Skill-Biased Technology Transfer

Evidence Factor Biased Technological Change in Developing Countries[*]

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ABSTRACT

This paper investigates the skill-bias of technological change in developing countries using a global sample of manufacturing industries. We report a striking increase in demand for skilled workers in the 1980s in middle income countries (GDP/capita between $2000 and $10,000). This increase is mostly due to skill-upgrading within industries rather than a reallocation of employment from low to high-skill industries and cannot be explained by capital-skill complementarity, thus indicating skill-biased technological change. Furthermore, the same industries that substituted toward skilled labor in middle-income countries in the 1980s had been doing so in the U.S. through the 1960s, 1970s and 1980s. We conclude that recent skill-biased innovations migrated rapidly from developed to middle income countries, but find no evidence of transfer to low income countries.

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I. INTRODUCTION

This paper investigates the role of skill-biased technological change in increasing demand for skills in the manufacturing industries of developing countries. The effects of technology on relative wages are of particular interest in developing countries for three reasons. First, if increased demand for skills is exacerbating income inequality in developing countries, the social and political implications may be quite extreme in countries with larger initial inequality and inherent political instability. Second, observed patterns of factor-bias in developing countries potentially allow us to track and analyze technology *transfer* through factor-biased innovations. Third, understanding the causes of trends in the demand for skill in developing countries may help us understand not only *intra*-national inequality, but also the importance of factor-bias in the persistence of massive *inter*-national inequality in income and human well-being.

Our conclusions are best stated at the outset: We find strong evidence of increased demand for skills in the 1980s in the manufacturing sectors of middle income countries (with middle income defined as 1985 gdp/capita between $2000 and $10,000). Our analysis clearly links this demand shift to skill biased technological change as cross-country correlations of shifting skill demand tend to be positively correlated. Furthermore, patterns of skill-upgrading in developing countries in the 1980s are well predicted by indicators of recent skill-biased technological change in the OECD, indicating skill-biased technology transfer.

Since our findings are rooted in the literature on demand for skills in the *developed* world, a brief review is necessary. A now large literature has documented the decline in the relative wages of less skilled workers in the United States and the concurrent decline in their employment in manufacturing.[2] A number have documented similar trends in wages, employment or unemployment in other OECD countries.[3] This literature has proposed several explanations for the declining demand for unskilled labor, including both Stolper-Samuelson effects of increased exposure to trade from developing countries

[2] For work on the U.S., see for example, Murphy and Welch [1992, 1993], Bound and Johnson [1992], Katz and Murphy [1992], and Blackburn, Bloom and Freeman [1990]. A recent review on this work is Katz and Autor (1999).

[3] For work on OECD countries see Freeman [1988], Freeman and Katz [1994], Katz and Revenga [1989], Katz, Loveman and Blanchflower [1995], Davis [1992], Machin [1996a], and Nickell and Bell [1995].

(including those through foreign outsourcing [Feenstra and Hanson, 1996]) and skill biased (or unskilled labor saving) technological change (SBTC). The profession seems to be near a consensus,[4] as the combination of seven findings generate compelling evidence that increased demand for skill in the OECD is due to SBTC:

1) despite the increase in the relative cost of skilled labor, the majority of U.S. industries have had within sector shifts in the composition of employment toward skilled labor [Bound and Johnson, 1992; Katz and Murphy, 1992; Lawrence and Slaughter, 1993; Berman, Bound, and Griliches, 1994 (BBG)]. This is true even within narrowly defined employment categories;

2) employment shifts to skill-intensive sectors seem too small to be consistent with explanations based on product demand shifts, such as those induced by trade, or Hicks-neutral, sector biased technological change [Bound and Johnson 1992; Katz and Murphy 1992; BBG; Freeman and Katz 1994];

3) there appear to be strong, within sector correlations between indicators of technological change and increased demand for skills [Berndt, Morrison and Rosenblum 1994; BBG; Autor, Katz and Krueger 1997; Machin 1996b; Machin and Van Reenen, 1998 (MVR)];[5]

4) Case studies conducted by the Bureau of Labor Statistics Office of Productivity and Technology which indicate the nature of innovations almost always mention innovations that lowered or are expected to lower production labor requirements [Mark, 1987];

5) Estimated elasticities of substitution indicate that while capital complements skilled labor more than it does unskilled labor [Griliches 1969], that effect is too small to explain the increased demand for skilled workers within industries [BBG];

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[4] Adrian Wood, one of the strongest proponents of the view that trade with developing countries has increased the skill premium [Wood, 1994], has recently endorsed the Berman, Bound and Machin [1998] estimate of trade accounting for at most 10% of the shift [Wood, 1998].

[5] Plant level studies using finer measures of technology adoption, such as use of computer aided manufacturing, yield mixed results. Doms, Dunne and Troske [1997] find that technology adoption is not correlated with changes in the proportion of nonproduction workers, though computer investment is. Siegel [1995] finds that technology adoption is correlated with increased proportions of high skill occupations.

6) Substitution toward skilled labor was pervasive in the manufacturing sectors of other OECD economies in the 1970s and 1980s and had the same within-industry characteristic [Berman-Bound and Machin, 1998 (BBM); MVR];

7) These shifts were concentrated in the same industries in different countries [BBM; MVR].

These last two findings establish the *pervasive* nature of SBTC, which is a necessary part of the argument in two senses. First, if one believes that technology transfers across borders then SBTC cannot be present in the U.S. and absent in other developed countries. Second, if international prices of tradeable goods influence local wages, the more pervasive the SBTC, the greater its potential to influence skill premia [Krugman, 1995; BBM]. Indeed, in the extreme, local SBTC could have no effect on wages under strict Heckscher-Ohlin-Vanek assumptions [Leamer 1994].

A growing body of evidence suggests that SBTC in the 1970s and 1980s continues a trend that has proceeded for most of this century. SBTC is present in U.S. manufacturing dating back to the late 1950s [BBG]. Goldin and Katz [1996, 1998] document the role of electrification and the new production methods of continuous-process and batch processing in increasing demand for nonproduction workers in U.S. manufacturing in the 1910s and 1920s.[6] The trend SBTC hypothesis offers a simple explanation for the historical skill-premium. The skill premium has declined when supply outstripped demand (in the early 1900s [Goldin-Katz, 1999] and in the 1970s) and has increased when the supply of educated workers did not keep pace with demand.

If we accept the view that most technological change in U.S. manufacturing this half-century (at least) has been skill-biased, and combine it with evidence of common SBTC among technological leaders, then developing countries must be choosing from a menu of best practices that includes an ever increasing proportion of skill-biased technology. A skill-biased interpretation of U.S. technological history suggests global SBTC, with the testable implication that technology absorption should be skill-biased in currently developing countries.

A sprinkling of evidence in the literature from the developing world is consistent with the hypothesis of a long trend of SBTC. Several studies have found *increased* relative wages of skilled labor

[6] An exception is Henry Ford's assembly process, which complemented unskilled workers.

in several developing countries despite widespread trade liberalization in the 1980s which would predict the opposite through the Stolper-Samuelson mechanism [Feliciano, 1995; Hanson and Harrison, 1995; Robbins, 1995; BBM].

This paper investigates the factor-bias of technological change with data on employment, wages and production for manufacturing industries of a variety of countries sampled from the entire globe. This rich data set reflects the unique capability of the United Nations in compiling data by soliciting contributions from the statistical agencies of each country. Figure I illustrates the sample, which is divided into three income groups: a high income group with GDP per capita exceeding $10,000 (1985 US$) in 1980, a middle income group with GDP per capita between $2,000 and $10,000 in 1980 and a low income group with GDP per capita below $2,000.

Using the wagebill share of nonproduction workers as a measure of demand for skill, we report three major findings about changes in the relative demand for skills. First, demand for skill accelerated in the middle income group in the 1980s to a rate exceeding the trend in the high income group. The evidence from the low income group is much less precise, but there is no indication of a comparable increase in demand for skill there. Second, in all income groups, increased demand for skill is predominantly a within-industry phenomenon, a pattern that is consistent with SBTC but inconsistent with explanations based on reallocation of demand from low to high skill industries, such as those due to trade, taste, or (factor neutral) technology shifts. Thirdly, the extent of capital-deepening in almost all of these countries is an order of magnitude too small for capital-skill complementarity to explain the increased demand for skill.

This pattern is consistent with the hypothesis of a global trend of SBTC, where industries in developing countries sequence through the technologies historically used by technological leaders. That is the "appropriate" technology approach of [Basu and Weil 1998; Schumacher, 1973], which stresses the need for human and physical capital accumulation in order to absorb new technology. An alternative interpretation is that *new* skill-biased technologies enable such large efficiency gains that they are adapted across industries and economies with wide ranges of human and physical capital levels on the one hand and factor prices on the other. This form of technological determinism is related to recent work on General Purpose Technologies [Bresnahan and Trajtenberg, 1995].

Building on the finding that recent technological change has had a skill-bias, we use cross-country correlations of increased skill use within industries to examine the timing of technology transfer, using evidence of skill-bias as an indicator of technology transfer. This method allows us to extend the literature on technology transfer into developing countries, as we are not forced to rely on indicators such as R&D spending and patents which are typically not present outside the OECD.[7]

Evidence of a trend of SBTC in high and middle income countries invites renewed consideration of the underlying causes of skill bias. We offer "technology-biased skill change" as a straightforward alternative answer to the question of why technological change tends to be skill-biased. We argue that a factor-neutral technological change will appear to be skill-biased if individuals and educational institutions can predict the flavor of future technologies and endogenously adjust skill-accumulation to complement new technologies.

The paper proceeds as follows. Section II describes the data and uses it to describe trends in the global market for skills. Section III outlines a very general empirical framework capable of distinguishing skill-biased technological change from other explanations for increased demand for skills, such as increased Heckscher-Ohlin trade or capital-skill complementarity. It then documents within-industry increases in demand for skill. Section IV examines the effects of capital-skill complementarity. Section V investigates whether increased demand for skill in the 1980s in middle income countries is due to absorption from the developed world of new skill-biased technologies or of mature skill-biased technologies. Section VI discusses technology-biased skill change, a possible explanation for the skill-bias of technological change. Section VII concludes with a discussion of the implications of global SBTC for education, income inequality and growth.

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[7] See, for example, Eaton and Kortum [1996,1999] for evidence of technology transfer using R&D and patent statistics. Coe, Helpman and Hoffmaister [1997] provide evidence of R&D spillovers through trade from developed to developing countries.

II THE MARKET FOR SKILLS IN GLOBAL MANUFACTURING

To investigate the use of skilled labor in the manufacturing industries of the world we use the United Nations General Industrial Statistics Database [United Nations 1992]. It includes manufacturing employment, wagebill, investment and output data for a large number of countries. It covers 28 manufacturing industries at (broadly) the 2 to 3-digit level, consistently defined across countries and years. Data are collected by the United Nations directly from the appropriate statistical agencies in each country.[8] We have (laboriously) selected those countries that provide data of consistent quality over time.

Descriptive statistics for the 37 countries used in this study are reported in Table I. They are ranked by income, from Ethiopia at $324 of GDP per capita in 1980 to the U.S. at $15,311 (all figures reported in constant 1985 dollars, using the GDP deflators and 1985 exchange rates from the Penn World Tables [Summers and Heston, 1991]. Countries are arranged into three income groups, a high income group with GDP per capita exceeding $10,000 (1985 US$) in 1980, a middle income group with GDP per capita between $2,000 and $10,000 in 1980 and a low income group with GDP per capita below $2,000.

The lower income group includes seven Asian and African countries, ranging in per capita product from Ethiopia to the Philippines, at $1882. It is dominated by India, with sampled manufacturing employment of almost 7 million. Note that production worker wages and manufacturing value added are not much higher (and sometimes even lower) than per capita product. The middle income group includes 18 countries from Asia, Europe and South America, ranging from Guatemala at $2574 to Venezuela at $8076. This group includes several countries with large manufacturing sectors: Poland, Czechoslovakia, Korea, Hungary and Spain.

The high income group (focused on before in Berman, Bound and Machin, 1998) includes 12 countries ranging in income from Japan to the U.S. The choice of 1985 exchange rates favors the U.S., but note that U.S. value added per worker is twice as high in 1980 as that of West Germany, the second-

[8] The main purpose of these data is to facilitate international comparisons relating to the manufacturing sector. Concepts and definitions are drawn from the International Recommendations for Industrial Statistics [Statistical Papers, Series M, No 48/Rev 1, United Nations Publication] and the classification by industry is taken from the International Standard Industrial Classification (ISIC) of All Economic Activities [Statistical Papers, Series M, No 4/Rev 2, United Nations]. For details see the Data Appendix in Berman, Bound and Machin [1998].

ranked country in this group. The U.S. is also the largest manufacturing employer in this group, with 19m workers, followed by Japan with 10.5m, the UK with 6.5m and West Germany with 6.3m.

Our measure of skill in these data is the classification into nonproduction and production workers (operatives and nonoperatives in UN terminology). A production worker usually refers to employees directly engaged in production or related activities of the establishment, including clerks or working supervisors whose function is to record or expedite any step in the production process. Employees of a similar type engaged in activities ancillary to the main activity of the establishment and those engaged in truck driving, repair and maintenance and so on, are also considered to be operatives.

This is a far cry from the ideal measure of "skill," which would be years of education completed.[9] Clearly the educational level of each of these categories of worker differs across countries, yet we are confident that nonproduction workers have higher educational attainment than production workers for two reasons: 1) cross-tabulations of matched worker and employer surveys at the plant in the U.S. in 1990 reveal a fairly tight relationship between years of schooling, occupation and nonproduction categories[10] [Berman, Bound and Machin, 1997]. An analogous effort at the industry level in the UK reveals a similar mapping [Machin, Ryan and Van Reenen, 1996]. Harris [1999] reports the results of a similar exercise at the plant level, which also reveal that nonproduction workers have a higher educational level. 2) Nonproduction workers are uniformly better paid. Quality indices based on a comparison of CPS and ASM data in the U.S. suggest that about ½ of skill upgrading in U.S. manufacturing took place within nonproduction and production categories [BBG] over the 1980s. We conclude that while the aggregation problems are worse than usual for these categories, within country comparisons are probably reasonable measures over periods as long as a decade, while between country comparisons, especially across income ranges should be viewed with caution.

With that caveat, we (cautiously) report on skill-upgrading and patterns of relative wages by income groups in Figures II and III. The proportion of nonproduction workers has increased quickly and

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[9] The term "skill" in skill-bias is an unfortunately vague expression we inherit from the literature. In our discussion "skill"can be interpreted as education.

[10] 75 percent of nonproduction workers are in white collar occupations, while 81 percent of production workers are in blue collar occupations. 76 percent of nonproduction workers have at least some college education, while 61% of production workers have a high school education or less.

fairly monotonically in all income groups. This is consistent with educational figures in Barro and Lee [1997] but probably understate the extent of human capital accumulation. The relative wages of nonproduction workers were very high in 1970 in the middle and low income countries, declined sharply over the 1970s and then declined slowly over the 1980s. The decline in relative wages in low and middle income countries is quite dramatic, but not unprecedented. It is a time-compressed version of the decline documented for the UK, US and Canada in the first half of this century, when relative wages of skilled workers declined from about 2.5 to about 1.6 [Chiswick 1979, Anderson 1998]. These patterns are fairly consistent with returns to education reported for developing countries by Psacharopoulos [1994,1999], which decline with income both in the cross-section of countries and within countries over time. The high income group experienced a decline the relative wage of nonproduction workers in the 1970s and an increase in the 1980s which were large by postwar historical standards but are dwarfed by the (cautious) comparison to fluctuations in middle and low income countries.

III. GLOBAL CHANGES IN DEMAND FOR SKILLS IN MANUFACTURING

Manufacturing industries make up only a portion of the demand for both skilled and unskilled labor, so that the supply of both categories of worker is influenced by multiple factors in the rest of the economy. There is considerable evidence that despite the tradeable nature of manufactured goods, supply shifts have large effects on wages. (See for example Katz and Murphy [1992].) In order to distinguish the effects of supply from those of demand we take the following approach.

Define the wagebill share of skilled workers

$$Sn \equiv \frac{w_S S}{w_S S + w_U U} = \frac{w_S S}{wE},$$

which can be decomposed as follows

$$\text{Log}(Sn) = \log(w_s/w) + \log(S/E).$$

If the elasticity of substitution between S and U, ?, is unity, then Sn is constant along a labor demand curve, so that the log change in relative wages and that of relative employment sum to zero

$$? \text{Log}(Sn) = ? \log (w_s/w) + ? \log(S/E) = 0.$$

Figure IV graphs ? log (w_s/w) against ? log(S/E) for high income countries, annualized and reported separately for each decade. A diagonal is drawn in for reference to describe a stable labor demand curve assuming ?=1. Observations for the 1980s are in regular font and those for the 1970s are in italics. Countries in the upper right hand corner clearly have demand shifting toward skills as they have both increasing relative wages for skilled (i.e., nonproduction) labor and increasing employment shares of skilled workers. The US and seven (of ten) other countries are in this category in the 1980s. Five of twelve countries are in this category in the 1970s.

What can we say about the remaining countries in the bottom right quadrant, with declining relative wages of skill and increasing shares of skilled labor in employment? Assuming that ?=1, a position above the diagonal indicates a shift in demand toward skill. That would imply a shift in demand toward skills for *all* countries in the high income sample. One advantage of the diagram is that the reader can make visual inference with her own choice of substitution elasticity. (The literature seems to favor elasticities between 1 and 2 [Autor, Katz and Krueger, 1998], while the Katz-Murphy [1992] estimated ? is 1.4). Even assuming ?=2, the US, UK and Norway in the 1970s and Finland in the 1980s can be classified as having a shift in demand toward skills, along with the countries in the upper right-hand corner. That is, even with an extreme assumption about ?, among the four most important manufacturing countries in the world, only Japan in the 1970s would be classified as not having a shift in demand toward skill.

Figure V repeats the same exercise for middle income countries, revealing a striking increase in demand for skills between the 1970s and the 1980s. All but Turkey show an increasing proportion of nonproduction workers in employment. Observations for the 1980s (in regular type) are almost uniformly above the diagonal, and sometimes far above it, indicating large increases in wagebill shares. Assuming ?=1, the middle income group averaged little or no shift in demand toward skills in the 1970s but experienced strong acceleration in the 1980s. Note that in comparison to the high income group, the scale has been compressed, so that Hungary, Portugal and Turkey represent shifts that would have been off the scale in Figure IV. This almost uniform increase in demand for skill in the middle income countries is a new finding, though it is consistent with results reported for individual countries such as Mexico [Feliciano, 1995].

Figure VI extends the same analysis to the manufacturing industries of the low income countries. While there is evidence of shifts in demand toward skills (i.e., to the northeast) in the Philippines, Pakistan, Bangladesh, Egypt, Tanzania and Ethiopia, the interpretation of this diagram entirely depends on how much weight is given to India, which accounts for 3/4 of sampled employment in this income group. India shows no shift in demand toward skill (assuming ?=1). The Indian data (which we also have in more detail from India for cross-validation) show a disturbing amount of year to year variation in relative wages, especially for such a large country, making us uncomfortable about drawing inferences about the low income group.

Table II summarizes the results for all three groups, reporting the average changes in wagebill shares for each group. The top two rows report changes in wagebill shares, ? Sn , weighted by national wagebills. The high income group shows a slight acceleration between the 1970s and 1980s, with ? Sn increasing from 0.33 to 0.42. The middle income group accelerates from - 0.02 in the 1970s to an increase of 0.45 in the 1980s. The low income group decelerates from 0.23 to 0.05. The fourth row reports that the results are qualitatively the same if exiting and entering countries are removed from the analysis, though acceleration in the middle income group is smaller. The fifth row reports unweighted results, showing that there is considerable acceleration in wagebill shares of nonproduction workers in the low income group if India is treated like just another country. In sum, no matter how we treat the data there is strong evidence of shifts in demand toward skilled labor in middle and high income countries in the 1980s, and weaker evidence of the same effect in low income countries.

"Within-Between" Decompositions

How much of the shift in wagebill shares toward skilled workers can be attributed to technological change? If ?=1 changes in wagebill shares provide a measure of demand shifts robust to changes in relative wages. Yet aggregate demand shifts at the industry level may be due to reallocations of employment from low-skill to high-skill industries for any number of reasons, such as trade shifts, taste shifts, or changes in fiscal policy.

We therefore consider a decomposition of changes in wagebill shares into *within*- and *between*-industry components.

$$\Delta Sn = \sum_i \Delta Sn_i \overline{W_i} + \sum_i \Delta W_i \overline{Sn_i} \,,$$

$$where \quad Sn \equiv \frac{w_S S}{w_S S + w_U U} \,, \quad W_i \equiv \frac{WB_i}{\sum_i WB_i} \,,$$

S are skilled workers, U are unskilled, E is employment, ‘ i ’ is an index of industry, and an overstrike indicates a simple average over time. The weights, W, are the industry wagebill shares in manufacturing wagebill. Within-industry shifts in the wagebill indicate a shift in demand within industries. Those could be due to SBTC or capital-skill complementarity (which we consider below), but cannot be due to shifts in the industrial distribution. The latter are reflected in the “between” industry term.

The results of this decomposition are reported in Table III. For the high income countries (in panel C) all 12 countries except Belgium report increased wagebill shares of nonproduction workers, with most upgrading occurring within industries in all but two instances.[11] Japan, Germany, the UK and the US all experienced large increases in the wagebill shares of nonproduction workers which range from 76% to 98% “within.”

Of 18 middle income countries with data available in the 1980s, 16 experienced increased wagebill shares for nonproduction workers and in all but Korea the majority of that shift occurred within industries. The 1970s showed much less evidence of skill-upgrading in the middle income group. Only 7 of 10 experienced increased wagebill shares of nonproduction workers, and of those only Chile, Venezuela and Greece experienced substantial shifts in demand toward skill which was mostly due to within industry skill-upgrading.

[11] These results are identical to those reported in BBM Table III, except for the addition of West Germany in the 1980s, for which data were unearthed during the data cleaning for this project.

Within industry shifts in demand for skills are much weaker in the low income group. In the 1970s only the Philippines experienced substantial within-industry skill upgrading. In the 1980s Ethiopia, Tanzania, Pakistan and Egypt report substantial within-industry shifts toward nonproduction workers.

Panel D. summarizes the results, reporting arithmetic means by income group and period. In the 1970s the high income countries experienced strong shifts in wagebill shares toward skilled labor, most of which where due to within industry skill upgrading, while most low and middle income countries showed little change. In contrast, the 1980s were a decade of rapid shifts in demand toward skilled workers in most countries in all income groups, and most of that shift occurred within (2/3 digit) industries.

This entire analysis is premised on the assumption that ?, the elasticity of substitution between skilled and unskilled labor, is unity. If it is not, then these calculations are only an approximation of the true degree of demand shifts toward skill. An analysis free of assumptions can find SBTC only in the case of countries with simultaneous increases in relative wages and employment shares of skilled labor. For the middle income countries in the 1980s, that would confine the analysis to eight countries: Peru, Chile, Poland, Malta, Portugal, Ireland and Spain. For these, the same decomposition that was conducted in Table III for wagebill shares can be conducted for employment shares. For these eight countries the vast majority of increased employment shares of skilled labor occurs within (as opposed to between) industries. For details see Appendix Table A. Cross-country correlations of skill upgrading reported in Section V below will provide further evidence implicating SBTC, without assuming a unitary elasticity of substitution.

IV. SBTC OR CAPITAL-SKILL COMPLEMENTARITY?

A generalized Cobb-Douglas production function with quasi-fixed capital yields share equations of the form

$$w_s S/wE = a + \text{ß}\ln(w_s/w_u) + ?\ \ln(K/Y),$$

where ?>0 reflects capital skill complementarity (see Berman, Bound and Griliches [1993] for a derivation).

Inserting industry (i) and time (t) subscripts and differencing over time,

$$? (w_s S/wE)_{it} = ? a + ß? \ln(w_s/w_u)_t + ? ? \ln(K/Y)_{it} .$$

If ?=1 then ß=0, since the wagebill share is constant along the demand curve. The sum of the LHS weighted by the industry wagebill share, $\overline{W_{it}}$ is exactly the "within" term in the decomposition above, so the equation allows a further decomposition of "within" industry shifts in the wagebill share of nonproduction workers into a term due to capital-skill complementarity and a residual due to skill-biased technological change

$$\underset{i}{\mathbf{j}} \; ? Sn_i \overline{W_i} \;\; ' \;\; \underset{i}{\mathbf{j}} \; \mathrm{a} \overline{W_i} \;\; \% \;\; \underset{i}{\mathbf{j}} \; ?? \ln(K/Y)_{it} \overline{W_i}$$

Calibrating ?=0.038 using a generous estimate from the literature [BBG], we can estimate an upper bound on the within-industry shift in the nonproduction wagebill net of the effect of capital-skill complementarity.

To construct a capital stock for this purpose we use a sum of T lagged investments for each industry and the earliest available lag, depreciated and multiplied by coefficients b^T and c^T

$$\hat{K}_t^T \;\; ' \;\; b^T \underset{t ' 1}{\overset{T}{\mathbf{j}}} (1\&\mathrm{d}) I_{t\&\mathrm{t}} \;\; \% \;\; c^T I_{t\&T}.$$

We chose d=.05. The coefficients b and c are estimated using investment and capital data from the U.S. Annual Survey of Manufactures at the 2 digit level (20 industries) [Bartelsman and Gray, 1994]. The R^2 in this prediction equation is generally around 0.98. The available lag length T varies from country to country, so b^T and c^T are estimated separately for each lag length.[12] Investment is deflated by a country-specific Penn World Tables GDP investment deflator.

Table IV reports results for all countries with available data. The calculation of capital stocks limits the exercise to the 1980s. In most countries capital-skill complementarity cannot explain much of the increase in demand for skills because capital-output ratios are not increasing nearly fast enough. Exceptions are Czechoslovakia on the one hand, where a capital accumulation is particularly large, and

[12] Results are available from the authors upon request.

Egypt, Cyprus and Sweden on the other, where a reduction in the capital/value added ratio is large enough to predict a substantial decrease in the demand for skill. In eight of the ten high income countries available, the share weighted average growth rate of capital/output ratios declines. We conclude that the within industry shift in the nonproduction wagebill share is generally not due to capital-skill complementarity. Capital-skill complementarity is a theory with excellent predictive power in cross-sections of industries [Griliches, 1969]. Yet the estimated ? coefficients from BBG (which are very similar to those in Autor, Katz and Krueger [1998]), would have required capital/output ratios to more than double over the 1980s to predict the increases in wagebill shares of 4.5 and 4.2 percentage points in the middle and high income countries respectively.

Note that this calculation does not reject a role for a more refined version the capital-skill complementarity hypothesis, in which the coefficient ? varies with the vintage of capital, with new vintages more complementary of skill. This approach is taken by BBG and Autor, Katz and Krueger. Their results can be interpreted as finding that computer equipment and R&D capital have higher skill-complementarity than conventional capital, but still do not explain all of the observed skill-upgrading in the 1980s. Conceptually, this is a particular case of the SBTC hypothesis. The general case allows for SBTC which is not embodied in capital.

V. WHICH TECHNOLOGIES TRANSFER?
THE NEW AND FLEXIBLE OR THE MATURE BUT APPROPRIATE?

The finding that technological change tended to be skill-biased in the 1980s in the majority of countries sampled has a useful implication for research. We can use a measure of common skill-bias to measure the extent of technology transfer within industries across countries.

Two broad classes of technology transfer models are relevant. The "appropriate" technology model (Schumacher [1973]; Basu & Weil [1998]) posits that new technologies are not absorbed immediately in developing countries because of a lack of human or physical capita, differences in production technologies in use, or differences in factor prices. Absorption-costs models [Grossman-Helpman, 1991] and lagged absorption models [Krugman, 1979] have the same prediction. In contrast, the conventional assumption in growth theory is of *pervasive* technological change which applies to all countries. This would make sense for an innovation so potent that its efficiency increase induces adoption across a wide range of industries, factor price combinations and local technological capabilities. That concept is related to recent work on “General Purpose Technologies” [Bresnahan and Trajchtenberg, 1995; Helpman 1998], such as electrification and information technology which increase productivity in a wide range of industries.

How similar are production technologies in different countries? Figure VII illustrates the proportion of nonproduction workers used, by industry and income group. For most industries, and especially in the higher “tech” industries, high income countries average a much higher proportion of nonproduction workers in employment. Only about 20% of the aggregate gap between the proportion of nonproduction workers in high income countries and that in low income countries is due to the distribution of industries, with about 80% due to within-industry differences in skill use. This probably underestimates the difference in human capital use between groups, a gap suggesting that the “appropriate technology” approach is relevant.

In levels this pattern is consistent with either different production technologies (i.e. different machines) in use in developing countries or with less intensive use of relatively more expensive skilled labor (on the same machines) in low income countries (Figure III).

Figure VIII illustrates some evidence for the general purpose nature of technological innovation, graphing the change in proportion of nonproduction workers used in each of 28 industries against the aggregate change in relative wages for four leading industrial economies. The top line illustrates, for example, that (assuming an elasticity of substitution of unity between production and nonproduction workers) all 28 subindustries of UK manufacturing shifted demand towards skills in the 1980s. Not only did average manufacturing industry shift demand towards skill, but the vast majority of industries did so in the 1980s, from low to high skill industries. With the possible exception of Japan, the same is true of the 1970s. If skill-biased innovations are productive enough to induce their adoption in a wide range of industries one might expect them to be introduced in a wide range of countries as well, despite differences in technological level and factor prices.

Figure IX illustrates the use of an indicator of common skill-bias in innovation to measure the extent of common technological change within industries across countries. It graphs the change in wagebill share of nonproduction workers in West German industries against the same change in U.S.

industries. The size of the text labeling the industry is proportional to its weight in the manufacturing wagebill. Four large industries dominate skill-upgrading, machinery, electrical machinery, transportation equipment and printing and publishing. The share-weighted correlation coefficient corresponding to this graph is 0.65 (p=.001). Changes in wagebill shares are highly correlated across manufacturing industries within the high income countries. All nine such pairwise correlations with the U.S. are positive in the 1980s and six are significantly positive. (A similar result is familiar for employment shares from BBM, though the inclusion of West Germany is an innovation.)

We use the same method to track diffusion of technological innovations from developed to developing countries, using U.S. changes in wagebill shares as an indicator of SBTC in developed countries. High cross-country correlations, within-industry, in R&D between the U.S. and other leading industrial countries [MVR] support this choice. Figure X illustrates the same pattern for the U.S. and Turkey, a country at the low end of the middle income group, with per capita income below $2900 in 1980. The correlation is positive (r=.42, p=.03) with skill upgrading in electrical machinery notably common in both countries.

Table V reports a Table of correlations in increased wagebill shares between the U.S. and middle income countries. The industrial distribution of skill upgrading in the 1980s in these countries shows remarkable similarity to that in the U.S. in the 1980s (column 2), with 11 of 12 correlations positive. Skill upgrading in Guatemala, Turkey, Columbia, South Korea, Malta and Ireland have substantial positive correlations with the U.S. pattern of SBTC in the 1980s. Skill upgrading in the U.S. is surprisingly good predictor of skill-upgrading in middle income countries. Note that this is true of *multiple decade*s of U.S. manufacturing technological change. For example, skill upgrading in Portugal and Spain is much better predicted by the U.S. pattern of SBTC in the 1970s than that in the 1980s. Czechoslovakia's skill upgrading is best predicted by the U.S. in the 1960s. The table suggests different patterns in different countries, providing limited evidence that the U.S. pattern of SBTC in the 1970s and 1980s is a better predictor than the SBTC of the 1960s.

Table VI summarizes results for the entire sample. Within the manufacturing industries of *developed* countries skill upgrading is highly correlated, especially in the 1980s, but also across decades. As we saw in Table V, the 1980s US pattern of skill upgrading is positively correlated with that of all 9 high-income countries in the sample, and significantly correlated with 5 of them. The 1960s and 1970s US pattern is only a slightly worse predictor for the other high income countries in the 1980s. These strong cross-country similarities in skill-upgrading are true of the 1970s as well, within the high income countries. US patterns of skill upgrading are positively correlated with 10 of 11 other countries in the high income sample for the 1970s, using either the US 1960s or the US 1970s as a predictor.

For *middle income* countries the pattern of technology transfer differs from decade to decade. While U.S. skill upgrading in the 1980s is a very good predictor correlated with skill upgrading in middle income countries in the 1980s (11 of 12 positive, 2 significantly so) it doesn't do nearly as well in the 1970s (7 of 8 positive, none significant). Moreover, there is much less skill upgrading to explain in the 1970s in the middle income countries, (Table II and Figure V).

As in the high income countries, the pattern of technology transfer in the middle income countries indicates that U.S. skill upgrading in the 1960s, 1970s and 1980s are all very good predictors of skill upgrading in middle income countries in the 1980s. Note that the 1960s and 1970s in the US predict the 1980s in the middle income countries better than they do the same decade in the middle income countries, indicating that all vintages of technology seem to transfer better in the 1980s.

In contrast to this clear pattern of technological diffusion into middle income countries, there is no evidence that skill-biased technologies from high income countries transferred to low income group in the 1970s or the 1980s.

Technology Indicators

An additional testable implication of skill-biased technology transfer is that indicators of technological change in high income countries be able to predict skill-upgrading in developing countries. We fall back on a well established finding in the literature of investments in computers and in R&D being positive predictors of skill upgrading at the industry level [BBG, MVR], both within and across OECD countries.

As indicators we use a) computer use from the US 1984 Current Population Survey aggregated to the 2.5 industry level; and b) R&D / value added ratios for the OECD as a whole. Summary statistics are provided in Table VII for these two variables.

Table VIII reports how well these indicators of technological change in the US and OECD predict skill upgrading in middle income countries. Of 12 countries in the 1980s middle income sample 8 have positive correlations with the R&D intensity variable [13] (3 statistically significant) and 9 with the US computer use variable (2 significant). This pattern is slightly weaker, but consistent with the evidence of technology transfer presented in Table V, using skill-upgrading as a predictor. Both indicate that technological activity in high income countries caused an increase in demand for skills in middle income countries in the 1980s.

Table IX summarizes correlations between technology indicators and skill-upgrading in all three income groups over two decades. The three major findings of Table VI appear here again: first, technological change in the high income countries consistently predicts skill-upgrading in high income countries in both the 1970s and the 1980s, as in MVR; second, the evidence of technology transfer between high and middle income countries is strong in the 1980s but much weaker in the 1970s; third, there is no consistent evidence of technology transfer from high to low income countries.

Taken together, Tables VI and IX provide evidence that in the 1980s skill-biased technological change of several vintages migrated from high income countries. It arrived in a set of middle income countries which are geographically disperse and institutionally diverse.

VI. WHY IS TECHNOLOGICAL CHANGE SO OFTEN SKILL-BIASED?

The cross-country evidence offered so far for SBTC in high and middle income countries reinforces the historical evidence of SBTC in U.S. manufacturing indicating a long run trend of skill-bias in technology. Why should technological change so often be skill-biased? The literature has suggested a number of answers to this question. Zeira [1998] hypothesizes that machines replace unskilled but not skilled workers. Bresnahan [1999] and Bresnahan, Brynjolfsson and Hitt [1998] have emphasized the role of technology-induced workplace reorganization in shifting demand toward skilled workers. Acemoglu [1998] develops a model with increasing returns, in which an anticipated increase in supply of skilled

[13] The transportation equipment industry is excluded from the R&D regressions as that research is largely military with limited technology transfer potential. Correlations are smaller when that industry is included, but the overall pattern of Tables VIII and IX is largely unchanged.

workers induces development of a technology that will create a demand for them. Nelson and Phelps [1966] and T.W. Schultz [1975] hypothesize that skill is particularly valuable in periods of rapid technological change. Galor and Tsiddon [1997] and Galor and Moav [forthcoming] emphasize the importance of this type of skill in the context of the recent expansion in wage inequality.

We offer "technology-biased skill change" as a straightforward alternative answer to the question, which may complement other explanations. We argue that a factor-neutral technological change will appear to be skill-biased if individuals and educational institutions can predict the flavor of future technologies and endogenously adjust skill-accumulation to complement new technologies.

Technology-biased skill change: An illustrative model

Imagine a world in which farmers are distributed around the circle in the figure, with each interval describing a distinct crop. (Alternatively they could be programmers - or poets, working in different languages, or researchers in different fields). The farmers are all identical. An individuals' entire harvest of any crop sells at the same price, p=1.

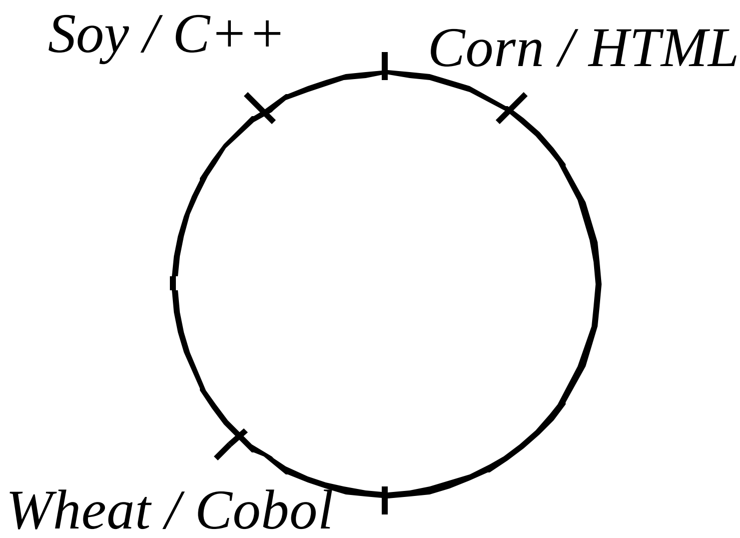

Figure XI: A Circle of Farmers

Now introduce exogenous technological change which arrives once per period, dropping instruction manuals on only one interval, raising productivity additively by a>0 in the interval. This process is repeated stochastically, with a equal probabilities of arrival across intervals.

Define the skill level of farmers in interval i, s_i, as the cumulative number of manuals read. Thus income is $1 + s_i a$. Note that technological change is skill-neutral because of the uniform distribution of manual arrivals.

Individuals have the option of either producing or moving to the neighboring field in a given period. Technological change leads location if the net present value of moving exceeds forgone income.

Now perturb the skill-neutral world of these farmers to make the location of new technology predictable. Individuals will move in anticipation of technological advances (if the net present value of increased income exceeds foregone earnings), creating a positive correlation of skill and technological change. That correlation is *observationally equivalent* to SBTC, though it is driven by the combination of skill-neutral TC and endogenous skill-accumulation.

Note that this "technology-biased skill change" is distinct from a) true SBTC that by its' nature replaces less-skilled workers (or just serial correlation in the location of manuals arriving); b) Skill that improves accommodation of technological change, (e.g. roller-blades for moving nimbly around the unit circle); or c) Technology directed endogenously to high skill intervals.

Consider the real world in which horizontal relocation is facilitated by formal education. If the choice of educational content were exogenous, technology may be education-neutral. But content is endogenous and technological changes are predictable. So efficient educational institutions adjust curricula, competing to best augment the earnings of graduates by preparing them for the set of technologies they are likely to need during their working lives. There is plenty of evidence that educational institutions efficiently redesign curricula and guide students to fields where progress is likely to occur. They replace traditional corn with hybrids, Greek with COBOL, COBOL with HTML, SAS with Stata, Keynesian Macro with natural experiments and RBC models, etc.. In short, endogenous design of training to complement predicted technological change is a plausible alternative to other explanations for skill-biased technological change.[14]

VII. Conclusions

Demand for skills accelerated in the manufacturing industries of middle income countries in the 1980s to a rate matching even that of high income countries. This increase is mostly due to skill-upgrading within industries rather than a reallocation of employment from low to high-skill industries and cannot be explained by capital-skill complementarity. Those two findings lead us to conclude that skill-biased technological change is responsible.

The same industries that substituted toward skilled labor in middle-income countries in the 1980s had been doing so in the U.S. through the 1960s, 1970s and 1980s. We conclude that skill-biased

[14] While the model is meant for illustration and testing is beyond the scope of this paper, it has two implications: 1) Predictability is likely to be better in technology absorbing countries, implying that formal education should be relatively more important that on the job training. 2) "Skill-bias" will be more often observed in the presence of flexible educational institutions.

technologies are being transferred rapidly from developed to middle income countries. Both new and mature skill-biased technologies are apparently being transfered from high income to middle-income countries.

We find no general evidence of transfer to low income countries of skill-biased technologies, though there is evidence of within-industry skill upgrading in low income countries other than India.

Why did technologies migrate so quickly in the 1980s and not in the 1970s? Why to middle income countries but not to low income countries? Possible explanations are: a) increased trade, b) improved protection of property rights, including intellectual property right, c) converging factor prices, and d) improved technological infrastructures. These topics are ripe for investigation now that we are armed with an indicator of technology absorption which is applicable to developing countries.

Figure III suggests that the depression in skill-premia in middle and low income countries due to factor accumulation may be exhausting itself. To the extent that the current crop of skill-biased technologies in high income countries have not yet reached the rest of the world, this paper predicts a possible increase in skill-premia and an accompanying increase in wage inequality for developing and middle income countries. This possibility deserves further investigation as increased income inequality may create a particularly combustible situation in some low and middle income countries.

Finally, this evidence for global SBTC suggests a unified explanation for both growing income inequality within countries and the puzzle of the lack of convergence of per-capita income between countries. We propose a reinterpretation of the dual findings of nonconvergence in GDP/capita and convergence conditional on educational levels [Barro, 1991; Mankiw, Romer and Weil, 1992].[15] The skill-bias of technological change implies that technology favors countries with larger proportions of skilled labor, a force that would moderate Solow-convergence through factor accumulation along the convergence path. That topic we leave to future research.

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[15] Zeira [1998] makes a similar point, though he emphasizes the role of differences in factor prices in dictating the adoption of a skill-biased technology.

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Table I: Descriptive Statistics - 1980

Country	gdp/capita (1985 $)	Manufacturing Value Added per Worker ($)	Manufacturing Employment (1000s)[1]	Production Wage ($)	Nonproduction Wage ($)	Proportion Nonproduction	Manufacturing Value Added % of gdp[2]	Note
A: Low Income Group								
Ethiopia	324	6106	74	1043	2596	0.22	8	
Tanzania	480	1533	83	1218	2375	0.21	-	
India	882	1202	6992	1032	1858	0.23	18	
Bangladesh	1085	1214	409	740	1130	0.2	18	
Pakistan	1111	3604	449	1365	1716	0.22	16	
Egypt	1647	1876	857	1301	4014	0.19	12	
Philippines	1882	1258	804	1118	3019	0.2	26	1977
B: Middle Income Group								
Guatemala	2574	8291	82	1963	5681	0.22	17	
Turkey	2872	5780	795	3290	4312	0.22	14	1983
Peru	2877	-	273	-	-	0.32	20	
Colombia	2948	4662	508	2660	5139	0.27	23	
Korea	3093	6764	2015	3346	4772	0.21	28	
Malaysia	3477	8720	489	2505	7152	0.1	21	1983
Czech Rep.	3731	5651	2472	2780	3064	0.27	-	
Chile	3898	7472	206	4711	14496	0.27	21	
Poland	4417	-	3890	-	-	0.26	-	
Malta	4488	7790	25	5826	11584	0.15	-	
Portugal	4982	2390	663	4157	6766	0.14	-	
Hungary	4990	2771	1384	1760	2178	0.21	-	
Uruguay	5089	-	145	-	-	0.22	26	
Cyprus	5289	6990	36	4884	7252	0.16	-	1981
Greece	5897	5148	367	7306	13011	0.27	16	
Ireland	6828	11894	212	12929	18383	0.19	-	
Spain	7391	8835	1159	11842	16478	0.23	-	
Venezuela	8076	20725	411	6239	35833	0.25	16	1981

C: High Income Group

Country	gdp/capita ($)	Manufacturing Value Added per Worker ($)	Manufacturing Employment (1000s)	Production Wage ($)	Nonproduction Wage ($)	Proportion Nonproduction	Manufacturing Value Added % of gdp	Note
Japan	10068	18467	10500	10506	11908	0.46	29	1975
UK	10161	13988	6462	14559	19045	0.3	27	
Austria	10499	15657	679	11602	19309	0.3	25	1981
Finland	10843	16256	531	13645	20597	0.24	28	
Belgium	11096	15488	640	15913	30890	0.24	21	
Denmark	11333	15664	381	22356	29948	0.28	20	
Luxembourg	11894	14967	27	22859	42635	0.21	-	
West Germany	11916	20262	6302	20810	31450	0.28	-	1979
Norway	12141	14360	354	18619	25869	0.26	15	
Sweden	12447	17813	853	17520	27207	0.29	23	
Australia	12518	15702	1138	16380	19517	0.26	19	
US	15311	40078	19200	18357	28145	0.28	22	

Notes: All figures are author's calculations from the United Nations General Industrial Statistics Database, with the exception of GDP/capita, which is from the Penn World Tables. All pecuniary figures reported in 1985$ deflated by the implicit Laspeyres GDP deflator in the Penn World Tables.

[1] Employment reflects the sample rather than the population. Samples typically include only plants with ten or more employees.
[2] Source: 1999 World Development Indicators.

Table II: Change in Wagebill Shares by Income Groups

Weighted by wagebills.

	Low	Middle	High
1970s	0.23	-0.02	0.33
	(0.06)	(0.14)	(0.09)
1980s	0.05	0.45	0.42
	(0.13)	(0.14)	(0.08)
Differences	-0.18	0.47	0.09
	(0.14)	(0.20)	(0.12)
Number of observations	10	21	23
Balanced Panel			
Differences	-0.17	0.33	0.09
	(0.12)	(0.20)	(0.12)
Number of observations	8	16	22
Unweighted (unbalanced)			
Differences	0.23	0.54	-0.02
	(0.21)	(0.19)	(0.11)
Number of observations	11	21	23

Note: Calculated from UN GIS database. All countries in figures IV, V and VI included, with the exception of Peru, Uruguay, Chile and Poland for which wagebills could not be converted reliably into dollars. Heteroskedasticity-consistent standard errors in parentheses.

Table III: Proportion of Increased Wage Bill Share of Skill "Within" Industries

A: Low Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Ethiopia	-	-	-	0.58	91	-1.64	n/a,80,88
Tanzania	-0.43	93	-5.15	0.65	84	-2.38	1970,80,85
India	0.19	-11	-2.22	-0.08	303	-0.33	1970,80,88
Bangladesh	0.21	152	-2.39	0.32	20	1.28	1970,80,88
Pakistan	-	-	-	0.5	72	2.62	n/a,80,88
Egypt	0.23	49	-2.95	0.44	83	-0.81	1971,80,88
Philippines	0.68	46	5.28	-	-	-	1970,77,n/a

B: Middle Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Guatemala	0.36	50	-1.28	0.96	69	-2.91	1973,80,87
Turkey	-	-	-	0.6	79	3.8	n/a,83,90
Peru	0.13	-247	-2.24	1.38	103	3.43	1972,80,88
Colombia	-0.13	145	-2.22	0.66	84	-0.17	19728090
Korea	-	-	-	0.08	36	-0.98	1973,80,90
Malaysia	-	-	-	-0.35	86	4.74	n/a,83,90
Czechoslovakia	0.06	61	-0.42	0.22	92	-0.16	1970,80,89
Chile	1.12	92	0.95	0.05	153	0.1	
Poland	-	-	-	0.06	80	0.58	1970,80,89
Malta	-0.26	43	-1.7	0.72	76	0.43	1970,80,88
Portugal	-0.97	96	-4.74	0.48	90	2.02	1972,80,87
Hungary	-	-	-	0.93	96	4.55	n/a,80,90
Uruguay	-	-	-	0.17	51	-0.05	n/a,80,88
Cyprus	-	-	-	-0.07	108	-0.86	n/a,81,91
Greece	0.38	104	-1.41	0.93	90	-0.91	
Ireland	0.02	25	-0.76	0.58	75	0.39	19708089
Spain	-	-	-	0.7	92	2.18	n/a,80,90
Venezuela	0.78	141	-0.81	0.56	62	-0.25	1970,81,91

C: High Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Japan	0.37	98	-2.18	0.14	98	0.36	1969-75,78-90
UK	0.39	91	-0.29	0.62	92	1.37	
Austria	0.69	93	0.69	0.36	76	0.72	1970,81,90
Finland	0.27	82	-1.13	0.7	83	-0.18	
Belgium	0.77	86	0.77	-0.06	92	-1.11	1973,80,85
Denmark	0.12	42	-1.62	0.64	89	0.81	1973,80,89
Luxembourg	0.9	95	0.57	0.73	123	1.58	
West Germany	0.67	95	0.64	0.42	83	0.55	1970,79,90
Norway	0.33	76	-0.3	-	-	-	1970,80,n/a
Sweden	0.38	81	0.36	0.07	25	-0.27	
Australia	0.06	52	-1.69	0.42	92	0.05	1970,80,87
US	0.19	86	-0.16	0.51	76	0.70	

D: Means

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)
High	0.43	81	-0.36	0.41	85	0.42
Middle	0.11	58	-2.12	0.48	85	0.88
Low	0.18	66	-1.49	0.4	70[1]	-0.21

1. Excludes India

Table IV: Skill-Upgrading Net of Capital-Skill Complementarity 1980s, by Income Group

Country	Change in % nonproduction (annualized)	% within	Aggregate change in log (K/Y)	% within net of capital-skill complementarity
A: Low Income Group				
Ethiopia	0.58	91	1.05	84
Egypt	0.44	83	-6.31	138
B: Middle Income Group				
Turkey	0.6	79	-0.11	80
Colombia	0.66	84	1.46	76
Czechoslovakia	0.22	92	5.26	1
Poland	0.06	80	0.84	25
Malta	0.72	76	1.79	67
Portugal	0.48	90	2.49	70
Hungary	0.93	96	-0.23	97
Cyprus	-0.07	108	-1.81	8
Ireland	0.58	75	-3.03	95
Spain	0.7	92	0.02	92

C: High Income Group

Country	Change in % nonproduction (annualized)	% within	Aggregate change in log (K/Y)	% within net of capital-skill complementarity
Japan	0.14	98	-1.98	156
UK	0.62	92	-0.86	97
Austria	0.36	76	-1.26	90
Finland	0.7	83	2.27	70
Denmark	0.64	89	-0.11	89
Luxembourg	0.73	123	-0.29	124
West Germany	0.42	83	-0.83	91
Sweden	0.07	25	-0.71	63
Australia	0.42	92	0.35	89
US	0.51	76	-0.89	83

Note: The rightmost column reports the proportion of the change in % nonproduction (column 2) attributable to within-industry skill upgrading net of the change in log(K/Y) (column 4) according to the decomposition in the 3rd equation of section IV, with a calibrated coefficient reflecting capital-skill complementarity.

Table V: Correlations of Within-Industry Changes in Nonproduction Wagebill Shares: Middle Income Countries 80-90

	US 1980s	US 1970s	US 1960s
US 1970s	-	-	.69* (.00)
US 1980s	-	.29 (.14)	.43* (.02)
Guatemala	.33 (.09)	.11 (.58)	.13 (.52)
Turkey	.42* (.03)	.01 (.96)	.12 (.54)
Columbia	.23 (.23)	.21 (.28)	-.15 (.44)
S. Korea	.34 (.08)	.31 (.11)	.11 (.57)
Czechoslovakia	.07 (.73)	.11 (.58)	.30 (.12)
Malta	.53* (.01)	-.01 (.98)	.21 (.35)
Portugal	.05 (.82)	.52* (.01)	.07 (.73)
Hungary	.03 (.88)	.33 (.10)	.34 (.08)
Cyprus	-.001 (.99)	.25 (.24)	.15 (.49)
Greece	.13 (.50)	.01 (.96)	.16 (.43)
Ireland	.40 (.05)	-.02 (.92)	.09 (.67)
Spain	.05 (.79)	.43* (.03)	.37 (.06)
Countries	12	12	12
# positive	11	11	11
sig. pos. at a=.05	2	2	0

These are cross-country correlations of ? Sn_{ci} and ? $Sn_{c'i}$ for countries c and c' and industries i. Observations are weighted by industry wagebill shares averaged over time and across all countries in the middle income group. The number in brackets is the significance level of a two-tailed test that the correlation is zero. The 28 industries are those defined by ISIC Revision 2.

Table VI: Correlations with US Skill Upgrading

	1980s			1970s	
	US 1980s	US 1970s	US 1960s	US 1970s	US 1960s
High Income Group					
Countries	9	9	9	11	11
Positive	9	9	9	10	10
Significant Positive	5[1]	2[2]	4[3]	1[6]	3[7]
Significant Negative	0	0	0	0	0
Middle Income Group					
Countries	12	12	12	8	8
Positives	11	11	11	7	5
Significant Positives	2[4]	2[5]	0	0	0
Significant Negatives	0	0	0	0	1
Low Income Group					
Countries	6	6	6	5	5
Positives	5	3	3	3	4
Significant Positives	0	0	0	1	0
Significant Negatives	0	1	0	0	0

1. Australia, Denmark, Finland, UK, West Germany.
2 UK, West Germany.
3. Denmark, Finland, UK, West Germany.
4. Malta, Turkey.
5. Portugal, Spain.
6. Austria.
7. Austria, Germany, Sweden.

Table VII: Summary Statistics: R&D and Computer Use variables

	Mean	s.d.	Min	Max
US Computer use, 1984 October CPS	**.1922**	**.1111**	**.0504**	**.4385**
OECD R&D intensity, industry mean 1973-80	**.0435**	**.0441**	**.0042**	**.1479**
OECD R&D intensity, industry mean 1980-90	**.0565**	**.0605**	**.0045**	**.1996**

R&D intensity = (R&D expenditure)/(value added), from OECD STAN/ANBERD industrial statistics database supplement; 15 industrial categories with transport excluded

Computer use: proportion in industry using computer at work, from October 1984 CPS; 28 industrial categories

Table VIII: Technology Indicators Predict Technology Transfer

1980 to 1990 Within-Industry Changes in Non-Production Wagebill Shares:
Middle Income Countries

Dependent Variable:	**OECD R&D Intensity, 1980-1990 average**		**US Computer Use 1984**	
	Coeff.	P-value	Coeff.	P-value
Guatemala	.0995*	.039	.0177	.349
Turkey	.0505	.155	.0017	.903
Colombia	.0195	.385	.0005	.946
S.Korea	-.0011	.948	.0003	.962
Czechoslovakia	.0080	.215	.0039	.123
Malta	.0704*	.070	.0270*	.081
Portugal	.0048	.902	.0063	.617
Hungary	-.0031	.808	-.0015	.733
Cyprus	-.0114	.619	-.0179	.177
Greece	.0300	.367	.0232*	.034
Ireland	.0636*	.003	.0154	.106
Spain	-.0153	.732	-.0037	.663
Countries	12		12	
# Positive	8		9	
sig. pos. at a=.10	3		2	

*indicates significance at 10% level or less

These are cross-country correlations of ? Sn_{ci} and technology indicators for industry i. Observations are weighted by industry wagebill shares averaged over time and across all countries in the middle income group. R&D correlations exclude the “transportation equipment” industry.

Table IX: OECD Technology Indicators Predict Skill Upgrading

Correlations of Technology Indicators and Increased Nonproduction Wagebill Shares, across industries.

	1980s		1970s	
	US Computer Use 1984	OECD R&D 1980-90	US Computer Use 1984	OECD R&D 1973-80
High Income Group				
Countries	10	10	12	12
Positive	10	8	10	10
Significant Positive	5	4	6	4
Significant Negative	0	0	1	1
Middle Income Group				
Countries	12	12	8	8
Positive	8	9	5	4
Significant Positive	3	2	3	1
Significant Negative	0	0	1	2
Low Income Group				
Countries	6	6	5	5
Positive	3	3	4	2
Significant Positive	1	1	0	0
Significant Negative	1	0	0	1

Note: As in Table VIII, these figures refer to the sign and significance (a=.10) of cross-country correlations of ? Sn_{ci} and indicators of technological change. Observations are weighted by industry wagebill shares averaged over time and across all countries in the income group. Transportation equipment excluded from R&D correlations.

Appendix Table A: Proportion of Increased Use of Skills "Within" Industries

A: Low Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Ethiopia	-	-	-	0.77	90	-1.64	n/a,80,88
Tanzania	0.76	83	-5.15	0.96	86	-2.38	1970,80,85
India	0.54	85	-2.22	0.00	1617	-0.33	1970,80,88
Bangladesh	0.54	108	-2.39	0.05	-51	1.28	1970,80,88
Pakistan	-	-	-	0.02	-617	2.62	n/a,80,88
Egypt	0.59	80	-2.95	0.43	96	-0.81	1971,80,88
Philippines	-0.26	90	5.28	-	-	-	1970,77,n/a

B: Middle Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Guatemala	0.45	69	-1.28	1.38	84	-2.91	1973,80,87
Turkey	-	-	-	-0.08	99	3.80	n/a,83,90
Peru	0.62	40	-2.24	0.56	104	3.43	1972,80,88
Colombia	0.36	82	-2.22	0.60	96	-0.17	19728090
Korea	1.59	99	-7.98	0.25	67	-0.98	1973,80,90
Malaysia	-	-	-	-0.45	81	4.74	n/a,83,90
Czechoslovakia	0.14	81	-0.42	0.25	89	-0.16	1970,80,89
Chile	0.65	98	0.95	0.02	582	0.1	
Poland	0.41	88	-7.32	0.43	104	0.58	1970,80,89
Malta	0.07	314	-1.70	0.43	64	0.43	1970,80,88
Portugal	0.10	89	-4.74	0.10	142	2.02	1972,80,87
Hungary	-	-	-	0.13	82	4.55	n/a,80,90
Uruguay	-	-	-	0.13	58	-0.05	n/a,80,88
Cyprus	-	-	-	0.07	84	-0.86	n/a,81,91
Greece	0.58	107	-1.41	1.03	93	-0.91	
Ireland	0.14	53	-0.76	0.41	84	0.39	1970,80,89
Spain	-	-	-	0.22	122	2.18	n/a,80,90
Venezuela	0.69	53	-0.81	0.57	95	-0.25	1970,81,91

C: High Income Group

Country	1970-1980 Change in % nonproduction (annualized)	1970-1980 % within	1970-1980 Change in wage ratio % (annualized)	1980-1990 Change in % nonproduction (annualized)	1980-1990 % within	1980-1990 Change in wage ratio % (annualized)	Note
Japan	0.94	99	-2.18	0.05	231	0.36	1969-75,78-90
UK	0.41	91	-0.29	0.29	93	1.37	
Austria	0.46	89	0.69	0.16	68	0.72	1970,81,90
Finland	0.42	83	-1.13	0.64	79	-0.18	
Belgium	0.45	74	0.77	0.17	96	-1.11	1973,80,85
Denmark	0.44	86	-1.62	0.41	87	0.81	19738089
Luxembourg	0.57	90	0.57	0.30	144	1.58	
West Germany	0.46	93	0.64	0.25	79	0.55	1970,79,90
Norway	0.34	81	-0.30	-	-	-	1970,80,n/a
Sweden	0.26	70	0.36	0.12	60	-0.27	
Australia	0.39	88	-1.69	0.38	92	0.05	1970,80,87
US	0.20	81	-0.16	0.30	73	0.70	

Appendix Table B: Correlations with US Skill Upgrading

	1980s			1970s	
	US 1980s	US 1970s	US 1960s	US 1970s	US 1960s
High Income Group					
Japan	-0.07	0.05	0.17	0.05	0.23
	(0.74)	(0.8)	(0.39)	(0.81)	(0.27)
UK	0.61*	0.42*	0.64*	0.26	0.36
	(0.00)	(0.03)	(0.00)	(0.18)	(0.06)
Austria	0.14	0.22	0.27	0.39*	0.61*
	(0.48)	(0.26)	(0.17)	(0.04)	(0.00)
Finland	0.68*	0.22	0.50*	-0.06	0.32
	(0.00)	(0.27)	(0.01)	(0.75)	(0.10)
Belgium	0.40	0.22	0.30	0.32	0.33
	(0.08)	(0.34)	(0.20)	(0.17)	(0.16)
Denmark	0.61*	0.11	0.47*	0.28	0.29
	(0.00)	(0.58)	(0.01)	(0.14)	(0.14)
Luxembourg	-	-	-	0.52	0.38
				(0.15)	(0.31)
West Germany	0.65*	0.61*	0.71*	0.42	0.63*
	(0.00)	(0.00)	(0.00)	(0.053)	(0.00)
Sweden	0.27	0.19	0.23	0.32	0.49*
	(0.17)	(0.34)	(0.24)	(0.10)	(0.01)
Norway	-	-	-	0.35	0.36
				(0.08)	(0.07)
Australia	0.38*	0.37	0.36	0.22	-0.08
	(0.045)	(0.051)	(0.058)	(0.25)	(0.67)
Middle Income Group					
Guatemala	0.33	0.11	0.13	0.06	-0.21
	(0.09)	(0.58)	(0.52)	(0.75)	(0.29)
Turkey	0.42*	0.01	0.12	-	-
	(0.03)	(0.96)	(0.54)		
Colombia	0.23	0.21	-0.15	0.20	-0.02
	(0.23)	(0.28)	(0.44)	(0.31)	(0.93)
Korea	0.34	0.31	0.11	0.05	0.33
	(0.08)	(0.11)	(0.57)	(0.82)	(0.09)

Czechoslovakia	0.07	0.11	0.30	0.01	0.02
	(0.73)	(0.58)	(0.12)	(0.98)	(0.91)
Malta	0.53*	-0.01	0.21	-0.41	-0.64*
	(0.01)	(0.98)	(0.35)	(0.10)	(0.01)
Portugal	0.05	0.52*	0.07	0.05	0.03
	(0.82)	(0.01)	(0.73)	(0.81)	(0.89)
Hungary	0.03	0.33	0.34	-	-
	(0.88)	(0.10)	(0.08)		
Cyprus	-0.00	0.25	0.15	-	-
	(0.99)	(0.24)	(0.49)		
Greece	0.13	0.01	0.16	0.12	0.18
	(0.50)	(0.96)	(0.43)	(0.54)	(0.35)
Ireland	0.40	-0.02	0.09	0.08	0.30
	(0.054)	(0.93)	(0.67)	(0.77)	(0.28)
Spain	0.05	0.43*	0.37	-	-
	(0.79)	(0.03)	(0.06)		

Low Income Group

Ethiopia	0.10	0.17	-0.06	-	-
	(0.65)	(0.45)	(0.80)		
Tanzania	0.01	0.01	-0.06	0.08	0.06
	(0.98)	(0.97)	(0.80)	(0.76)	(0.82)
India	0.20	-0.03	0.14	-0.25	0.06
	(0.31)	(0.89)	(0.48)	(0.24)	(0.77)
Bangladesh	0.20	-0.34	0.07	0.34	0.26
	(0.33)	(0.10)	(0.73)	(0.10)	(0.21)
Pakistan	0.22	0.18	0.13	-	-
	(0.26)	(0.35)	(0.52)		
Egypt	-0.12	-0.41*	-0.34	0.44*	0.05
	(0.53)	(0.03)	(0.08)	(0.02)	(0.81)
Philippines	-	-	-	-0.16	-0.14
				(0.45)	(0.52)

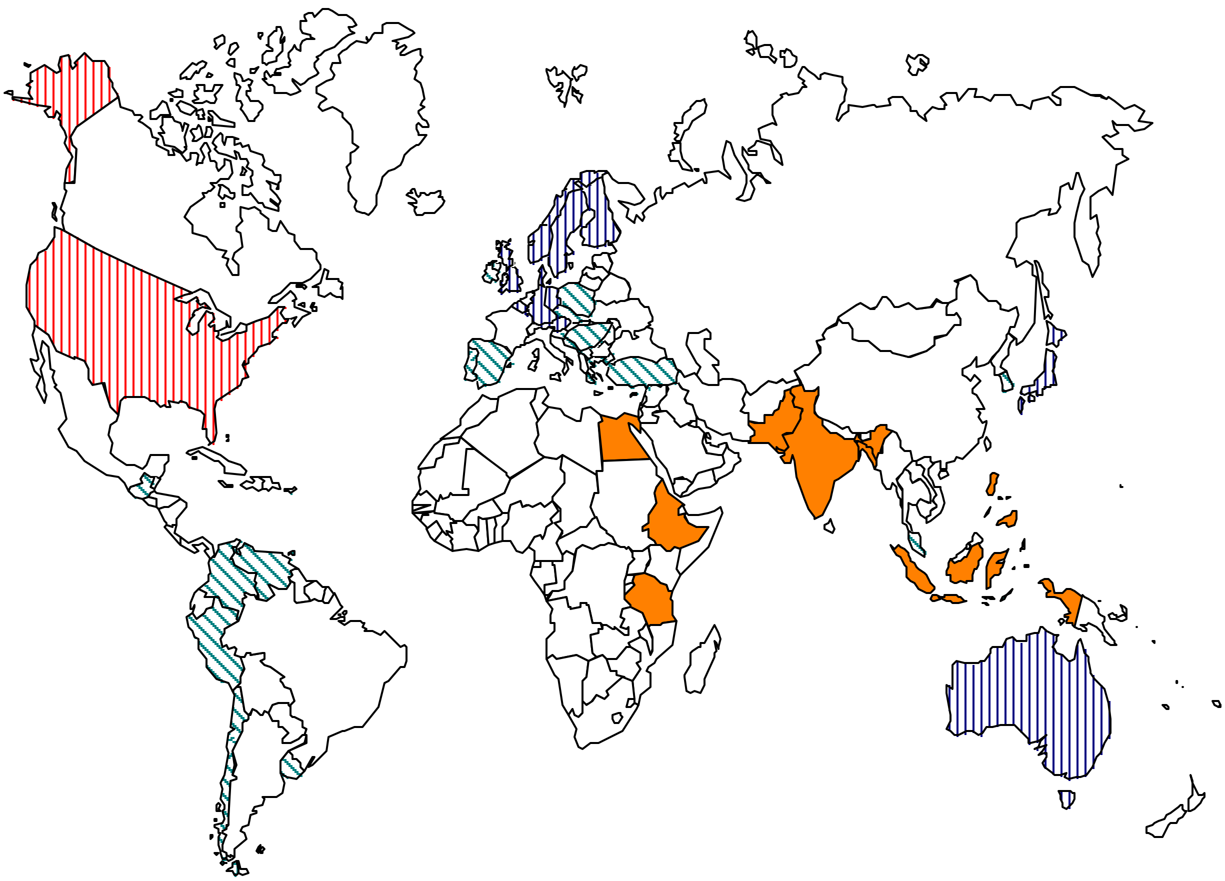

Figure I: Countries Sampled

Note: Vertical lines indicate “high” income countries with GDP/capita above $10,000 US (1985), diagonal lines indicate middle income countries (GDP/capita between $2000 and $10,000), shading indicates low income countries (GDP/capita below $2000).

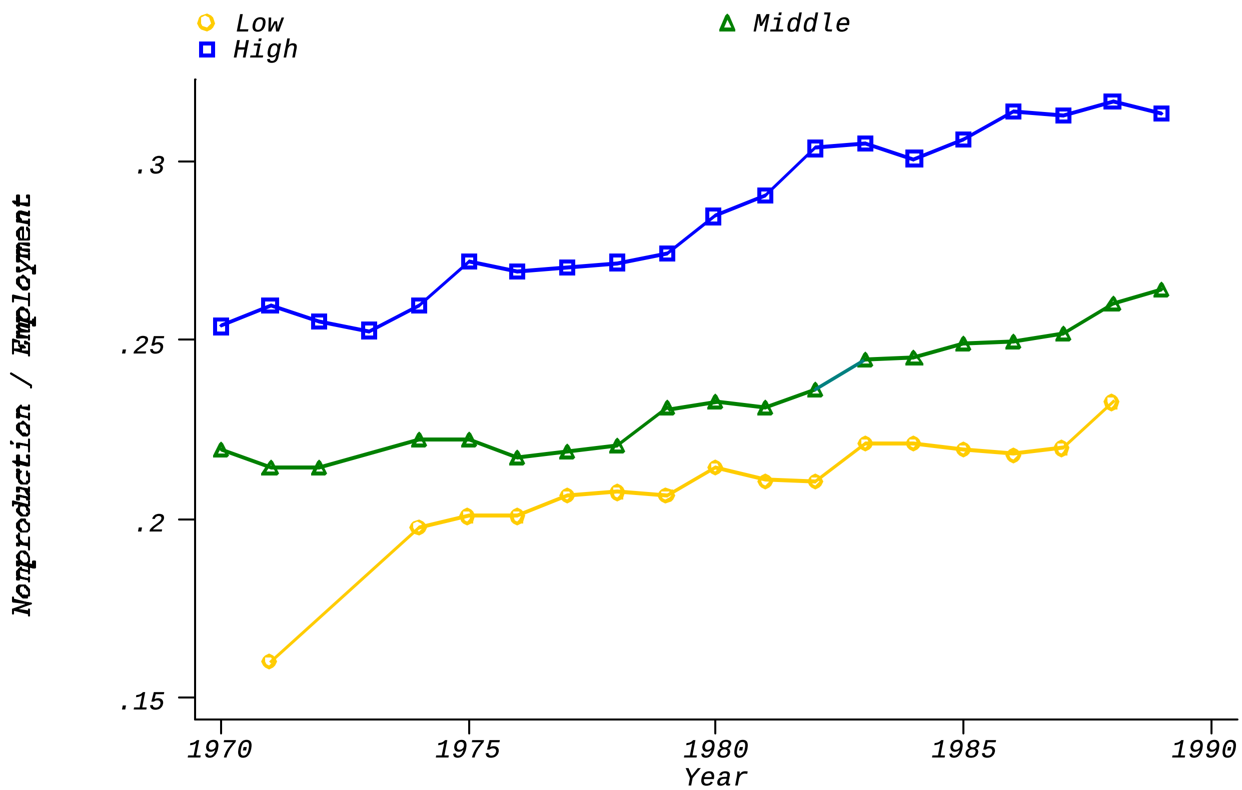

Figure II: Skill Accumulation by Income Group

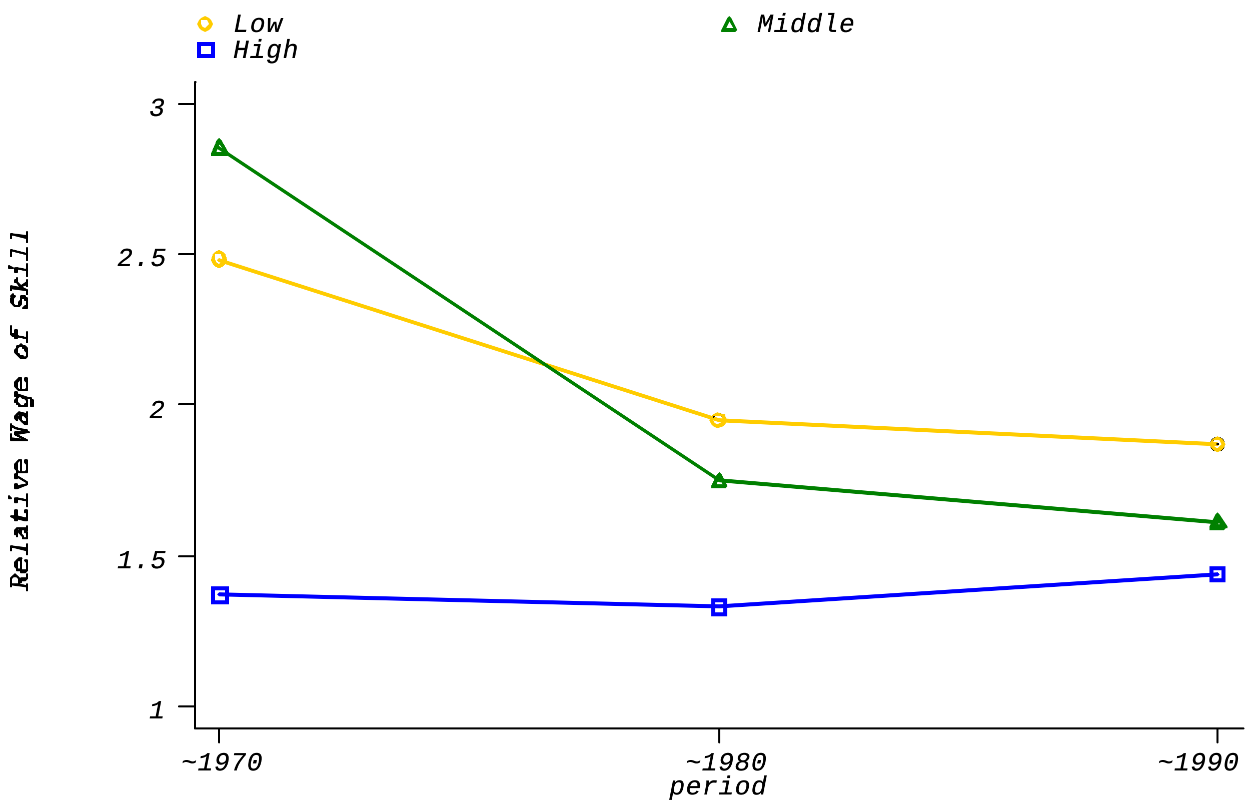

Figure III: Relative Wages by Income Group

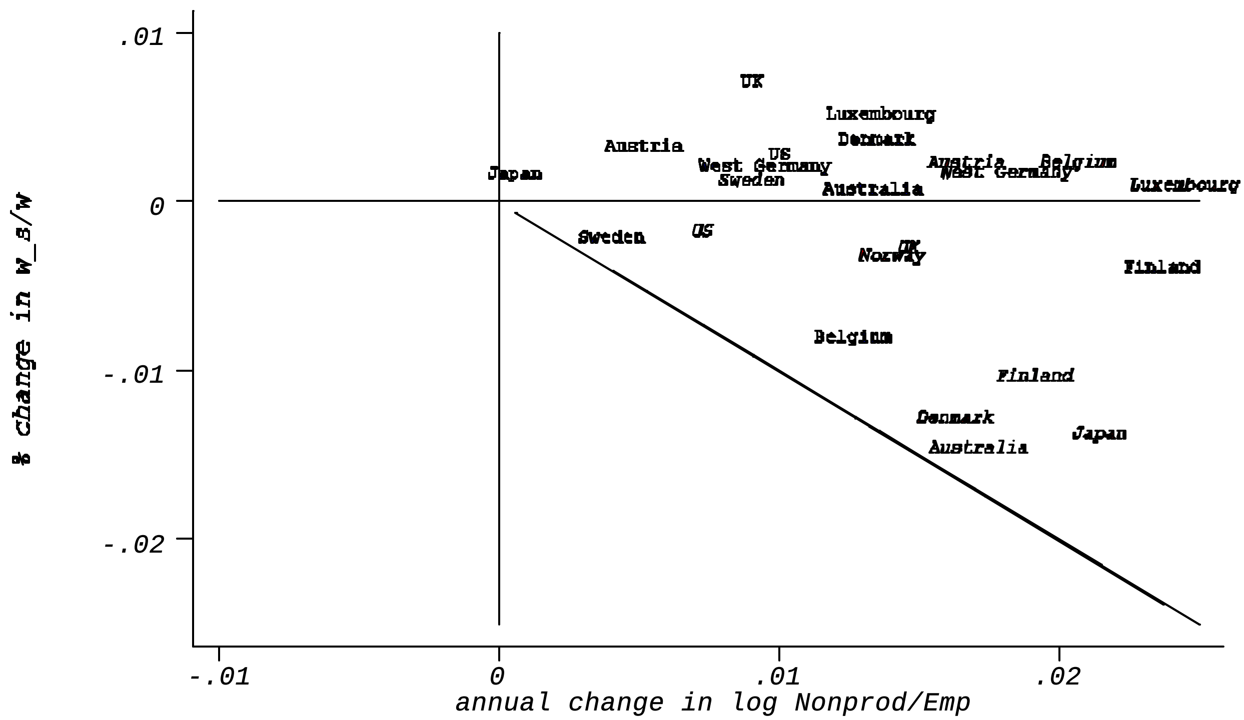

Figure IV: Shifts in Skill Demand - High Income Countries

Note: Italics indicate country sampled in 1970s while regular font indicates country sampled in 1980s.

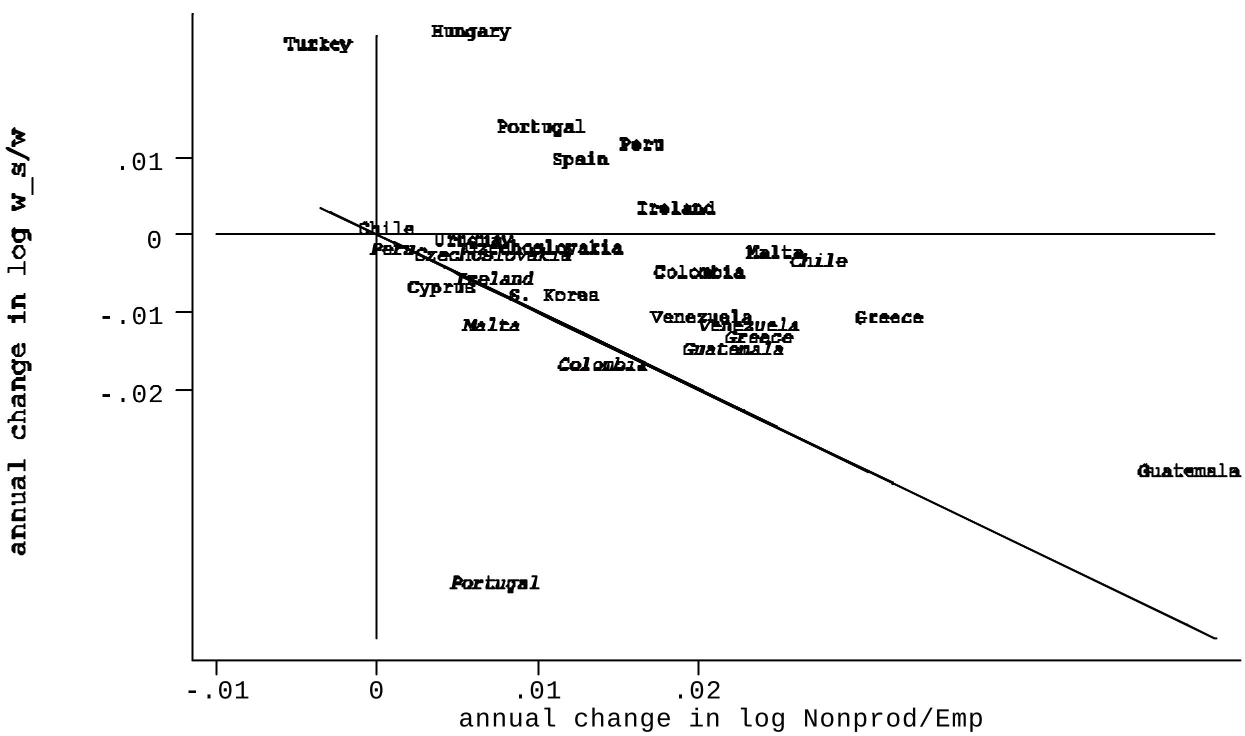

Figure V: Shifts in Skill Demand - Middle Income Countries

Note: Italics indicate country sampled in 1970s while regular font indicates country sampled in 1980s.

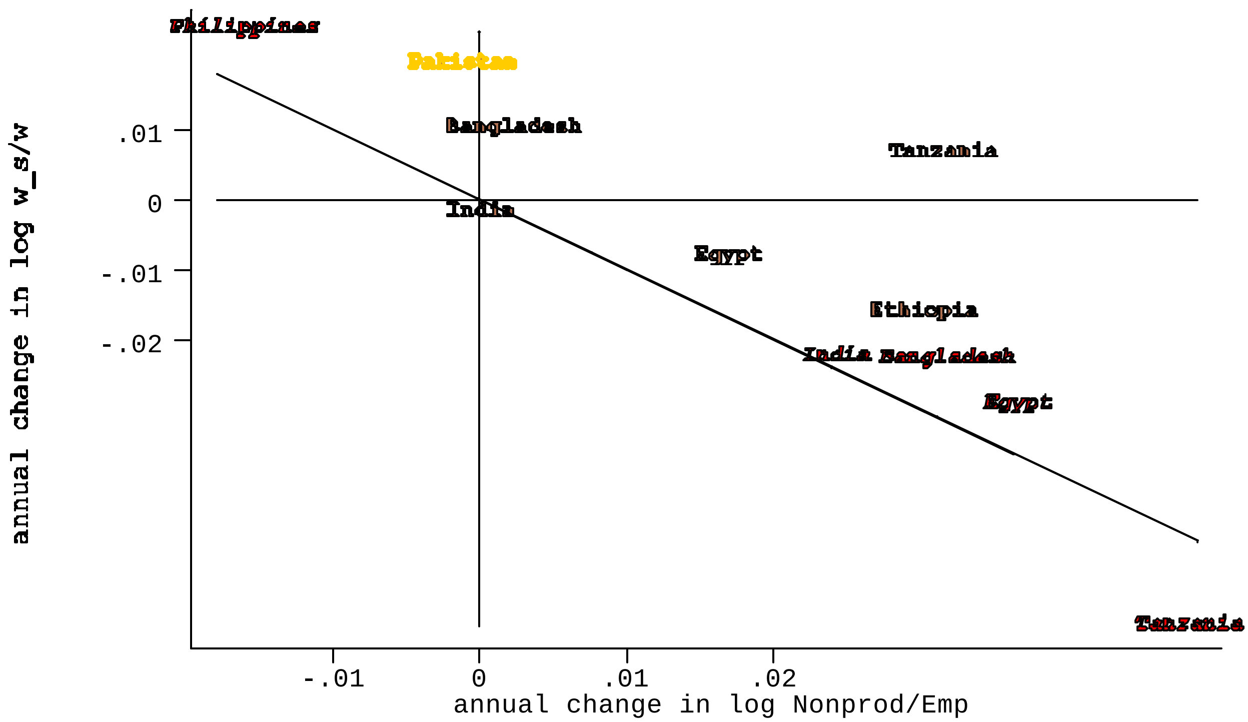

Figure VI: Shifts in Skill Demand - Low Income Countries

Note: Italics indicate country sampled in 1970s while regular font indicates country sampled in 1980s.

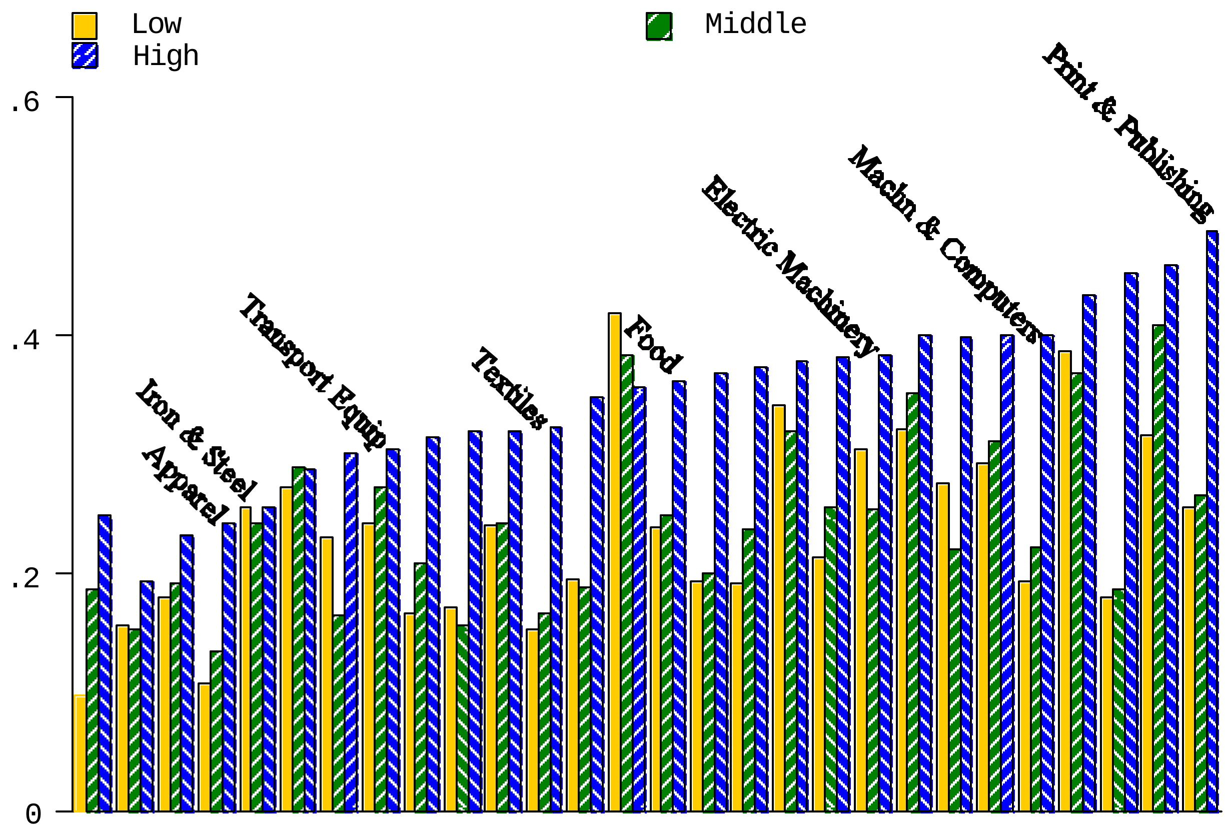

Figure VII: Skill Intensity by Industry and Income Group

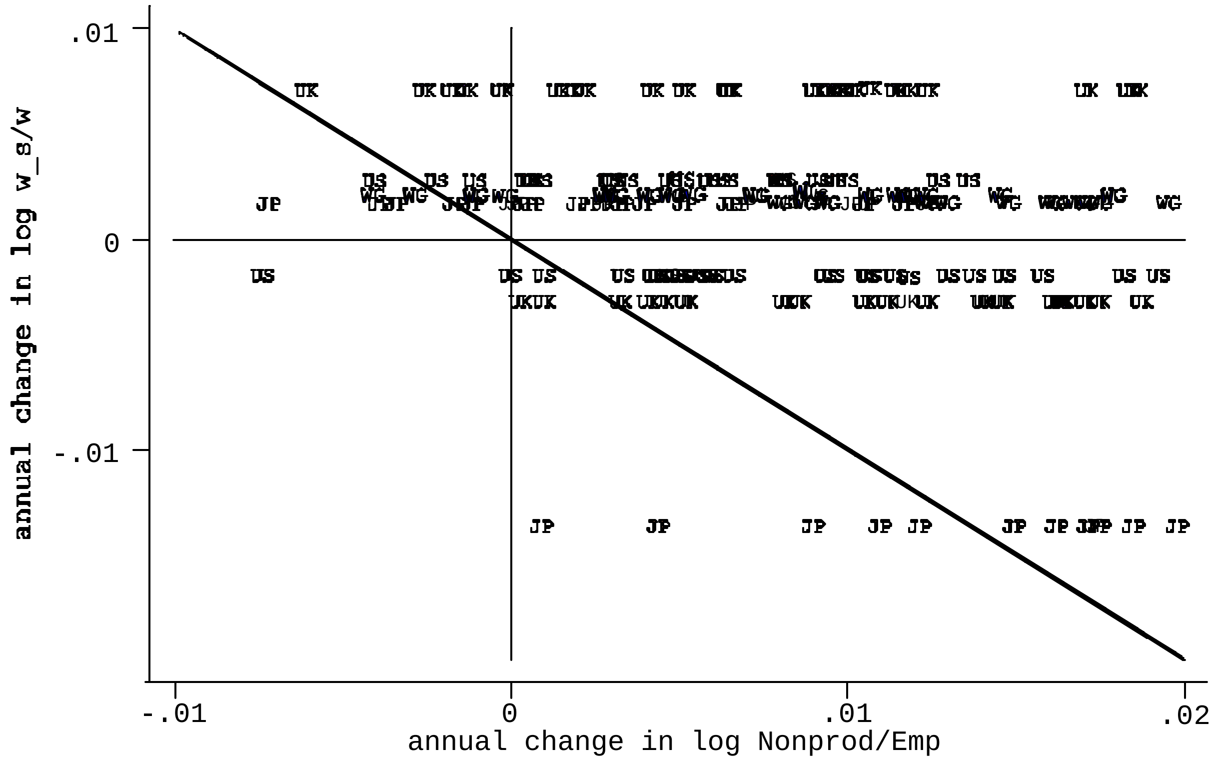

Figure VIII: Shifting Demand for Skill by Industry
US, UK, W. Germany, Japan

Figure IX: Changes in Nonproduction Wagebill Shares, US and West Germany

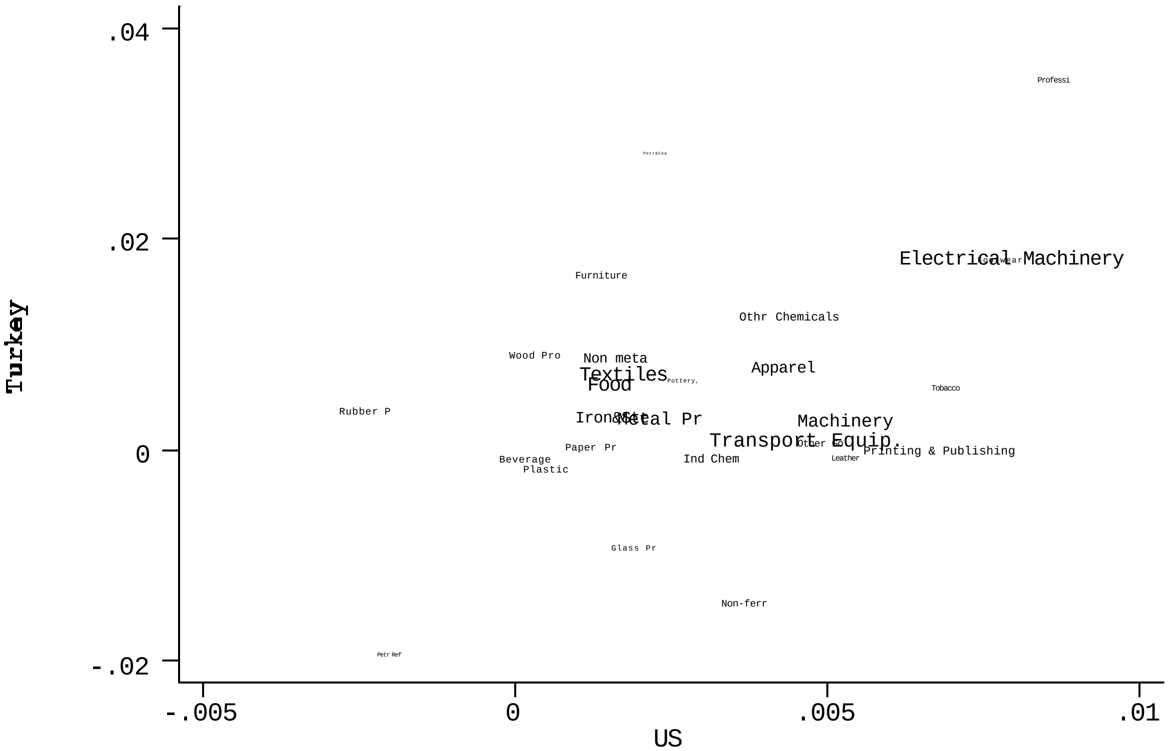

Figure X: Changes in Nonproduction Wagebill Shares, US and Turkey