percent by $\tau = 10$ years.

What shapes the magnitude of these productivity gains from learning? One hypothesis suggested by the literature is skills training.[18] Numerous micro studies show that the productivity advantage of introducing a new technology is seldom realized without a great deal of experimentation and trial-and-error,[19] the introduction of new forms of work organization, and training programs to provide workers with the new and upgraded skills to use the new technology effectively. To test this hypothesis, we use information on worker training from three establishment surveys—in 1988, 1994 and 1996—linked to 11,239 firm-year observations in our industrial panel data. Since training information is only available at three points in time, we make the (crude) assumption that training data in 1988 are relevant for the 1985-88 period, the 1994 data apply to the 1989-1993 period, and the 1996 data apply to the 1994 and 1995 period. On this basis, we split the sample into two—a sample of 7,066 firms that did not provide formal training, and a sample of 4,163 firms that trained workers—and then estimated production functions separately for the two groups.

The second and third columns of Table 7 report the production function results for the non-training and training samples. We note in passing that the estimated labor parameters of PTM and skilled production workers are larger in training firms than those estimated for non-training firms. Of greater interest are the estimated learning effects of IT use. The τ -profiles indicate that other than the first year, <u>learning effects from IT use in training firms are much larger than those in non-training firms</u>. For example, at $\tau = 1$, productivity gains in training firms are 6 percent as compared to 8 percent in non-training firms. By $\tau = 4$, however, productivity gains are 31 percent in training firms, 14 percent in non-training firms, and the corresponding gains by $\tau = 7$ are 43 and 36 percent, respectively. If companies are to use IT effectively, these results highlight the importance of complementary investments in worker training and skills upgrading to realize the productivity potential of IT once firms have introduced it.

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[17] $\tau = 0$ references the year of first IT adoption, as well as all other firms that do not adopt IT. As such, the estimated parameters for $\tau > 0$ measure the extent to which positive years of experience using IT contribute to productivity.

[18] We also tested the hypothesis that post-IT adoption learning effects are larger the higher is the employment share of PTM staff by interacting the τ indicator variables with the PTM share. The interactions were never statistically significant, which may simply reflect the fact that the production function already (implicitly) incorporates the effects of PTM staff and other skill groups.

[19] In fact, introduction of new technologies may actually result in disruption in production processes and a concomitant decline in productivity, at least initially, until the new technology is mastered. See Setzer (1974), Bell and Pavitt (1992), and Pack (1992).

VI. SUMMARY

We have used panel establishment data from Malaysian manufacturing to study the relationship between technological change and skills demand. We identified a rising secular trend over the 1977 to 1995 period in the employment of highly skilled professionals, managers and technician (PTM) workers, and sought to explain this trend—repeated in many other industrialized economies—in terms of technological change. The hypothesis—that technological change proxied by total factor productivity growth (TFP) is skill-biased—was strongly supported for the most highly skilled group of PTM workers, but interesting only for male but not for female PTM employees. Output growth and increased capital intensity tended to benefit female PTM workers and other highly skilled groups, both male and female; however, capital and unskilled labor appeared to be substitutes.

The skills-biased technological change hypothesis also finds strong empirical support using an alternative technology measure—use of new information and communications technologies (IT). Information on the adoption and use of IT, elicited in a specialized 1997 enterprise survey linked to a subset of the panel establishment data, permitted detailed analyses of the dynamic role of workforce skills in technology adoption and use, and its productivity outcomes. The analyses highlighted the pivotal role of PTM staff in technology adoption, the deliberate way in which employers vary their skill mix both before and after IT adoption, and how these changes in skill mix are accompanied by changes in labor productivity, capital intensity, and wage gains. The analysis also found evidence of significant "learning effects", productivity gains that accrue with years of experience using IT, and for larger learning effects when IT adoption and use is accompanied by worker training.

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ANNEX 1.
Annual TFP Growth Rates by Industry 1985-1995

Firm-level TFP measures can be aggregated to provide insights into industry-level TFP performance. Industry-level TFP estimates can be calculated as the market-share weighted sum of firm-level TFP measures in industry ***i*** as follows:

$$\ln TFP_i = \sum_f \theta_{ft} \ln TFP_{ft} \qquad (2)$$

where θ_{ft} is the value of firm ***f*** sales relative to total industry ***i*** sales in year ***t***.

Table A.1 reports the market-share weighted annual TFP growth rates by industry over the 1990-1995 period, as well as for two sub-periods, implied by the firm-level TFP estimates. For comparison, we report the corresponding industry-level TFP measures estimated from production functions that control for capacity utilization using a proxy variable—log of energy expenditures. For the manufacturing sector as a whole, the weighted mean of all industry annual rates of TFP growth was 6.2 percent over the 1985-1995 period. By sub-period, mean annual TFP growth rates was 6.9 percent in 1985-1990, declining slightly to 5.1 percent in the second sub-period, 1990-1995. These estimates are broadly similar when TFP growth rates are estimated controlling for rates of capacity utilization.

Table A.1 TFP Growth Rates by Industry (1985-1995)

percent

Industry	**TFP Growth Rates Without Capacity Utilization**[1]			**TFP Growth Rates with Capacity Utilization**[2]		
	85-95	**85-90**	**90-95**	**85-95**	**85-90**	**90-95**
Food & beverages	9.3	12.1	6.6	9.4	11.5	7.3
Textile & apparel	6.4	11.6	1.3	7.1	13.0	1.1
Wood products	4.6	8.2	0.9	3.2	6.0	0.4
Furniture	1.6	-2.3	5.4	2.5	-1.6	6.6
Paper & printing	1.6	-0.6	3.8	2.2	0.6	3.9
Chemicals	8.3	5.4	11.1	3.9	6.4	1.5
Rubber products	2.6	3.5	1.7	2.9	3.3	2.6
Glass & clay products	7.4	5.1	9.6	7.6	5.8	9.4
Basic metals	14.6	20.0	9.2	14.6	20.0	9.2
Fabricated metals	6.0	4.7	7.3	5.8	4.3	7.4
General machinery	8.3	10.5	6.1	8.8	10.9	6.6
Electric machinery	5.2	1.9	8.6	6.1	3.1	9.1
Transport equipment	5.1	11.3	-1.2	5.0	12.4	-2.4
Other n.e.c.	1.4	-2.7	5.4	2.4	-1.4	6.2
All Manufacturing[3]	**6.2%**	**6.9%**	**5.1%**	**6.4%**	**7.2%**	**6.0%**

Notes: 1. TFP weighted by the establishment's share of industry value-added in that year
2. Like 1, except TFP estimated with energy use as a control for capacity utilization.
3. Industry-level TFP weighted by industry share of output for all manufacturing.

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