Recent Twists of the Wage Structure
and Technology Diffusion[*]

by

James D. Adams
University of Florida and Center for Economic Studies,
U.S. Bureau of the Census

March 1994

Abstract

This paper is an empirical study of the impact on U.S. wage structure of domestic technology, foreign technology, and import penetration. A model is presented which combines factor proportions theory with a version of growth theory. The model, which assumes two levels of skill, suggests that domestic technology raises both wages, while foreign technology, on a simple interpretation, lowers both. Trade at a constant technology, as usual, lowers the wage of that class of labor used intensively by the affected industry, and raises the other wage.

The findings support the predictions of the model for domestic technology. On the other hand, they suggest that technological change, and perhaps other factors, have obscured the role of factor proportions in the data. Indeed, foreign technology and trade have the same effect on wages at different skill levels, not the opposite effects suggested by factor proportions. Finally, a simple diffusion story, in which foreign technology lowers all U.S. wages, is also rejected. Instead, uniformly higher U.S. wages, not lower, appear to be associated with the technology and trade of the oldest trading partners of the U.S., the economies of the West. Not so for Asia, especially the smaller countries which have recently accelerated their trade with the U.S. Their effects are uniformly negative on wages, suggesting a distinction between shock and long run effects of foreign technology and trade.

KEYWORDS: Wages, Technical Change, Science, R&D, International Trade

* Leo Wierzbowski programmed extraction of the wage data from the CPS tapes, while Hamid Baradaran and Jennifer Cuppy assisted in the collection of the data on trade and technology. Ellen Jamison of the Center for International Research, Bureau of the Census provided access to detailed reports on scientists and engineers in major R&D countries during the 1980s. Leo Sveikauskas alerted me to the existence of similar data collected by Manuel Zymelman of the World Bank for 1960 and 1970. I thank Julie Hotchkiss, Larry Kenny, Luis Rivera-Batiz, Don Siegal, and Curtis Simon for comments, as well as seminar participants at Census, Clemson University, and the University of Florida.

I. Introduction

This paper is an empirical study of the effect of technology and trade on U.S. wages, relying on the general equilibrium theory of factor prices for its foundations. Ever since Stolper-Samuelson (1941), economists have been clear on the relation between trade and real wages at a constant technology. If a more open economy raises the share in production of the skill intensive good, then the skilled wage increases, and conversely for an increase in the good which is intensive in unskilled labor. The clarity of the theorem has made it a powerful tool of general equilibrium analysis. However, the importance of investments in technology has risen in recent years, as has the significance of international competition through technology, and these considerations may obscure the role of factor proportions. Reflecting this change in fundamentals, Krugman (1979) and Grossman and Helpman (1991) develop a product cycle approach which abstracts from output composition, emphasizing instead the flow of technology from advanced to developing nations and the comparative advantage in invention on the part of advanced countries[1]. Setting aside spillover benefits from foreign technology, an increase in product innovation confers rents on labor in the advanced countries, while an increase in the rate of imitation by developing countries detracts from those rents. The cogency of the product cycle approach has secured it a place beside Stolper-Samuelson in the economist's tool-kit of general equilibrium wage theories. Thus the twin pillars of the general equilibrium analysis of wages have been industry differences in the factor intensity of production and national differences in technology creation and diffusion. And since product cycle is associated with unidirectional changes in wages across skill levels, in contrast with opposite changes by level of skill in factor proportions theory, it may be possible to identify the relevance of each approach for wages.

The two broad forces are likely to be closely intertwined in actual data. To see this, consider an advanced nation. Rising innovation in competitor nations would lower skill-based wage differentials in such a country if the innovations were concentrated in skill-intensive industries, or they could lower both wages, if there are elements of rent in wages which are associated with industries undergoing transient shocks from their replacement by foreign competitors. At the same time, negotiated reductions in tariffs combined with technological improvements in transportation could independently raise imports that are intensive in unskilled labor. The problem of disentanglement is further complicated by skill-biased technical change within industry and by changes in the size of age-skill groups.

The recent history of wages in the United States has been interpreted in terms of all these influences. Most significant is the seeming slowdown in the growth of real wages since the early 1970s, which coincides, it has been claimed, with a general tendency towards declining U.S. competitiveness[2]. In addition, recent work has documented a rise in the earnings premium for college trained workers during the 1980s despite a large increase in the skilled labor force. In their work on the wage structure Murphy and Welch (1993) uncover a wavelike pattern to school-related wage differences since the 1960s. The premium to college completion rises until the early seventies, falls until the end of that decade, and rises to record levels by the late 1980s. In part the pattern can be attributed to the baby boom, as in Welch (1979). The rest arises from changes in labor demand [Murphy and Katz (1993)], especially the recent pattern of simultaneous increases in relative supply of the college educated and rising rewards to school completion. Juhn, Murphy, and Pierce (1993) carry the argument further, arguing that the recent rise in wage inequality within groups is due to rising price of unobserved skills. Mincer (1990) explores time series wage premia for schooling and work experience, finding that R&D per worker explains the rise in returns to schooling and job training during the 1980s.

The discussion suggests three factors that shift the demand for labor by skill: domestic technology, import penetration, and the diffusion of technology from advanced economies to those less advanced. In this paper I introduce separate proxies for domestic technology, trade penetration, and foreign technology, corresponding to these proposed sources of change in the U.S. wage structure. I believe that an important step towards separating the effects of pure factor proportions from technology is taken by separating these three factors.

Section II presents an analysis of wage determination in a growth model with endogenous technology. As in the opening arguments, the discussion revolves around changes in the above three factors, but the model extends that discussion, first by allowing for spillover benefits from foreign technology, and second by allowing for rents from industry-specific training. Section III discusses the nature of the evidence that I have collected on wages, cohort size, domestic and foreign technology, and trade.

Section IV presents the findings. Holding constant controls for import penetration and time, I find that domestic technology is associated with higher wages at all skill levels. When the effects of time are held constant, perhaps surprisingly, foreign technology aggregated across the eleven competitor countries in our sample is also associated with higher wages, especially college trained workers, while aggregate import penetration is generally insignificant. However, a decomposition of foreign technology and trade by region of the world turns up provocative results in this respect. Asian technology indicators, which represent recent entrants into innovation, have a strongly negative impact on wages, particularly for the less skilled. European and Canadian technology indicators, which represent the technologies of established competitors to the U.S., are associated with higher wages, again for the less skilled. The reverse is true for Asia. Asian and European effects are again different in regards to import penetration. Asian import penetration lowers wages across schooling groups, probably because of shock effects of import competition. On the contrary, European and Western Hemispheric imports result in higher wages, especially for more skilled workers. These results are not consistent with a simple factor proportions story, since wages move in the same direction across skill levels, but rather point to an extended version of the product cycle approach which emphasizes endogenous technology.

Additional evidence for the impact of technology and trade on the log variance of earnings closes out Section IV. The evidence suggests a positive effect of Asian technology and trade on wage dispersion, but a negative effect of the West. Section V concludes.

II. Analytical Framework

The following model blends factor proportions with the theory of innovation and diffusion. The model is a variant of the "Quality Ladders" approach to growth through quality improvement [Grossman and Helpman (1991)]. However, my goal is not to test a particular theory of growth, since a similar story could be told in terms of cost-reducing innovation. Rather it is to provide a story for the domestic labor market that yields a closed form solution for labor market equilibrium and interesting comparative statics. The real concern is with disturbances to the structure of wages, especially trade and technology. The analysis focuses on a single advanced country.

The economy has three sectors: high technology production, low technology production and R&D. To provide a sense of wage structure, I allow for both high and low skilled labor in production. There is no physical capital in the model. The discussion proceeds first by defining demand and cost conditions in the goods markets, followed by domestic goods market equilibrium, all culminating in the analysis of the structure of wages.

A. Demand Conditions

I assume Cobb-Douglas preferences defined over a continuum of high technology goods with discrete qualities, and one low technology good. Let s be the share of high technology products in consumption and let these products vary continuously over j from 0 to N.Where time is J, let $x_{mJ}(j)$ be the amount of the good, of quality m and type j, and let $q_m(j)$ be the quality m. Quality improves according to the difference equation $q_0=1$, $q_m=8q_{m-1}$, so that $q_m= 8^m$, $8>1$. Finally, let 1-s be the share of the low technology good, whose quantity is y_J.

Let E_J be world-wide expenditures. Consumers spend a fraction sE_J on high technology goods, and they spend the same amount sE_J/N on each variety. The different quality levels for a variety j are perfect substitutes, so consumers concentrate all their expenditures on the quality whose value is highest in comparison with price. I assume this is the highest quality level. Since goods can be produced in the home country or rest of the world, it is necessary that domestic and international costs differ by less than the quality gain 8 offered by the highest quality. The latest generation drives lower quality goods out of the market if price is less than 8 times the cost of such goods, implying that demand for the latest version of j is

$$x_{i\tau}(j) = \begin{cases} \dfrac{sE_{\tau}}{Np_{m\tau}(j)} & i=m, \\ 0, & i<m. \end{cases} \qquad (1)$$

The corresponding demand for the low technology good y is

$$y_{\tau} = \frac{(1-s)E_{\tau}}{p_{y\tau}}. \qquad (2)$$

Hereafter expenditures and prices are treated as constant over time, so all growth occurs through quality improvement[3]. By (1) and (2) $x=sE/Np_x$, $y=(1-s)E/p_y$. Finally, constant expenditures imply that the interest rate equals the rate of time preference, so r=D.

B. Domestic Goods Markets

Consider production in the home country. Goods are produced according to Cobb-Douglas, constant returns technologies that depend on skilled labor h and unskilled labor R. High technology goods x are more skill-intensive than y. Since wages of unskilled and skilled labor are w_{RJ} and w_h , it follows that average and marginal costs of x and y are

$$c_i = b_i w_{\ell}^{\alpha_i} w_h^{1-\alpha_i}, \qquad i=x,y \qquad (3)$$

where $b_i= "_i^{"i}(1-"_i)^{(1-"i)}$. Good y is intensive in unskilled labor so $"_x < "_y$. Domestic R&D, R_D, uses high skilled labor alone. Since a_R units of h are required per unit of research, average and marginal costs of R&D are $c_R=a_R w_h$.

Domestic production of high technology goods is determined as follows. Producers of the previous generation reside either in the home country or rest of the world (ROW). Assuming that ROW is cheaper its costs of producing the lower quality are $c_x^* < c_x$. Now we allow the quality step 8 to differ depending on whether a foreign or domestic producer is being superseded. The price set by a domestic producer of the latest generation whose nearest competitor is foreign is marked up slightly less than 8_F (>1) times c_x^*, since their price is driven to c_x^* and the latest version is 8_F times better than the foreign good. By the same logic the latest generation producer whose product is 8_D times better than its domestic competition marks up that product by $8_D c_x$. By the demand assumptions (recall that $x=sE/Np_x$), profits in these two cases are

$$\begin{aligned}\pi_{Fx} &= (p_{Fx}-c_x)\,x = \frac{sE}{N}\left(1-\frac{c_x}{\lambda_F c_x^*}\right)\\ \pi_{Dx} &= (p_{Dx}-c_x)\,x = \frac{sE}{N}\left(1-\frac{1}{\lambda_D}\right)\end{aligned} \qquad \textbf{(4)}$$

It is clear from (4) that $A_{Fx}=A_{Dx}$ only if $8_F c_x^* = 8_D c_x$, so that the effective quality step for the domestic producer who competes against foreign firms must be larger than the quality step for the domestic producer who competes against domestic firms, and larger by an amount that exactly compensates for lower costs of production by foreign firms. Moreover, since we assume the fecundity of domestic invention is the same for all j, we are really assuming that the foreign quality step is lower by the appropriate amount so that $8_F = 8_D c_x / c_x^*$. This condition that sets the two profits equal and allows for coexistence of the two types of innovation, is assumed hereafter.

Each stream of profits has the same present value PV, not only because profits are equal, but because the probability of termination by later and better is the same for all j. Now, a domestic firm that spends $c_R R_D$ on R&D acquires PV with probability R_D. But free entry into R&D implies that c_R=PV. Hence a monopolistically competitive equilibrium prevails in high technology. In the steady state the share of domestic high technology goods, D_x/N, is determined by equality between the ouflow of domestic goods replaced abroad and the inflow of goods newly produced at home, and it equals the share of domestic R&D in world R&D[4].

Good y is competitively produced in the amount D_y. Therefore, equilibrium in the domestic market for y implies $p_y = c_y$, where p_y is the world price.

Finally, the steady state also requires balanced trade. The condition for trade balance is that the value of high technology goods produced plus domestic y production equal the total value of consumption of high technology products plus y consumed. Let the share of the country in world income and consumption be F. It follows that home country consumption is a fraction F of the value of world demands (3) and (4). From what has gone before, trade balance entails

$$p_y D_y + p_x D_x \bullet x = \sigma (p_y y + p_x N \bullet x) = \sigma \bullet E, \qquad (5)$$

where home production and consumption are on the left and right. Since the country is advanced, it is a net importer of y, so Fy>D_y, and a net exporter of x, so FN<D_x.

C. Innovation

The setup concludes with equilibrium in the market for domestic innovation. Let dPV/dJ be the capital gain or loss on the present value of the innovation, B be its current return, and . be the probability that the product will be superseded, the sum of the domestic and foreign probabilities R_D and R_F that the producer will be overtaken and the present value entirely lost. Under risk neutrality the sum of these gains and losses must equal the return on a riskless investment in PV, or rCPV. The return on innovation must therefore satisfy

$$\frac{dPV}{d\tau}+\pi-M\cdot PV=r\cdot PV. \qquad (6)$$

In the steady state wages and prices are constant, and PV equals its cost: PV=$a_R w_h$. Thus dPV/dJ=0. Solving (6) for the profit rate we find that B/PV= .+r. Now use PV=$a_R w_h$, (4) with the condition that sets A_{Fx}=$A_{Dx,}$, and the definition of the probability of being superseded . = R_D+R_F to solve for R_D:

$$R_D=\left(1-\frac{1}{\lambda}\right)\frac{sE}{a_R w_h N}-(R_F+r). \qquad (7)$$

Equation (7) gives the equilibrium value of R&D for any variety of x.

D Labor Market Equilibrium

From the assumption of constant returns to scale total costs are TC_x= $c_x D_x x$, TC_y= $c_y y$, and $a_R w_h RN$. By Shephard's lemma the demands for unskilled labor derived from the commodities are L_x=$c_{Rx}D_x x$ and L_y=$c_{Ry}y$, where c_{Rx}= "$_x c_x/w_R$, c_{Ry}= "$_y c_y/w_R$. Likewise the derived demands for skilled labor are H_x=$c_{hx}D_x x$ and H_y=$c_{hy}y$, and L_R= a_RNCR, where c_{hx}= (1-"$_x$)c_x/w_h, c_{hy}=(1-"$_y$)c_y/w_h. Aggregate supplies of unskilled and skilled labor are inelastically supplied in the amounts L and H. Thus factor market clearing is given by

$$\begin{aligned} c_{\ell x}D_x x+c_{\ell y}D_y &= L \\ c_{hx}D_x x+c_{hy}D_y+a_R R\cdot N &= H. \end{aligned} \qquad (8)$$

Use the cost functions (3), the equilibrium condition c_y= p_y, and trade balance to reach

$$\begin{gathered}\frac{\alpha_x c_x}{w_\ell} D_x X + \frac{\alpha_Y}{w_\ell}(\sigma \cdot E - P_x D_x X) = L \\ \frac{(1-\alpha_x)\, c_x}{w_h} D_x X + \frac{(1-\alpha_y)}{w_h}(\sigma \cdot E - P_x D_x X) + a_R N \left[(1 - \frac{c_x}{P_x}) \frac{X}{a_R w_h} - r - F \right] = H.\end{gathered} \tag{9}$$

Equation (9) describes labor market clearing. Its main use is in understanding the impact of domestic technology, foreign technology, and trade on the simple wage structure comprised of w_R and w_h. Each effect is found by totally differentiating (9) (see the Appendix), yielding the displacement system:

$$\begin{bmatrix} -[(1-\alpha_x) L_x + L_y] & (1-\alpha_x) L_x \\ \left[\frac{\alpha_x (1-\alpha_x) D_x - \alpha_x N}{(1-\alpha_x) D_x}\right] H_x & -\left[\frac{\alpha_x (1-\alpha_x) D_x + (\frac{P_x}{c_x} - \alpha_x) N}{(1-\alpha_x) D_x} H_x + H_Y\right] \end{bmatrix} \begin{bmatrix} \frac{dw_\ell}{w_\ell} \\ \frac{dw_h}{w_h} \end{bmatrix} = \begin{bmatrix} (\frac{P_x}{c_x}\frac{\alpha_Y}{\alpha_x} - 1) L_x \frac{dD_x}{D_x} \\ a_R (R_D + R_F) N \cdot \frac{da_R}{a_R} + a_R \cdot R_F \cdot N \frac{dR_F}{R_F} - \left[1 - \frac{1-\alpha_x}{1-\alpha_Y}\frac{P_x}{P_Y}\right] H_x \frac{dD_x}{D_x} \end{bmatrix}. \tag{10}$$

Equation (10) calculates the impact of: (i), a decline in the share of high technology products that is domestically produced($-dD_x > 0$); (ii), a decrease in the cost of domestic R&D ($-da_R > 0$); and (iii), an expansion of foreign R&D ($dR_F > 0$). The solution of (10) for these effects, assuming a small markup (P_x/c_x), is:

$$\frac{dw_\ell}{w_\ell} \cong -\frac{1}{\Delta}\left(\frac{\alpha_y-\alpha_x}{\alpha_x}\right)\left(\frac{N}{D_x}H_x+H_y\right)L_x\frac{dD_x}{D_x}$$
$$\frac{dw_h}{w_h} \cong \frac{1}{\Delta}\left(\frac{\alpha_y-\alpha_x}{\alpha_x}\right)(L_x+L_y)\,H_x\frac{dD_x}{D_x}, \tag{11}$$

$$\frac{dw_\ell}{w_\ell} \cong -\frac{1}{\Delta}(1-\alpha_x)\,a_R\,(r+F)\,D_x L_x\frac{da_R}{a_R}$$
$$\frac{dw_h}{w_h} \cong -\frac{1}{\Delta}\left[(1-\alpha_x)L_x+L_y\right]a_R(r+F)\,D_x\frac{da_R}{a_R}, \tag{12}$$

$$\frac{dw_\ell}{w_\ell} \cong -\frac{1}{\Delta}(1-\alpha_x)L_x a_R R_F D_x\frac{dR_F}{R_F}$$
$$\frac{dw_h}{w_h} \cong -\frac{1}{\Delta}\left[(1-\alpha_x)L_x+L_y\right]a_R R_F D_x\frac{dR_F}{R_F}. \tag{13}$$

In the case where D_x falls (11) shows the impact of an increase in high technology import penetration. Since "$_y$>"$_x$-- because y uses unskilled labor more intensively than x--, the unskilled wage (w_R) increases. By the same token the skilled wage (w_h) decreases as D_x falls. We see that high technology import penetration changes factor proportions in favor of unskilled labor, evaluated at a constant technology. If D_x had risen the changes would have been reversed.

An improvement in domestic technology corresponds to a reduction in research costs (da_R<0). By (12) both wages increase. The intuition of this is as follows. A fall in a_R lowers the cost of R&D, but $a_r w_h$ = B/(. +r), which encourages a rise in domestic research R_D. To see this, note that $. = R_D + R_F$, and hold r, R_F, and w_h constant. It follows that the demand for skilled labor and its wage both increase. And since skilled and unskilled labor are substitutes, the unskilled wage also rises.

All else equal, (13) shows that an increase in foreign technology lowers both wages. The logic is the reverse of that applied to domestic R&D costs: R_D contracts and w_h declines, causing a decline in the demand for unskilled labor and the unskilled wage.

E. Additional Effects of Foreign Technology and Trade

The predictions concerning wage effects of foreign technology and trade have been obtained under very special circumstances. I now consider additional effects due to spillovers of foreign R&D on domestic R&D, and sector-specific skills.

If spillovers of foreign R&D take place then the effect of foreign technology is ambiguous. The reason is that foreign technology tends to raise the efficiency of domestic technology, if enough time has passed for "reverse diffusion". For example, a_R could be a negative function of lagged R_F, so that $a_{RJ}=a_R(R_{FJ-m})$, where $a'_{RJ+m}<0$ and m is the lag. In that case R_F could raise domestic wages at all levels if efficiency gains were sufficient, since R_F has an effect which is a mixture of (11) and (13). For example, improved Asian automobiles became targets for domestic imitation, eventually reducing the cost of domestic R&D, since imitation is cheaper than creation. This process of reverse spillovers is less likely during the formative period of foreign technology, but more likely in the steady state. Some evidence for this distinction is uncovered below.

Sector-specific skills introduce another complication because wages are not equal across industries for workers who have specialized in a prticular sector. In effect the sector-specific skill creates a wage premium relative to other sectors. At both skill levels we could observe $w_{Ri}>w_R$, $w_{hi}>w_h$, where i is the industry of specialization, and the wage subscripted by i is includesthe sectoral premium. In this setting import penetration, say by virtue of improved foreign technology, could depress wages at all levels of skill in view of the short run sectoral wage premium.. Given sufficient time to retrain however, the effect would disappear. With these considerations in mind, we turn to the empirical work.

III. Description of the Data

Dependent variables in the regressions come from individual wage data in the March Current Population Surveys for 1968-1988. This period is the most recent one for which wage, technology, and trade data are all available. I construct means and variances of log annual, weekly, and hourly wages by educational level, work experience, and major industry from the individual data, thereby reducing the role of individual wage elements in order to concentrate on aggregate movements. The method of constructing mean wages follows that of Murphy and Welch (1993). The sample is restricted to white males in order to abstract from changes in the wage structure by race and sex, and it is limited to full-time participants in the labor force to yield reliable wage estimates.

An important difference from previous work is that the wage cells are classified by major industry as well as by education and work experience, partly to take advantage of variation by industry in import penetration and domestic and foreign technology. The inclusion of industry reflects an interest in industry wages and industry-specific skills, and in the differing impact of technology and trade by industry, but its addition requires aggregation of work experience into broad intervals rather than single years because of sample size considerations. Otherwise cells would be quite small, and sampling errors correspondingly large.

The four educational categories are 9-11 years of school, high school graduates, 1-3 years of college, and college graduates and above. The five work experience classes are: 1-5, 6-10,
11-20, 21-30, and 31-40 years of experience. The six industry groups, selected to meet data availability constraints on technology and trade, are agriculture, mining, and construction; high technology manufacturing; other manufacturing; transportation, communication, and public utilities; wholesale and retail trade; and services. The resulting 120 cells of wage data in each year are based on an average of 160 observations per cell. This procedure is repeated for each year of the data. Table 1 describes the wage and other data used in this paper. In the interests of a more complete description I also include a series of graphs. Figures 1 and 2 present ribbon graphs of means and variances of weekly earnings by year, where each ribbon indicates the time series of the mean or variance for an industry[5]. Mean wages are generally declining with time, while variances rise slightly.

Since there are few surprises in the wage data, I move next to a discussion of the technology, trade, and cohort size variables. The tables and graphs concentrate on the science indicators since these are the most novel data. Main technology variables include indicators of science and technology in the United States as well as overseas and relative efficiency in R&D of other countries compared with the United States. Trade effects are captured by import penetration, defined as the ratio of imports to U.S. output, classified by major industry group and region of the world. Demographic shifts are represented by cohort size variables.

The first group of technology variables measures domestic absorption of science. In a similar manner to my previous studies (Adams [1990, 1993], Adams and Sveikauskas [1993], absorption is measured by an industry science intensity, defined as $(3R_iCK_i)/L$,. The numerator is the sum over science fields of the product of scientists R_i in a field and industry, times the world-wide stock of scientific papers K_i in that field measured in hundred thousands. The denominator is the number of workers L in that industry[6]. Supplementary Appendix A, available on request, explains the methodology underlying domestic science intensity: the calculations yielding domestic scientists by science field and industry and world-wide article counts accumulated into stocks by

Table 1
Description of the Variables

Name	**Dimension**[a]	**Definition**	**Source**
mean log of deflated weekly wage	education, experience, industry, and year	sum of log individual annual wages over sum of individual weeks worked in a cell	Current Population Survey Tapes, Years 1968-1988
foreign science intensity	industry and intermittent year; available separately by region of the world	product of total number of foreign scientists divided by foreign labor force, times weighted average of world-wide stocks of scientific papers	Foreign scientists are taken from Zymelman (1980) and Center for International Research (various years). Labor force data are drawn from International Labour Organization (1989, various years). Article count data are described in Adams (1990)
domestic science intensity	industry and year; available separately by region of the world	product of total number of domestic scientists divided by domestic labor force, times weighted average of world-wide stocks of scientific papers	Domestic scientists and article count data are described in Adams (1990). Domestic labor force data are taken from Statistical Abstract of the United States (various years)
relative patenting efficiency	year; available separately by region of the world	weighted mean ratio in other countries of patenting by residents to scientists, divided by the U.S. ratio of resident patents to scientists	patents are derived from World Intellectual Propery Organization (various years). National counts of scientists are taken from UNESCO (various years)
import penetration	industry and year; available separately by region of the world	ratio of nominal imports to nominal domestic industry output	import data are taken from Highlights of Foreign Trade, U.S. Department of Commerce (various years), data on nominal domestic industry output are drawn from Economic Report of the President (various years).
cohort size	education, experience, and year	fraction of a given educational group falling in a given experience group	Current Population Reports, Series P-27, U.S. Department of Commerce (various years)

Notes. [a] Educational groups are 9-11 years of school, high school graduates, 1-3 years of college, and college graduates and higher. Experience groups are 1-5 years, 6-10 years, 11-20 years, 21-30 years, and 31-40 years of work experience. Industry groups are: agriculture, mining, and construction; high technology manufacturing (chemicals, machinery, electrical equipment, transportation equipment, and instruments); other manufacturing; transportation, communication, and public utilities; wholesale and retail trade; and services.

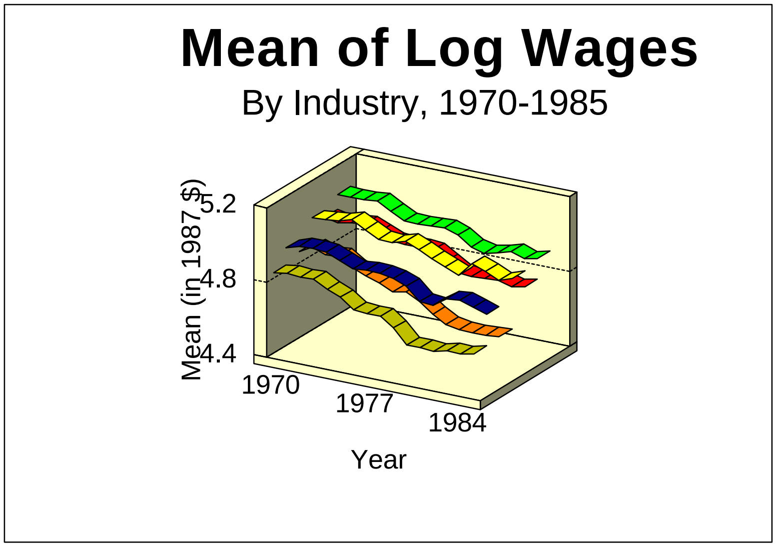

Figure 1- Deflated mean wages by industry. From front to back industries are services; agriculture, mining, and construction; trade; transportation, communication, and utilities; low technology manufacturing; and high technology manufacturing.

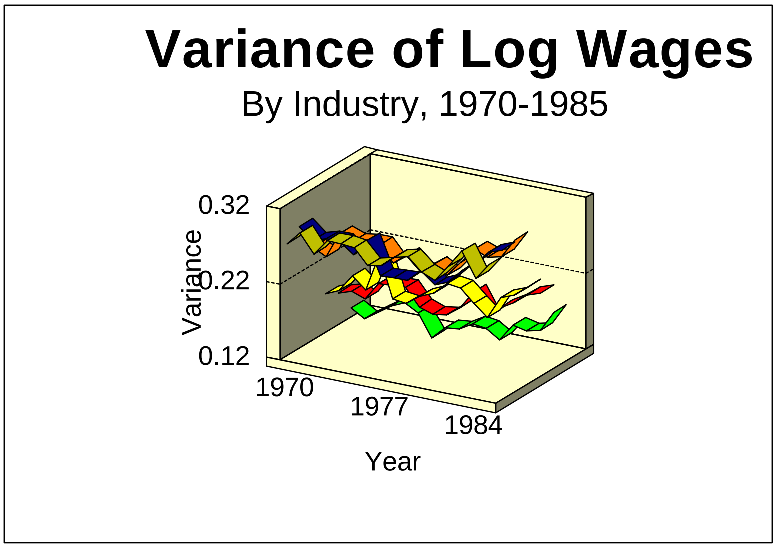

Figure 2- Variance of log wages by industry. Ordering of the industries follows that of figure 1. The variance tends to rise slowly over time.

science field. The numerator of the industry knowledge index is like the simple knowledge production functions in growth theory; see for example, Grossman and Helpman (1992). These imply proportional learning of the form RCK, where R is science resources and Kis the stock of knowledge. Our knowledge index is however, divided by industry labor force on the grounds that effects of industry learning are amortized by size of the industry. I divide by labor force rather than output since only labor force is available for the foreign calculations described below.

Table 2 reports summary statistics on domestic science indicators, including the knowledge index, by highly aggregated industry divisions. The divisions are high technology manufacturing, other manufacturing, and nonmanufacturing. As expected, scientists and engineers are much more common in the high technology sector. Furthermore, except for high technology, scientists have not increased relative to the labor force. Nevertheless, the knowledge index grows substantially because it is an interaction between largely stable intensities of domestic scientific employment and growing world-wide stocks of scientific papers. Figure 3 is a graph of domestic science intensity for six major industry groups over time. These groups, an attempt to match the available categories in the foreign technology data, include services; agriculture, mining, and construction; trade; transportation, communication, and utilities; other manufacturing; and high technology manufacturing[7]. The graph shows how the large science intensity of high technology manufacturing dominates the intensities in other industries. All the intensities grow much faster after the late 1970s, and yet all grow more slowly than their foreign counterparts.

The second group of science indicators represents absorption of science by foreign countries by a measure analogous to the domestic knowledge index. The form of the index is again ($3R_iCK_{i)}$/L, where R_i is science resources in field i, K_i is the stock of knowledge in i, and L

Table 2
Domestic Science Indicators

Group, Statistic	Year of the Data			
	1970	1975	1980	1985
High Technology Manufacturing[a]				
S&E/ Labor Force[b]	0.074	0.073	0.071	0.092
Industry Science Intensity[c]	0.177	0.216	0.272	0.495
Other Manufacturing				
S&E/ Labor Force[b]	0.017	0.013	0.013	0.013
Industry Science Intensity[c]	0.040	0.040	0.049	0.067
Nonmanufacturing[c]				
S&E/ Labor Force[b]	0.011	0.011	0.012	0.012
Industry Science Intensity[c]	0.023	0.027	0.037	0.053

Notes. [a] High technology manufacturing consists of chemicals, machinery, electrical equipment, transportation equipment, and instruments. [b] S&E/Labor Force: scientists and engineers as a fraction of the labor force. [c] The industry science intensity is the product of scientists and engineers as a fraction of the labor force and the industry knowledge stock. The industry stock of knowledge is defined as

$$KN_i = \Sigma_{j=1}^{F} \frac{\ell_{ij} N_j}{L_i},$$

where ℓ_{ij} is the employment of industry i scientists in field j, the N_j are stocks of scientific papers in field j, and L_j is the labor force in industry i. [c] Nonmanufacturing includes agriculture, mining, and construction; transportation, communication, and public utilities; trade, and services.

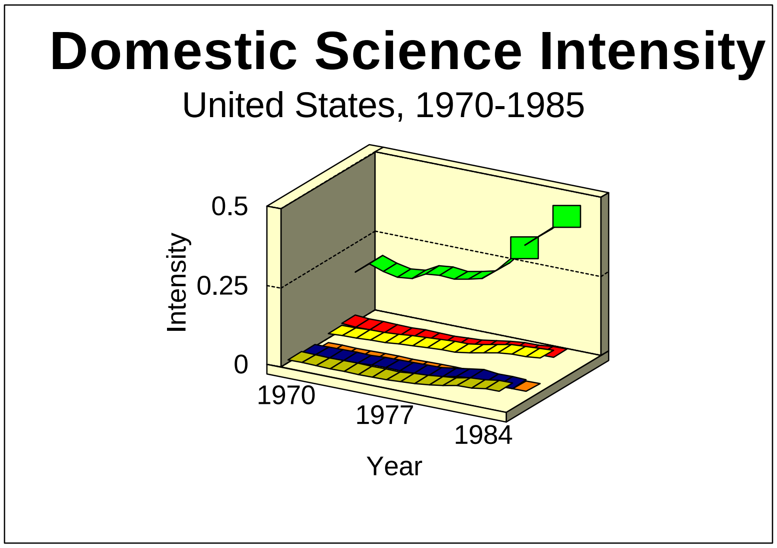

Figure 3-Domestic Science Intensity by industry. Industry groups are as in figure 1. The intensity of the last industry is high technology manufacturing. This conceals the rise in the much smaller intensities of other industries.

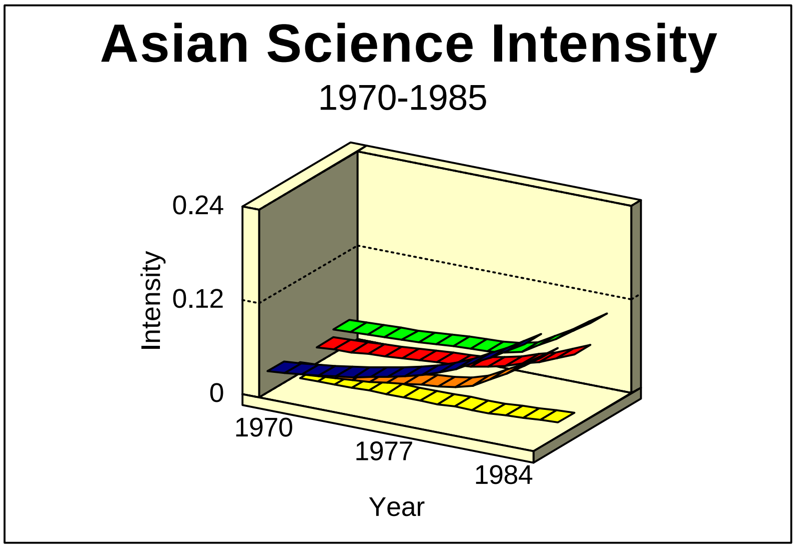

Figure 4- Asian science intensity by broad industry. Industry groups from front to back are: services; agriculture, mining, and construction; trade; transportation, communication, and utilities; and manufacturing. Aggregation of manufacturing is imposed by the data. The flatness of the trade intensity is an illusion due to its small size. Note the low level of the initial intensities.

is labor force. The data on foreign scientists and engineers are limited by country differences in the definitions of specialties and industries compared with domestic data. Because of these differences I was able to obtain only employment of natural scientists and engineers by industry, rather than the more detailed U.S. breakdown[8]. I then use the U.S. breakdown of natural scientists among science specialities to distribute the total, accepting the resulting errors in allocation as the lesser evil compared with equal or no allocation. Furthermore, scientific and engineering employment are not available separately for high technology and other manufacturing.   Appendix B, which is available on request, describes how the data on foreign scientists and engineers were processed.

Table 3 reports briefly on the foreign science indicators. As in the United States, science employment intensities stay the same during the 1970s but rise during the 1980s. The European intensity rises more within manufacturing but less in remaining industry groups compared with Asia. The greater rise in European science intensity within manufacturing seems counterintuitive given the perceived increases in Asian technology, but it should be noted that Asian labor forces also grew at a faster rate than Europe, so scientific employment does rise faster in Asia. The larger knowledge index in Europe in addition reflects the greater importance there of science compared with engineering and the larger volume of published research in science.

Figures 4 and 5 are graphs of the science intensities for Asia and Europe by industry group and year. There are only five industry groups, rather than the six in the U.S. data, since manufacturing is treated as a single aggregate in the foreign data. A comparison of Figures 3, 4, and 5 shows that science intensities rise more rapidly in both regions than in the U.S. As noted, the intensities usually rise more rapidly in Asia than in Europe, though this requires careful

Table 3
Foreign Science Indicators

Group, Statistic	Year of the Data 1970	1975	1980	1985
Manufacturing				
S/Es per LF in Europe	0.028	0.028	0.028	0.039
S/Es per LF in Asia	0.016	0.015	0.014	0.021
Industry Science Intensity, Europe[a]	0.067	0.083	0.108	0.207
Industry Science Intensity, Asia[a]	0.039	0.045	0.053	0.112
Nonmanufacturing				
S/Es per LF in Europe	0.012	0.013	0.013	0.018
S/Es per LF in Asia	0.010	0.011	0.012	0.018
Industry Science Intensity, Europe[a]	0.028	0.034	0.045	0.077
Industry Science Intensity, Asia[a]	0.022	0.030	0.044	0.084

Notes. Countries for which industry science indicators exist include France, Germany, the United Kingdom, Canada, Japan, Korea, Taiwan, Singapore, Malaysia, and Hong Kong. [a] The industry science intensity for a region is the weighted average of the intensity in country i and industry j summed across countries in that region,

$$FKN_j = \Sigma_{i=1}^{N} \frac{L_{ij}}{L_j} \frac{(NS_{ij} N_{NS} + ENG_{ij} N_{ENG})}{L_{ij}} .$$

NS_{ij} and ENG_{ij} are scientists and engineers in i, N_{NSij} is the weighted stock of scientific papers in natural science as determined by the U.S. proportions in science specialties and the stocks of scientific papers in those specialties, and N_{ENgij} is the stock of scientific papers in engineering. L_{ij} is industry employment in country i and industry j, and L_{ij}/L_j is the weighting factor, the share of country i in regional employment for industry j.

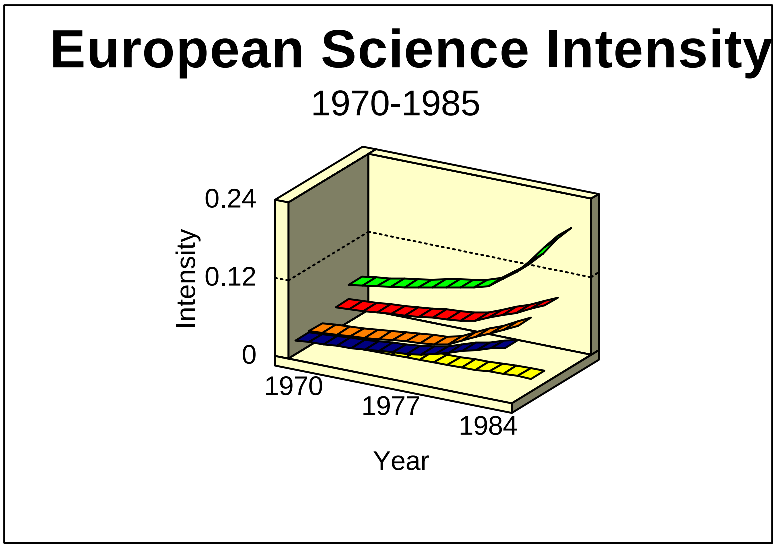

Figure 5- European Science Intensity by Industry. Groups are exactly as in figure 4. Science intensities rise less rapidly than in Asia.

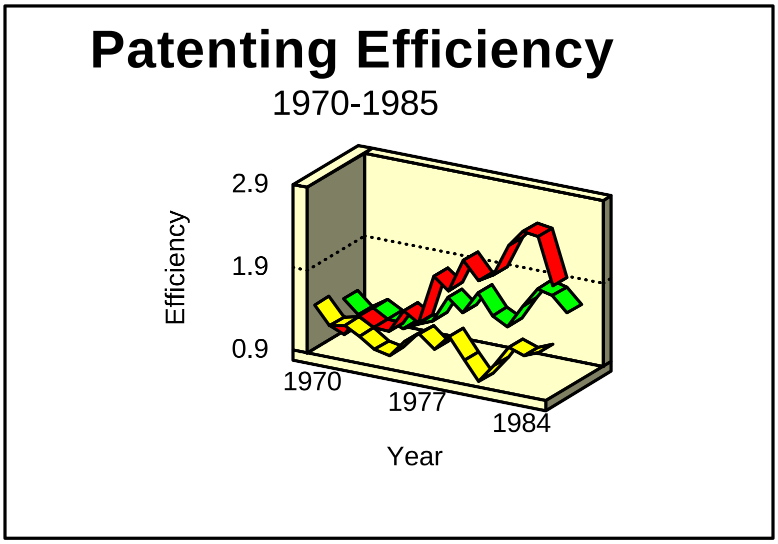

Figure 6- Patenting Efficiency of Other Regions divided by that of the U.S. Europe is in front, Asia appears next, and rest of the world is in the rear. Asian relative efficiency rises faster than the European.

scrutiny of the figures, given the low initial level of the Asian intensities.

Relative patenting efficiency by year is the third and final technology indicator. This is the ratio of patenting rates abroad to that of the United States. Each patenting rate measures the output of inventions per unit of R&D personnel. In particular, each is the ratio of patents by residents of a region divided by research scientists and engineers in that region. Relative R&D efficiency is then defined as the weighted average of the patenting rate in other countries divided by the U.S. rate[9]. I adopt this "ratio of a ratio" approach because I want to abstract from the world-wide decline in the patenting rate. This may or may not imply diminishing returns to invention, since rewards to patenting could have fallen (Griliches [1990]). In any event, relative patenting efficiency serves partly as a mechanical control for time, given its strongly trended nature. This is apparent in Figure 6, which graphs the relative efficiencies of Asia, Europe, and the two combined. Asia's relative efficiency clearly grows faster than Europe's.

The import penetration and cohort size variables remain to be discussed. Import penetration equals the ratio of nominal imports to nominal output by U.S. industry. Import penetration is calculated for all countries and for selected groups of countries classified into regions[10]. If import penetration mainly affects low skill industries, then unskilled workers should be harmed, not skilled. The findings below show that this interpretation is too simplistic.

Figures 7 and 8 display import penetration by Asian and European countries. The ribbons correspond to the rather broad industry groups for which such data are available: agriculture, mining, and construction; high technology manufacturing; other manufacturing;

and rest of the economy (the inclusive concept of " services" used in the trade dat). The figures show how import penetration varies by region and industry. Asian countries increase their penetration
most rapidly in manufacturing, but have virtually no presence in services. European penetration rises more gradually, except for services.

Cohort size is the share of the work force in a schooling class falling in a given age bracket[11]. This variable is a straight interpretation of Welch (1979), in which workers with different educational attainment perform separable tasks, and within each task, workers of different ages engage in weakly separable sub-tasks. Thus, cohort size should reduce wages, assuming that it changes markedly for a given schooling group. Cohort size increases for workers with at least some college, but decreases otherwise. Because of its familiar nature, no tables or graphs of cohort size are included.

Table 4 reports simple correlations for a representative selection of the variables. Signs of the correlations between domestic wages and domestic and foreign technology mimic the signs of the regression coefficients reported below. Another feature is that cohort size is orthogonal with the technology and trade variables. The correlation between European and Asian technology indicators amounts to a warning that it may be difficult to more finely separate the detailed regional and national effects of foreign technology given the data that are presently available. This concludes the discussion of the data that have been collected to study the problem of the relationship between wages, domestic and foreign technology, and trade.

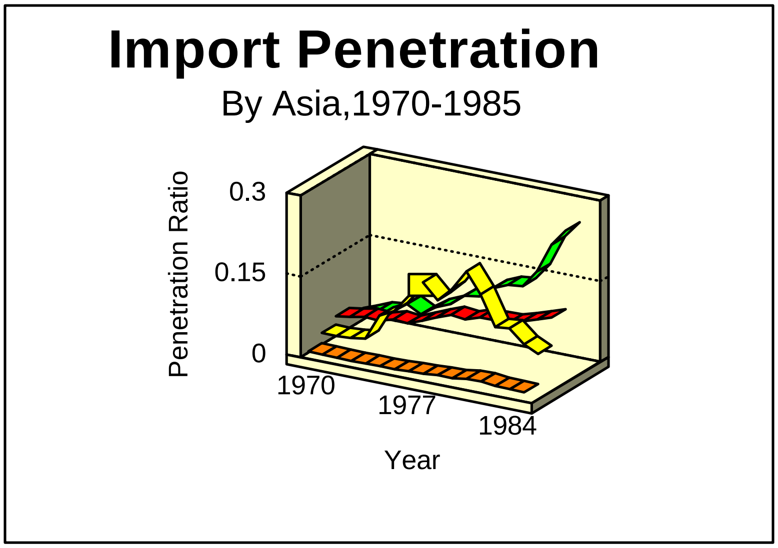

Figure 7- Import penetration by Asian countries, by industry. Industries are those in figure 4. The sharply peaking curve is agriculture, mining, and construction, while the rapidly rising curve in the rear is high technology manufacturing.

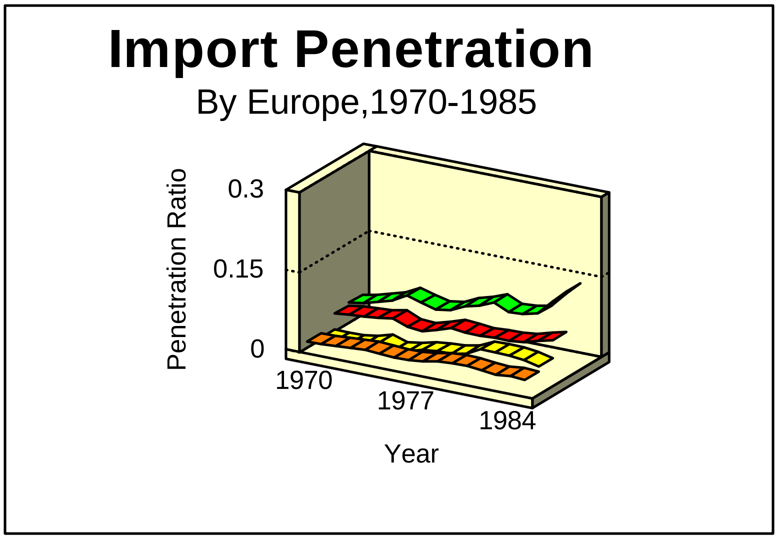

Figure 8-European Import Penetration by industry. Industry groups follow the pattern of figure 4. Note the much slower rate of increase in manufacturing compared with the Asian data shown in Fig. 7.

Table 4
Simple Correlations Among the Principal Variables

	Log of weekly wages	**Domestic Science Intensity**	**European Science Intensity**	**Asian Science Intensity**	**Relative Patenting Efficiency**	**Import Penetration**	**Cohort Size**
Log of weekly wages	1	0.13	0.08	-0.05	-0.15	0.08	-0.45
Domestic Science Intensity		1	0.66	0.40	0.20	0.60	0
European Science Intensity			1	0.77	0.44	0.56	0
Asian Science Intensity				1	0.52	0.33	0
Relative Patenting Efficiency					1	0.23	0
Import Penetration						1	0
Cohort Size							1

IV. Findings

Regression findings are presented in Tables 5-8. Throughout these Tables I stratify by schooling groups. Thus, industry, experience, and year are the remaining dimensions in the wage data serving as the dependent variable. Table 5 is the basic set of regressions for our two main schooling groups, high school and college graduates. Because technology data for most Asian countries are missing outside of the period 1970-1985, Table 5 is correspondingly limited. Equations 5.1-5.4 and 5.5-5.8 are estimates for high school and college graduates. Estimates for grade school and some college are omitted to save space, since results for these groups are extrapolations of the reported findings. Table 5 begins simply, adding trade and other variables to test the robustness of domestic and foreign technology to inclusion of other variables. We see that the sign of domestic technology is in fact robust, but that the sign of foreign technology depends on the inclusion of regressors representing time. Equations 5.1 and 5.5 omit import penetration and relative patenting efficiency, 5.2 and 5.6 add import penetration, and 5.3 and 5.7 add import penetration and relative patenting. Finally, 5.4 and 5.8 replace relative patenting, considered as time trend, with year dummies. All equations include experience dummies.

Domestic science intensity is associated with higher wages for both schooling groups, but more so for the college trained. Foreign science intensity unambiguously lowers wages in 5.1-5.2 and 5.5-5.6, and apparently more so the wages of high school graduates. However, the sign of foreign science is reversed by the inclusion of relative patenting efficiency and time in

5.3-5.4 and 5.7-5.8. Effects of time absorb the negative effect impact of foreign science intensity, as is shown by 5.3-5.4 and 5.7-5.8. Foreign technology generally seems to favor the college trained.

Table 5
Log Weekly Wage Regressions
by Schooling Class
(Asymptotic t-Statistics in Parentheses)[a]

Variable or Statistic	**High School Graduates**				**College Graduates**			
	5.1	**5.2**	**5.3**	**5.4**	**5.5**	**5.6**	**5.7**	**5.8**
Constant	4.68	4.68	4.84	4.36	4.96	4.96	5.32	5.04
Time Dummies	No	No	No	Yes	No	No	No	Yes
Foreign Science Intensity	-0.66 (-3.6)	-0.70 (-3.6)	0.29 (1.7)	1.00 (7.9)	-0.37 (-1.8)	-0.43 (-2.1)	0.66 (3.3)	1.08 (6.5)
Domestic Science Intensity	0.50 (8.7)	0.47 (8.7)	0.37 (7.5)	0.29 (8.4)	0.62 (9.9)	0.58 (8.3)	0.47 (7.1)	0.38 (7.4)
Import Penetration		0.05 (1.1)	0.07 (1.6)	0.11 (2.7)		0.07 (1.3)	0.09 (1.7)	0.19 (4.7)
Relative Pat. Efficiency			-0.27 (-12.7)				-0.28 (-13.7)	
Cohort Size	-0.99 (-2.1)	-0.99 (-2.1)	-0.38 (-1.0)	0.16 (0.5)	-0.62 (-2.4)	-0.62 (-2.4)	-0.73 (-3.4)	-0.73 (-4.2)
Experience 6-10 Years	0.30 (10.7)	0.30 (10.7)	0.33 (13.4)	0.35 (16.9)	0.33 (11.5)	0.33 (11.4)	0.34 (14.6)	0.33 (18.4)
Experience 11-20 Years	0.44 (8.2)	0.44 (8.3)	0.50 (11.4)	0.55 (14.8)	0.48 (18.8)	0.48 (18.9)	0.47 (22.3)	0.47 (28.3)
Experience 21-30 Years	0.50 (8.6)	0.51 (8.5)	0.58 (12.1)	0.65 (15.7)	0.54 (13.4)	0.54 (13.5)	0.52 (15.7)	0.52 (19.5)
Experience 31-40 Years	0.45 (5.6)	0.45 (5.6)	0.55 (8.1)	0.64 (11.0)	0.48 (9.0)	0.47 (9.0)	0.45 (10.2)	0.45 (12.6)
Root MSE	0.12	0.12	0.11	0.09	0.13	0.13	0.11	0.09
Adjusted R^2	0.8	0.8	0.84	0.88	0.78	0.78	0.84	0.9

Notes. [a] t-statistics are computed using White's (1980) heteroscedasticity consistent standard errors of the coefficients. Work experience is coded 1 for the respective experience interval and 0 otherwise. Number of observations is 540. See Section III for definitions of variables.

In so far as the foreign science lowers both wages, it is consistent with a simple diffusion story; and yet we see that this is not so, controlling for patent trends or time. In contrast, domestic technology absorption raises wages at all levels, which is consistent with the countering of imitation and technology diffusion.

Remaining variables include import penetration, cohort size, and the experience dummies. Import penetration equals industry imports from all countries divided by domestic industry output. Holding technology constant trade has a rather meager effect. However, trade penetration has more varied effects, which are being concealed by aggregation, as we shall see in Table 6. Finally, cohort size is associated primarily with lower wages for the college trained, presumably because movements of cohort size by age are more pronounced in these data. As in other studies, wages grow until the final decade of work experience within each schooling group. For this reason, and because this same finding persists, experience dummies are suppressed in later tables.

Table 6 undertakes a decomposition analysis of foreign technology and trade by region of the world. The Table is more extensive given the variety of decompositions. Again the first four equations report findings for high school, while the last four report findings for college graduates.

We begin with high school graduates. Equations 6.1 and 6.2, which are restricted to the period 1970-1985, follow a regional aggregation of the data on technology and trade . The decomposition divides Asia from the West (including Canada). Equation 6.1 includes relative patenting efficiency separately for Asia and the West, while 6.2 substitutes year dummies in their place. Asian technology indicators that are invariably negative, including relative patenting efficiency. In contrast, Western variables are always positive. Furthermore, 6.3 and 6.4, the counterparts to 6.1 and 6.2, reveal that the Asian technology component is to the detriment of

Table 6
Log Weekly Wage Regressions by Schooling Class: Foreign Technology and Import Penetration by Region (Asymptotic t-Statistics in Parentheses)[a]

Variable or Statistic	High School Graduates				College Graduates			
	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Constant	4.61	4.42	4.58	4.69	4.97	5.04	4.96	5.16
Year Dummies	No	Yes	No	No	No	Yes	No	No
Experience Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asian Science Intensity	-3.72 (-20.7)	-3.45 (-18.5)			-2.09 (-10.1)	-1.85 (-8.8)		
Canadian-European Science Intensity	3.60 (18.0)	3.89 (21.1)			2.45 (11.7)	2.39 (11.4)		
Japanese Science Intensity			-1.61 (-9.8)	-1.50 (-10.5)			-1.01 (-8.6)	-0.65 (-5.5)
Canadian Science Intensity			0.16 (0.7)	0.01 (0.02)			-0.87 (-3.6)	-0.45 (-1.4)
European Science Intensity			1.30 (5.7)	2.39 (6.6)			1.75 (8.1)	1.91 (5.4)
Domestic Science Intensity	0.87 (10.9)	0.97 (13.1)	0.18 (5.0)	0.97 (9.6)	0.67 (8.2)	0.64 (7.9)	0.36 (8.6)	0.93 (8.3)
Asian Import Penetration	-1.00 (-5.8)	-1.18 (-7.2)			-1.35 (-5.8)	-1.16 (-5.3)		
Western Hemispheric Import Penetration	1.03 (7.3)	1.15 (7.9)			1.40 (6.8)	1.28 (6.5)		
European Import Penetration	-3.93 (-9.2)	-4.48 (-11.5)		-3.70 (-7.2)	-1.01 (-5.3)	-1.04 (-2.2)		-1.37 (-2.5)
Japanese Import Penetration				-0.97 (-2.9)				-1.43 (-3.7)
Canadian Import Penetration				1.14 (4.0)				1.04 (3.4)
Asian Relative Patenting Efficiency	-0.10 (-12.7)			-0.10 (-14.1)	-0.14 (-17.0)			-0.12 (-14.3)

Table 6
Log Weekly Wage Regressions by Schooling Class: Foreign Technology and Import Penetration by Region (Asymptotic t-Statistics in Parentheses)[a]

Variable or Statistic	High School Graduates				College Graduates			
	6.1	**6.2**	**6.3**	**6.4**	**6.5**	**6.6**	**6.7**	**6.8**
European Relative Patenting Efficiency	0.04 (1.9)			-0.04 (-3.3)	0.18 (7.1)			-0.01 (-0.9)
Cohort Size	-0.21 (-0.8)	0.16 (0.6)	-0.74 (-2.5)	-0.24 (-1.1)	-0.70 (-4.5)	-0.73 (-5.1)	-0.60 (-3.7)	-0.64 (-5.1)
Time Period	1970-1985	1970-1985	1968-1988	1968-1988	1970-1985	1970-1985	1968-1988	1968-1988
N	480	480	630	630	480	480	630	630
Root MSE	0.08	0.07	0.11	0.081	0.08	0.08	0.12	0.09
Adjusted R^2	0.92	0.94	0.84	0.91	0.91	0.92	0.81	0.88

Notes. [a] t-statistics are computed using White's (1980) heteroscedasticity consistent standard errors of the coefficients. [b]Work experience dummies are defined as in Table 5. See Section III for definitions of the variables.

the college trained, if to a smaller degree. This could represent a transientshock to domestic output. And since Asian countries are new to technology, the findings suggest a link between the break in trend in wages since the early 1970s and technology convergence in Asia.

Equations 6.1 and 6.2 break import penetration further into components classified by three major regions of the world: Asia, Western Hemisphere, and Europe. As before, import penetration is defined as imports divided by industry output. The results are again striking: Asian import penetration lowers wages at both levels, especially the college trained, whereas Western hemispheric and European trade favor wages, especially the college trained. The findings suggest that Asian trade is concentrated in skill-intensive industries compared with other regions. But they are not consistent with factor proportions, because wages fall at all levels. Nor are the results consistent with a simple diffusion story, because the European varaibles, which are more like the long run, raise wages at all levels.

Equations 6.3 and 6.4 carry out a different decomposition. Since technology data are available for the major competitors Canada, Britain, France, Germany, and Japan over the full period 1968-1988, we restrict the data to those countries in exchange for the extended time frame. Here foreign technology is distinguished between Canada, Europe, and Japan. The difference between the two regressions is that 6.3 omits while 6.4 includes, import penetration for Canada, Europe, and Japan, and relative patenting efficiency for Asia and Europe. Again I include both regressions to test robustness of the technology indicators. On this occasion all indicators retain their signs..

The table shows that Japanese technology has a negative effect, but, interestingly, weaker than the effect for all of Asia, which contains the youngest of the newcomers to technology. The technologies of Europe and Canada continue to be associated with higher wages at all skill levels. Having alreadyseen these unlike results, and knowing that Japan, and other Asian countries to a still greater extent, are recent users of technology, in a way that Canada and Europe are not, it would seem even more strongly that the Canadian and European results represent the long run effect of foreign technology, while the Asian effects represent short run effects[12]. Previous findings on import penetration likewise tend to be borne out: Japanese import penetration reduces wages, though again, not as strongly as for all Asia, while Western imports raise wages. As before domestic science raises wages.

Equations 6.5-6.8 contain the results for college graduates. The results bear a resmblance to those for high school. The main difference is that Japanese technology detracts less and European technology contributes less, to college wages. However, Japanese import penetration is more to the detriment of the college trained, and European import penetration less. Domestic technology has about the same effect on college wages as on high school.

Table 7 combines several data experiments. It begins by sharpening the comparison between the two levels of skill. The period is 1970-1985. Equations 7.1 and 7.2 report findings based on the difference between log college wages and log high school wage regressions[13]. In 7.1 foreign technology favors college wages over high school, as does domestic technology. Import penetration and patenting efficiency are neutral, and the cohort size variables perform as before. Equation 7.2 breaks up technology and trade into Asian and European subcategories. Asian technology favors college, while European technology does not. Asian import penetration weakly lowers relative college wages, while Western import penetration raises them. Domestic technology changes sign and now enters negatively.

Overall then, domestic technology appears to be skill neutral, wheras foreign technology increases skilled wages relative to unskilled.

Equations 7.3-7.6 represent a very different exercise, which seeks to highlight short run elements in the data. The method involves the calculation of deviations of log wages from their means over time, classified by experience and industry, and written as regression functions of analogous deviations of the right hand variables. Expressed in this way 7.3 and 7.5 seem to show that foreign science lowers high school wages but not college, while import penetration, though negative for both groups, is more negative for the college trained, as is relative patenting efficiency. The findings in 7.4 and 7.6 suggest that recent trends in Asian technology have dealt a a short run blow to earnings, while the reverse holds for the West.

Table 8 looks at the log variance of weekly wages within cells. If one accepts the hypothesis of Murphy, Juhn, and Pierce (1993), who argue that increases in wage inequality measure rising returns to skills not captured by education and experience, then a positive regression coefficient in Table 8 means that unobservable skill price has risen, whereas a negative coefficient means it has declined. The Table proceeds from simple specifications in equations 8.1 and 8.4 to more complicated ones. The basic finding in 8.1 and 8.4 is that foreign technology and trade have widened inequality--that is, favored unobservable skill, whereas domestic technology has resulted in more equal returns. It is intriguing that if one decomposes technology and trade into Asian and European components, as in 8.2-8.3 and 8.5-8.6, then it is the Asian technology and trade variables, not the European ones, which have widened wage inequality. The contrast is strongest at the high school level. Since the Asian effects are more like shocks, the regressions suggest that shocks favor unobservable skills. This extends the view of Bartel and Lichtenberg (1989) in their work on the link between technology and the demand for schooling.

Table 7
Log Weekly Wage Regressions:
Relative Wage and Wage Deviation Specifications[a]
1970-1985
(Asymptotic t-Statistics in Parentheses)[b]

Variable or Statistic	Relative Wage Regressions		Wage Deviation Regressions			
	College/High School	College/High School	High School		College	
	7.1	7.2	7.3	7.4	7.5	7.6
Time Dummies	No	No	No	No	No	No
Foreign Science Intensity	0.39 (2.5)		-1.54 (-7.3)		0.03 (0.1)	
Asian Science Intensity		1.64 (6.9)		-2.43 (-9.1)		-0.20 (-0.5)
European Science Intensity		-1.14 (-5.4)		1.10 (4.6)		0.61 (1.8)
Domestic Science Intensity	0.10 (2.1)	-0.20 (-2.4)	0.40 (3.8)	0.14 (1.3)	0.33 (2.1)	0.37 (2.3)
Import Penetration	0.02 (0.4)		-0.14 (-2.5)		-0.32 (-3.8)	
Asian Import Penetration		-0.36 (-1.8)		-0.18 (-1.1)		-0.74 (-3.1)
European Import Penetration		2.91 (6.5)		-0.32 (-0.8)		-0.50 (-0.9)
Western Hemispheric Import Penetration		0.38 (2.2)		0.21 (0.8)		1.23 (3.1)
Relative Patenting Efficiency	-0.01 (-0.8)		-0.12 (-7.7)		-0.28 (-12.3)	
Asian Relative Patenting Efficiency		-0.04 (-5.2)		-0.08 (-13.3)		-0.14 (-15.8)
European Relative Patenting Efficiency		0.13 (5.2)		0.09 (5.9)		0.19 (8.0)
) (Cohort Size)	-0.53 (-2.9)	-0.50 (-3.0)				
High School Cohort Size	-0.65 (-1.9)	-0.58 (-1.6)				
Cohort Size			-0.08 (-0.3)	0.02 (0.1)	-0.75 (-4.3)	-0.72 (-5.0)

Table 7
Log Weekly Wage Regressions:
Relative Wage and Wage Deviation Specifications[a]
1970-1985
(Asymptotic t-Statistics in Parentheses)[b]

Variable or Statistic	**Relative Wage Regressions**		**Wage Deviation Regressions**			
	College/High School	**College/High School**	**High School**		**College**	
	7.1	**7.2**	**7.3**	**7.4**	**7.5**	**7.6**
N	480	480	480	480	480	480
Root MSE	0.12	0.08	0.06	0.05	0.09	0.07
Adjusted R^2	0.11	0.25	0.49	0.64	0.26	0.5

Notes. [a] Relative wage specifications regress the log difference between college and high school wages on the difference of the right hand side variables. Wage deviation specifications regress the deviation of log wages from the mean over time for the education, experience, and industry group on the similar deviation of the right hand side variables. See the text for more details. [b] t-statistics are computed using White (1980) heteroskedasticity consistent standard errors of the coefficients.

Table 8
Variance of Log Weekly Wage Regressions by Schooling Class (Asymptotic t-Statistics in Parentheses)[a]

Variable or Statistic	**High School Graduates**			**College Graduates**		
	8.1	**8.2**	**8.3**	**8.4**	**8.5**	**8.6**
Constant	0.15	0.25	0.26	0.12	0.12	0.18
Year Dummies	No	No	No	No	No	No
Experience Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Science Intensity	-0.26 (-3.1)			-0.70 (-5.7)		
Asian Science Intensity		1.58 (12.4)			0.40 (2.5)	
Canadian-Europ. Science Intensity		-1.37 (-11.5)			-0.91 (-5.5)	
Japanese Science Intensity			0.75 (7.8)			0.44 (4.5)
Canadian Science Intensity			-0.51 (-3.4)			-0.88 (-3.6)
European Science Intensity			-0.52 (-2.8)			0.05 (0.2)
Domestic Science Intensity	-0.35 (-12.7)	-0.14 (-3.6)	-0.16 (-3.5)	-0.34 (-7.2)	-0.28 (-4.3)	-0.30 (-3.8)
Industry Import Penetration	0.10 (4.2)			0.03 (0.7)		
Asian Import Penetration		0.26 (2.3)			0.10 (0.5)	
Western Hemispheric Import Penetration		0.16 (1.8)			0.03 (0.2)	
European Import Penetration		-0.39 (-1.8)	-0.68 (-2.1)		0.17 (0.4)	0.11 (0.2)
Japanese Import Penetration			0.62 (3.9)			0.54 (2.0)

Table 8
Variance of Log Weekly Wage Regressions by Schooling Class
(Asymptotic t-Statistics in Parentheses)[a]

Variable or Statistic	High School Graduates			College Graduates		
	8.1	8.2	8.3	8.4	8.5	8.6
Canadian Import Penetration			-0.19 (-1.1)			-0.97 (-3.7)
Rel. Pat. Efficiency	0.10 (7.2)			0.10 (6.4)		
Asian Rel. Pat. Efficiency		0.02 (6.5)	0.04 (9.6)		0.03 (4.3)	0.04 (5.7)
European Rel. Pat. Efficiency		-0.01 (-1.1)	-0.01 (-2.8)		0.06 (2.6)	0.00 (0.3)
Cohort Size	0.06 (0.3)	-0.03 (-0.2)	-0.02 (-0.2)	0.06 (0.7)	0.10 (0.7)	0.18 (1.7)
Time Period	1970-1985	1970-1985	1968-1988	1970-1985	1970-1985	1968-1988
N	480	480	630	480	480	630
Root MSE	0.054	0.043	0.047	0.071	0.071	0.071
Adjusted R^2	0.40	0.62	0.56	0.36	0.36	0.41

Notes. t-statistics are calculated using White's (1980) heteroscedasticity consistent standard errors of the coefficients. Dependent variable is the variance of log weekly earnings in cells defined by schooling, experience, industry, and year.

V. Conclusion

This paper has provided theory and evidence concerning general equilibrium effects of trade and technology on wages. Since the results cover a wide range of materials, it is useful to provide a summary. The model, which assumed two levels of skill, suggested that domestic technology raised both wages, while foreign technology, on a simple interpretation, lowered both. The effect of trade at a constant technology, as usual, lowered the wage of the grade of labor used intensively by the affected industry, and raised the other wage.

The findings supported the predictions of the model for domestic technology. On the other hand, they suggested that technological change, and perhaps other factors, have obscured the role of factor proportions in the data. Indeed, foreign technology and trade had the same effect on wages at different skill levels, not the oppposite effects suggested by factor proportions. Finally, a simple diffusion story, in which foreign technology lowers all U.S. wages, was also rejected. Instead, higher U.S. wages, not lower, appear to be associated with the technology and trade of the oldest trading partners of the U.S., the economies of the West. Not so for Asia, especially the smaller countries which have recently accelerated their trade with the U.S. Their effects were uniformly negative on wages.

All of this points to a distinction between the short and long run. In the long run, there are mutual benefits to pooling of technology and trade in the world. The most signal gap in the work relates to shock versus long run effects. If a deeper view of technology and trade over time could be gained, then we could trace the true effects on wagesof the remarkable changes in trade that have recently taken place, and that seem destined to strengthen in force for the foreseeable future.

References

Adams, James D., "Fundamental Stocks of Knowledge and Productivity Growth," **Journal of Political Economy** 98 (August 1990): 673-702.

________________, "Science, R&D, and Invention Potential Recharge: U.S. Evidence," **American Economic Review, Papers and Proceedings** 83 (May 1993): 597-602.

Adams, James D., and Leo Sveikauskas, "Academic Science, Industrial R&D, and the Growth of Inputs," Working Paper, Center for Economic Studies, U.S. Bureau of the Census, January 1993.

Bartel, Anne P., and Frank Lichtenberg, "The Comparative Advantage of Educated Workers in Implementing New Technology," **Review of Economics and Statistics** 79 (February 1987): 1-11.

Borjas, George J., and Valerie Ramey, "Foreign Competition, Market Power, and Wage Inequality: Theory and Evidence," NBER Working Paper 4556, December 1993.

Evenson, Robert E., "International Invention: Implications for Technology Market Analysis", in Zvi Griliches, ed., **R&D, Patents, and Productivity**. Chicago: University of Chicago for National Bureau of Economic Research, 1984.

Grossman, Gene M., and Elhanan Helpman, "Quality Ladders and Product Cycles," **Quarterly Journal of Economics** 106 (May 1991): 557-586.

___________________________________, **Innovation and Growth in the World Economy**. Cambridge, Mass., MIT Press, 1992.

Griliches, Zvi, "Patent Statistics as Economic Indicators: A Survey," **Journal of Economic Literature** 28 (December 1990): 1661-1707.

___________, " ," **American Economic Review, Papers and Proceedings** (May 1994), forthcoming.

Jaffe, Adam B., "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," **American Economic Review** 76 (December 1986): 984-1001.

International Labour Organization, **Yearbook of Labour Statistics:Retrospective Edition**

on **Population Censuses, 1945-1989**. Geneva, Switzerland, 1992.

Krugman, Paul, "A Model of Innovation, Technology Transfer, and the World Distribution of Income," **Journal of Political Economy** 87 (April 1979): 253-266.

Lucas, Robert E., "On the Mechanics of Economic Development," **Journal of Monetary Economics** 22 (July 1988): 3-42.

Mincer, Jacob, "Human Capital, Technology, and the Wage Structure," Working Paper, Columbia University, November 1990.

Murphy, Kevin M., Chin-hui Juhn, and Brooks Pierce, "Wage Inequality and the Rise in Returns to Skill", **Journal of Political Economy** 101 (June 1993): 410-442.

Murphy, Kevin M., and Lawrence Katz, U.S. Wages, 1963-1987: The Role of Supply and Demand Factors," **Quarterly Journal of Economics** 103 (February 1992): 285-326.

Murphy, Kevin M., and Finis Welch, "The Structure of Wages," **Quarterly Journal of Economics** 103 (February 1992): 285-326.

Organization for Economic Cooperation and Development, **Main Science and Technology Indicators**. Paris, France, various years.

Rivera-Batiz, Luis A., and Paul M. Romer, "Economic Integration and Endogenous Growth", **Quarterly Journal of Economics** 101 (May 1991): 531-556.

Romer, Paul M., "Increasing Returns and Long-Run Growth," **Journal of Political Economy** 94 (August 1986): 1002-1037.

______________, "Endogenous Technological Change," **Journal of Political Economy** 98 (Supplement, October 1990): S71-S102.

Stolper, Wolfgang, and Paul Samuelson, "Protection and Real Wages," **Review of Economic Studies** 9 (January 1941): 58-73.

Welch, Finis, "The Effect of Cohort Size on Earnings: the Baby Boom Babies' Financial Bust," **Journal of Political Economy** 87 (Supplement, October 1979): S65-S98.

U.S. Department of Commerce, **Highlights of Foreign Trade:Imports and Exports**.

Washington, D.C., various years.

World Intellectual Property Organization, **Industrial Property Statistics**. Geneva, Switzerland, various years.

Zymelman, Manuel, **Occupational Structures of Industries**. Education Department, The World Bank: Washington, D.C., 1980.

Footnotes

1. Evenson (1984) confirms this pattern of comparative advantage in invention.

2. The apparent stagnation of real wages requires cautious interpretation. Griliches (1994) notes that the price indexes used to deflate wages are badly overstated by their failure to take quality change into account. The appropriate accounting for prices could convert wage stagnation into wage growth over the course of the sample period.

3. See Grossman and Helpman (1992) for a discussion of the calculationof the growth rate of utility.

4. The outflow is $R_F D_x$, where R_F is the fraction of domestic high technology goods D_x which is superseded by foreign firms. The inflow is $R_D(N-D_x)$, where R_D is the fraction of foreign high technology goods $N-D_x$ which is overtaken by domestic firms. Setting the two sides equal we find that $D_x/N=R_D/(R_D+R_F)$.

5. Since the wage data are originally classified by four education and five experience groups as well as industry and year, the means and variances are averaged over these groups in Figures 1 and 2.

6. See Table 2 for the algebraic definition of the industry knowledge intensity. The data on employment of scientists and engineers by field and industry come from Bureau of Labor Statistics (1973) and from unpublished data collected by the National Science Foundation. The data on stocks of scientific papers by field are taken from abstracts in the various fields. Annual flows of scientific papers were collected and accumulated into stocks using an 11% rate of obsolescence. Lags applied to the stocks are ten years for computer science and engineering, and 20 years for the remaining fields. The breakdown of fields and scientific employment is as follows: agriculture, biology, chemistry, computer science, engineering, geology, mathematics and statistics, medicine, and physics. The industry breakdowns match those in the wage data. For details on the original data sources, see my 1990 paper and Supplementary Appendix A.

In principal one could also measure interindustry flows of knowledge, following the approach of Jaffe (1986). However, I do not pursue this approach by reason of inadequate data..

7.High technology manufacturing includes chemicals, machinery, electrical equipment, transportation equipment, and instruments. These industries are classified as high technology because of their large R&D intensities.

8. See Table 3 for the algebraic definition of the foreign industry science intensity. Earlier data on foreign scientific employment by industry in 1960 and 1970 derive from extracts of foreign censuses carried out by Manuel Zymelman of the World Bank, and entitled Occupational Distributions by Industry.

Nearly all of the foreign data for the 1980s derive from censuses and by-censuses in the various countries. These have been processed and collected in special reports on science and engineering employment by industry by Ellen Jamison of the Center for International Research at the U.S. Bureau of the Census. Because the foreign dataultimately derive from decennial censuses and by-censuses the foreign data had to be interpolated for intermediate years.

Data on foreign work forces used to produce intensities of scientific employment are taken from International Labour Organization, Yearbook of Labour Statistics: Retrospective Edition on Population Censuses, 1945-1989. See Supplementary Appendix B for more details on the data construction.

9. The formula is

$$RELPAT = \Sigma_{i=1}^{N} w_i \left(\frac{RSE_i}{PAT_i} \div \frac{RSE_{US}}{PAT_{US}} \right)$$

where RSE= research S/Es, PAT=patents by residents. The weights referred to in the text are shares of each foreign country in the total population of foreign research S/Es. The data on research S/Es by country are drawn from various issues of the United Nations Statistical Yearbook and from OECD Main Science and Technology Indicators. The data on resident and non-resident patents by country are taken from Industrial Property Statistics, issued by the World Intellectual Property Organization, Geneva, Switzerland.

10. The import penetration data by industry for all countries derived as follows. The data on imports by industry are taken from **The Economic Report of the President**. The breakdown of imports, exports, and value of industry output is: agriculture, mining, and construction; high technology manufacturing; other manufacturing; and rest of the economy. Industry output is taken from various issues of the **Statistical Abstract of the United States** for the same industry aggregates as are defined above. Import penetration is then defined as the ratio of imports to domestic production. It is clear that the industry groups are more aggregative than the other data. This is because of the aggregation of services, which costly to monitor. The data on import penetration by industry and region of the world are drawn from U.S. Department of Commerce, **Highlights of Foreign Trade: Imports and Exports**, various years.

11. The mapping of age groups into work experience is 20-29 years for 1-5 years of experience, 25-34 when experience is 6-10, 35-44 when experience is 11-20, 45-54 when experience is 21-30, and 55-64 when experience is 31-40. The result is an assignment of age group shares within a schooling class to a level of work experience. It is clear that there are errors in the assignment of age group shares by schooling group, since no allowance is made for educational differences in the age groupings, but the calculation does control for cohort size. The data are taken from U.S. Bureau of the Census, **Current Population Reports**, Series P-20.

12. See Rivera-Batiz and Romer (1991) for a long run view of the relation between world growth and technology.

13. The regression is of the form $w_c - w_{hs} = x_c\$_c - x_{hs}\$_{hs}$, where $x_c = x_{hs}$ with the exception of cohort size. With the one exception, the reported coefficients are $)\$$. But for cohort size the relevant expression is $(x_c - x_{hs})\$_c + (\$_c - \$_{hs})x_{hs}$. This explains the appearance of high school cohort size and) (cohort size) among the regressors.