Does the Sector Bias of Skill-Biased Technical Change Explain Changing Skill Premia?*

Jonathan E. Haskel
Queen Mary and Westfield College and CEPR

and

Matthew J. Slaughter
Dartmouth College and NBER

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Abstract

This paper shows the sector bias of skill-biased technical change (SBTC) can help explain changing skill premia within countries in recent decades. First, using a two-factor, two-sector, two-country model we demonstrate that in many cases it is the sector bias of SBTC that determines SBTC’s effect on relative factor prices, not its factor bias. Rising skill premia are caused by SBTC that is concentrated in skill-intensive sectors, and falling premia by SBTC concentrated in unskill-intensive sectors. Second, we test the sector-bias hypothesis using industry data for ten OECD countries over the 1970s and 1980s. Our findings are consistent with sector bias being important. In countries when skill premia were falling we find that SBTC was generally concentrated in unskill-intensive sectors. In contrast, when skill premia were rising SBTC was generally concentrated in skill-intensive sectors.

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1 Introduction

Many economists have argued that skill-biased technological change (SBTC) has contributed to rising skill premia, in many countries. The bulk of empirical evidence supporting this "SBTC hypothesis" seems to be the occurrence of SBTC in many sectors.¹

There are at least two unresolved issues with the SBTC hypothesis. The first is empirical. Because the U.S. skill premium did not increase until about 1979, even though SBTC has been occurring for decades, some argue a 1980s acceleration in SBTC is necessary to explain rising skill premia. Evidence for this acceleration is somewhat mixed, however.² A second problem with the SBTC hypothesis is theoretical. The theoretical literature is inconclusive about whether the effect of technical change (TC) on wages depends on the factor bias of TC--i.e., whether TC favors a certain factor of production--or the sector bias of TC--i.e., whether TC occurs in certain sectors.³

There is some disjoint between these two issues surrounding the SBTC hypothesis. Empirical work, mostly by labor economists, ignores sector bias and documents factor bias and/or acceleration. Theoretical work, mostly by trade economists, ignores acceleration and focuses on factor bias versus sector bias. The goal of this paper is to take some initial steps to reconcile these two literatures.

We begin by analyzing sector bias, factor bias, and acceleration in a general-equilibrium model of TC. The key message is that in a multi-sector framework, in many cases it is the sector bias of TC, rather than the factor bias or any rate of change in factor bias, that determines TC’s effect on relative wages. In many cases rising skill premia are caused by TC that is concentrated in skill-intensive sectors, falling premia by TC concentrated in unskill-intensive sectors.

We then go to the data. There is extensive empirical work documenting SBTC in many sectors. However, to the best of our knowledge, there is no evidence on its sector bias. This

¹Important contributions include Bound and Johnson (1992), Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998), and Berman, Bound, and Machin (1998)).
paper provides such evidence for ten OECD countries during the 1970s and 1980s. We test the empirical implication of the multi-sector framework as follows. In periods with SBTC concentrated in skill-intensive sectors, wage premia should be rising; in contrast, in periods with SBTC concentrated in unskill-intensive sectors, wage premia should be falling. For the majority of country-decades in our data we find precisely this pattern, and it is robust to different measures of SBTC. This empirical evidence suggests that the sector bias of SBTC has been an important cause of both rising and falling skill premia over decades and across countries.

Our results offer an alternative to explanations for changes in skill premia that rely on pervasive and/or accelerating SBTC. We find that changes in the sector bias of SBTC are an important cause. Our results also offer an alternative explanation for cross-country differences in skill premia to explanations relying on different labor-market institutions mediating common demand shocks in different ways. We find that different demand shocks from different sector biases of SBTC also matter.4

In the rest of this paper Section 2 sets out the theory of TC in a general-equilibrium model. Section 3 presents our empirical results and Section 4 concludes.

2 Theoretical Framework: Technological Change and Relative Wages

To analyze how TC affects relative wages we use a standard two-factor, two-sector, two-country Heckscher-Ohlin (HO) model. We choose this framework both because it is commonly used and because it is sufficient to demonstrate the central issues involving sector bias. To motivate empirically testable predictions, we analyze three different cases: (1) one sector being produced; (2) two sectors produced with exogenous world product prices; (3) two sectors produced with endogenous world product prices. Section 2d summarizes our analysis.

In the home country the two factors are skilled and unskilled labor (S and U, respectively); the two products are machinery and apparel (M and A, respectively); and we assume that sector M employs factor S relatively intensively, while sector A employs U relatively intensively. We

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4 Proponents of the institutions explanation include Blau and Kahn (1996) and Fortin and Lemieux (1997).
also assume perfect interindustry factor mobility within each country, so there is one equilibrium national wage for S and U, \( w_s \) and \( w_u \), respectively. Output in sector \( k \), \( Y_k \), is produced according to a CES production function with elasticity of substitution \( \sigma \).

\[
Y_k = A_k \left( \delta_k S_k^{1-1/\sigma} + (1-\delta_k)U_k^{1-1/\sigma} \right)^{\sigma/(\sigma-1)}
\]

Each sector chooses employment of S and U to maximize profits subject to exogenous factor prices and production technology in (1). First-order conditions imply that optimal relative labor demand in each sector is

\[
\left( \frac{S}{U} \right)_k = \left( \frac{\delta_k}{1-\delta_k} \right)^{\sigma} \left( \frac{w_s}{w_u} \right)^{-\sigma}.
\]

Regarding the factor bias of TC, define \( SBTC \) as a rise in \( \delta_k \), whereby skilled workers become more efficient at some tasks formerly performed by unskilled workers.\(^5\) Factor-neutral TC is defined as a rise in \( A_k \), which does not affect \((S/U)_k\). Note that from (1) alone it is not clear if a rise in \( \delta_k \) reduces unit costs, because this raises marginal productivity for the skilled but lowers it for the unskilled. We shall assume that firms do not implement cost-increasing TC, so that any TC reduces unit costs. Below, we return to this cost issue.

Turning to the sector bias of TC, TC is \emph{sector-specific} when it occurs in one sector only and is \emph{sector-pervasive} when it occurs in all sectors. Sector-specific TC has an obvious sector bias; namely, towards the sector enjoying the change. We define sector-pervasive SBTC to be biased towards a sector when that sector experiences a larger increase in \( \delta_k \) than does the other sector. Similarly, sector-pervasive factor-neutral TC is biased towards a sector when it experiences a larger increase in \( A_k \). Our distinction between sector-specific and sector-pervasive is very important. Many \emph{empirical} studies have documented SBTC’s sector-pervasiveness. Almost all \emph{theoretical} work has considered sector-specific SBTC only.\(^6\)

\(^5\)Because we are interested empirically in SBTC we do not consider unskill-biased technical change (UBTC). Johnson (1997) labels our modeling of SBTC “extensive” SBTC, distinct from “intensive” SBTC in which skilled workers become more productive at the set of tasks they already perform.

\(^6\)It is important to note that different authors have used different definitions of various kinds of TC. For example, Berman, et al (1998) use “pervasive” to indicate TC occurring in many countries, not TC occurring in many sectors in a single country as here.
2a Technical Change in a One-Sector Economy

In the one-sector economy, by definition equation (2) describes national relative labor demand. This model can be closed by combining (2) with an upward-sloping relative-labor-supply curve. In equilibrium, national relative labor demand must equal national relative labor supply, \((S/U)^{SUP}\), so the change in the skill premium is (where "hats" denote percentage changes)

\[
\hat{\frac{w_s}{w_u}} = \left( \frac{\delta}{1 - \delta} \right) \frac{1}{\sigma} \left( \frac{\hat{S}}{U} \right)^{SUP}.
\]

In this framework SBTC raises \((w_s/w_u)\), while factor-neutral TC does not alter \((w_s/w_u)\). Thus, in a one-sector economy it is the factor bias of TC that affects relative factor prices. Changes in relative labor supply alter \((w_s/w_u)\), with the magnitude of wage effects varying with \(\sigma\).

2b Technical Change in a Two-Sector Open Economy With Exogenous Product Prices

Now suppose the home country makes both products in equilibrium, not just one. This assumption of a “diversified” product mix is standard in the HO model. To see how TC affects \((w_s/w_u)\) in this two-sector economy, we first assume that product prices \(P_A\) and \(P_M\) are exogenously determined abroad. With zero profits in both sectors, the equilibrium skill premium can be written as follows, where \(\omega_k\) is skilled labor’s share of sector k’s wagebill.\(^7\)

\[
\left( \frac{\hat{w_s}}{w_u} \right) = \frac{1}{\omega_M - \omega_A} \left( \frac{\hat{P}_M}{P_A} + \frac{\hat{A}_M}{A_A} \right) + \delta_M \left( \frac{\sigma}{\sigma - 1} \right) \left( \frac{\omega_M - \delta_M}{1 - \delta_M} \right) - \delta_A \left( \frac{\sigma}{\sigma - 1} \right) \left( \frac{\omega_A - \delta_A}{1 - \delta_A} \right).
\]

Equation (4) shows two standard outcomes of multi-sector HO models. First, a rise in \((P_M/P_A)\) raises \((w_s/w_u)\), a fall lowers it. This is the Stolper-Samuelson theorem stated in relative terms. Second, assuming a fixed national product mix and fixed product prices, factor supplies do not affect factor prices. Instead of changing wages, changes in factor supplies are absorbed via Rybczynski output-mix changes. Leamer and Levinsohn (1995) call this result the Factor-

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\(^7\) To derive (4) we totally differentiate each sector’s zero-profit condition \((P_kY_k = w_sS_k + w_uU_k)\) and then substitute out endogenous terms using the total differentials of equations (1) and (2). \(\omega_n > \omega_s\) by the assumption of sector skill intensities.
Price-Insensitivity (FPI) Theorem. FPI is a fundamental difference between wage setting in the one-sector and two-sector frameworks; we return to this point later.

Equation (4) also shows three implications of TC for \((w_s/w_u)\). First, suppose that TC is sector-specific. In this case, the sector bias of TC determines relative factor prices. Any sector-specific TC in machinery (i.e., rise in \(\delta_M\)) raises the skill premium; any sector-specific TC in apparel (i.e., rise in \(\delta_A\)) lowers it. This point is well-known.\(^8\) The intuition behind sector bias relies on changes in the relative profitability of sectors. Any sector-specific TC makes that sector profitable at fixed product prices and initial factor prices. Producers respond to this profit opportunity by trying to expand production in that sector. National relative labor demand therefore increases for the factor employed relatively intensively in that sector. Given fixed labor supply, relative wages adjust until the profit opportunities are arbitraged away. The central role for sector bias means, for example, that SBTC in apparel lowers \((w_s/w_u)\), the opposite of the one-sector result.

Second, suppose that TC is sector-pervasive. In this case, sector-pervasive TC or an acceleration of sector-pervasive TC has ambiguous effects on skill premia. From (4), if both \(\delta_M\) and \(\delta_A\) increase and/or accelerate, then the change in \((w_s/w_u)\) is unclear.\(^9\) Regardless of whether TC has any factor bias, knowing only that the TC is pervasive and/or accelerating is not sufficient to determine wage changes.

Third, the sector bias of sector-pervasive SBTC offers only suggestive evidence of changes in \((w_s/w_u)\). SBTC alters the profit-maximizing relative-employment mix within each sector. But this alone conveys no information on the change in relative profitability across sectors, which governs wage changes. For example, in (4) if \(\delta_M\) rises by more than \(\delta_A\), i.e., if sector-pervasive SBTC is machinery-biased, then the change in relative costs and thus in \((w_s/w_u)\) also depends on

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\(^8\)Findlay and Grubert (1959), Jones (1965), and Krauss and Johnson (1974) are early statements of this result. More recently, the point is made by Krugman (1995), Richardson (1995), Wood (1995), Leamer (1998), and Davis (1998). Note that in equation (4), a rise in \(\delta_M\) or \(\delta_A\) raises or lowers the skill premium, respectively, only if the quantity \((\sigma_0/\sigma_1) x ((\omega_k - \delta_k)/(1-\delta_k))\) is positive for either case. This restriction on technology parameters is the mathematical implication of our earlier assumption that firms implement SBTC only when it reduces unit costs.

\(^9\)An acceleration of sector-specific SBTC changes the skill premium -- but only according to its sector bias. For example, a faster rise over time in \(\delta_M\) increases the skill premium because of its machinery bias.
the magnitudes of \( \omega_k \) and \( \delta_k \). Without further information, the skill-premium change is unclear. Thus, the sector bias of sector-pervasive SBTC provides only suggestive information about wage changes because it provides only suggestive information about changes in costs and thus profitability across sectors. The sector bias of pervasive SBTC determines wage changes whenever more extensive skill-upgrading in a sector reduces costs more in that sector.\(^{10}\)

2c Technological Change in a Two-Sector Open Economy With Endogenous Product Prices

We now consider a two-sector economy where an economy’s TC can affect world product prices because that country is sufficiently large in the world economy to affect product prices. Now TC can affect wages not just directly at fixed \((P_M/P_A)\), as in equation (4), but also indirectly as TC-induced changes in \((P_M/P_A)\) induce Stolper-Samuelson effects.

These direct and indirect wage effects are set out in Figure 1. In the left panel, the SS schedule displays the Stolper-Samuelson link from \((P_M/P_A)\) to \((w_s/w_u)\) for constant technology parameters (i.e., the static analogue of (4)). Any TC in machinery shifts the SS curve rightwards to \(SS'\), raising \((w_s/w_u)\) for any \((P_M/P_A)\). Any TC in apparel shifts SS leftwards to \(SS''\), lowering \((w_s/w_u)\). This direct wage effect, indicated by the D arrows, was analyzed in 2b above. The right panel of Figure 1 shows the indirect effect. Here, world relative demand (RD) and supply (RS) determine \((P_M/P_A)\), where RS depends both on the world endowment of skilled labor relative to unskilled labor and on technology. If TC shifts RS out, then \((P_M/P_A)\) falls and \((w_s/w_u)\) falls in the left panel along the appropriate new SS curve, all indicated by the I’ arrows. If TC shifts RS in then the reverse happens: \((P_M/P_A)\) rises, and \((w_s/w_u)\) tends to rise as shown by the I’’ arrows.

The total wage effect of any TC is the sum of its direct and indirect effects. If the indirect effect reinforces the direct effect, then the sector-bias intuition of the fixed-price framework is reinforced. But if the indirect effect offsets the direct effect, then the total wage effect is unclear.

\(^{10}\)It is important to stress why sector-specific and sector-pervasive SBTC are so different. Any SBTC alters the relative profitability of skilled and unskilled employment within the sector(s) enjoying the change. If SBTC is sector-specific it also unambiguously alters profitability across sectors. Almost all the theoretical literature has confined itself to this case. But if SBTC is sector-pervasive, information on within-sector relative profitability alone is not enough to determine shifts in profitability across sectors. In contrast, the sector bias of sector-pervasive factor-neutral TC unambiguously determines wage changes because, as equation (4) shows, it unambiguously determines changes in relative profitability.
unless more structure is imposed. This ambiguity holds for any sector-specific TC. It also holds for any sector-pervasive TC: Section 2b showed its direct effect is ambiguous, and its indirect effect is ambiguous as well because the net shift in RS is unclear.

Figure 1 suggests that even with endogenous product prices, the sector bias of TC is still a key determinant of skill-premium changes whenever the indirect effect is sufficiently small relative to the direct effect. As the figure shows, the size of this indirect effect depends on shifts in \((P_M/P_A)\), which in turn depends on tastes, technology and endowments. Thus, the indirect effect could be sufficiently small in at least three cases.

First is the case where RD is sufficiently elastic. Higher demand elasticities mean flatter RD in Figure 1; in the limit, the small-country fixed-price case of Section 2b obtains for infinitely-elastic RD. In the majority of cases considered by Xu (1998, Tables 1 and 2), so long as this elasticity exceeds one then the sector bias of sector-specific TC dictates wage changes.

Second, for some production technologies the indirect effect of TC reinforces the direct effect. For example, with Leontief technology \((\sigma = 0)\), SBTC in machinery triggers reinforcing direct and indirect effects which both raise the skill premium. Davis (1998) assumes Leontief technology; Xu (1998) analyzes different values of \(\sigma\).

Third, the indirect effect is likely to be smaller when there exists a non-traded sector. In this case, RS in Figure 1 depends on the factor supplies allocated to tradables, not economy-wide factor supplies. If factors released by TC in tradables gain reemployment in the nontraded sector, then TC’s effect on RS—and thus the overall indirect effect—can be dampened.

Many studies in the literature do not analyze cases with endogenous product prices. Those that do examine a range of different cases. Baldwin and Cain (1997) and Davis (1998) examine cases such as sector-specific SBTC with Leontief technologies. Krugman (1995) focuses on the case of worldwide sector-specific TC, and asserts that endogenizing prices re-establishes the single-sector result that SBTC raises skill premia regardless of sector. But this need not be true

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11 Bhagwati and Dehejia (1994), Richardson (1995), and Wood (1995) point out that technology can change product prices. Leamer (1998) assumes an empirical link from technology to prices but provides no formal model. Findlay and Grubert (1959) and Krauss and Johnson (1974) discuss the direction of world-supply shifts, but do not link supply shifts back to wages.
for different technology and demand assumptions, as Davis (1998), Haskel and Slaughter (1998), and Xu (1998) discuss. Berman et al (1998) claim that worldwide sector-pervasive SBTC can raise the skill premium. But they consider only the indirect effect working through product prices (see their pages. 1252-1253), so by ignoring the direct effect they assume away any role for sector bias.\(^{12}\) Finally, Xu (1998) works through several cases of sector-specific TC with varying assumptions about \(\sigma\) and product-demand elasticities. Because different studies have examined very different cases, general conclusions should not be made from any single study.

2d Summary of Theory Discussion

The central message of this section is that in a multi-sector framework, in many cases it is the sector bias of TC, rather than the factor bias or any rate of change in factor bias, that determines TC’s effect on relative wages. In many cases rising skill premia are caused by TC that is concentrated in skill-intensive sectors, falling premia by TC concentrated in unskill-intensive sectors. For the fixed-price framework, this conclusion holds in the cases of any sector-specific TC or sector-pervasive factor-neutral TC, and in the case of sector-pervasive SBTC whenever more extensive skill-upgrading in a sector reduces costs more in that sector. For the flexible-price framework, this conclusion holds in cases where the indirect effect is sufficiently small relative to the direct effect.

Figure 2 summarizes the sector-bias result for the two-sector economy, either with fixed product prices or with flexible product prices but sufficiently small indirect effects. On the vertical axis two kinds of factor bias to TC are shown: factor-neutral and skill-biased. On the horizontal axis three kinds of sector bias to TC are shown: sector-specific occurring in machinery; sector-specific occurring in apparel; and sector-pervasive occurring in both sectors, which can be biased towards either sector. Each cell shows the change in the skill premium arising from that cell’s TC. The effects of sector bias are set out reading down column 1 and 2:

\(^{12}\)They ignore the direct effect by considering by assuming that sector-pervasive SBTC induces proportionate cost reductions in all sectors and thus no wage changes at initially fixed product prices. In terms of our equation (4), they assume that the SBTC terms on the right-hand side exactly cancel each other out.
given the sector bias of that column’s TC, the wage effect is the same regardless of the factor bias. Column 3, sector-pervasive TC, shows two possible wage changes in each cell, one for each kind of sector bias, but across the two cells the same sector bias generates the same wage change regardless of factor bias.

Given that a large number of empirical studies have documented sector-pervasive SBTC in many countries in recent decades, the empirically relevant case is the lower right cell of Figure 2. In linking sector-pervasive SBTC with rising skill premia, almost all these studies have implicitly or explicitly invoked the one-sector intuition. But from a multi-sector perspective, what matters in many cases is the sector bias of this sector-pervasive SBTC. To the best of our knowledge, there is no evidence on its sector bias. Thus the main contribution of the paper is to analyze the sector bias of SBTC on a sample of ten OECD countries. Of course, forces other than SBTC may also have affected wages. We return to this issue in Section 3d.

3 Empirical Evidence on the Sector Bias of SBTC and Skill Premia

3a Empirical Strategy

We begin by constructing several different measures of SBTC for each country-decade. We then measure SBTC’s sector bias in each country-decade. Finally, we examine whether the skill premium tended to rise in country-decades with SBTC concentrated in skill-intensive sectors and fall in country-decades with SBTC concentrated in unskill-intensive sectors.

To measure SBTC we use the standard approach of assuming that in each sector \( k \), capital is a quasi-fixed factor and that the industry minimizes the cost of skilled and unskilled labor according to a translog cost function with constant-returns-to-scale production technology. In each sector, cost minimization leads to an equation for the change in \( \omega_k \) over some time period.

\[
\Delta \omega_k = a_0 + a_1 \Delta \log \left( \frac{w_s}{w_u} \right)_k + a_2 \Delta \log \left( \frac{K}{Y} \right)_k + \varepsilon_k
\]

Here \( \Delta \omega_k \) is the level change in the nonproduction-labor share of the total wage bill, \( K \) is capital, \( Y \) is real value-added output, and \( \varepsilon_k \) is an additive error term.
For each country, if one pools all sectors and estimates equation (5) for changes over a decade, then variation in $\omega_k$ not explained by $\Delta \log(w_s/w_u)$ and $\Delta \log(K/Y)$ is attributed to SBTC. The $a_o$ measures the cross-sector average of SBTC, and $(a_o + \varepsilon_k)$ measures SBTC in sector $k$. The $(k \times 1)$ vector of $(a_o + \varepsilon_k)$ measures the sectoral distribution of sector-pervasive SBTC with larger elements indicating more extensive SBTC.\(^{13}\) Equation (5) follows Binswanger (1974) and Berndt and Wood (1982), and it has been used repeatedly in the empirical literature on SBTC.

To ensure the robustness of our results we also generated four alternative measures of SBTC, data permitting. Our second measure excludes $\Delta \log(w_s/w_u)$ from (5), since cross-sectional relative-wage variation might reflect (unobserved) skill-mix differences rather than exogenous wage differences. In this case $a_o$ accounts for wage changes common to all sectors, and SBTC is measured simply as $\varepsilon_k$. Our third measure also excludes $\Delta \log(w_s/w_u)$ from (5) but inserts a set of industry dummy variables constructed at a higher level of aggregation than the sectors. These dummies relax the assumption of our second measure that all sectors respond similarly to wage changes, and thereby allow greater cross-sector variation in production techniques. Here again, SBTC is measured as $\varepsilon_k$. Our fourth measure adds to (5) each sector’s intensity of computer investment, under the assumption that computers cause SBTC. We measure SBTC as the computer regressor times its estimated coefficient. Finally, our fifth SBTC measure is simply $\Delta \omega_k$. Our empirical results are very robust to measurement of SBTC. For each country-decade the correlation among our SBTC measures was usually high--often near 0.9.\(^{14}\)

To measure the sector bias of SBTC, for each country-decade we pool all sectors and regress SBTC against start-of-decade sector skill intensity measured as $(S/U)_k$.

\begin{align*}
(6) \quad SBTC_k &= \alpha + \beta_{\text{bias}} \left( \frac{S}{U} \right)_k + u_k
\end{align*}

\(^{13}\)The coefficient $a_1$ is positive or negative depending on whether $\sigma$ is below or above one. A positive $a_2$ indicates capital-skill complementarity.

\(^{14}\)For the United States in the 1970s, among the 450 four-digit sectors the correlation between measures one and five was 0.89. During the 1980s it was 0.93. But if SBTC is correlated across sectors within industries, however, the measure with industry dummies measure might underestimate SBTC. The SBTC measures which exclude the wage regressor are closer in spirit to our model which does not permit any cross-sector differences in wage changes. Other robustness checks not reported here included varying the years for our decades; disaggregating capital between plant and equipment; estimating equation (5) separately for each two-digit industry; and using unweighted ordinary least squares. We also obtained qualitatively similar results from measuring SBTC directly with data on computer usage.
SBTC_k is a \((k \times 1)\) vector of SBTC and \(u_k\) is an error term. The coefficient \(\beta_{\text{bias}}\) is our estimate of sector bias: a positive coefficient indicates SBTC was concentrated in skill-intensive sectors, a negative coefficient in unskill-intensive sectors.

For each country-decade we then compare \(\beta_{\text{bias}}\) with its actual change in the skill premium. If the sector-bias hypothesis is true, then a positive \(\beta_{\text{bias}}\) is associated with rising skill premia and a negative \(\beta_{\text{bias}}\) with falling skill premia. We interpret this pattern as evidence consistent with the hypothesis that the sector bias of SBTC helps explain recent wage changes in countries.

It is important to see how equations (5) and (6) build on our theory presented earlier. The most important change is that our model contained only two factors and two sectors, but equations (5) and (6) add capital as a third factor and allow for many more than two sectors.

To motivate equation (5), multiplying both sides of equation (2) by \((w_s/w_u)\) yields

\[
\left(\frac{\omega}{1-\omega}\right)_k = \left(\frac{\delta_k}{1-\delta_k}\right) \left(\frac{w_s}{w_u}\right)^{1-\sigma},
\]

which expresses sector \(k\)'s optimal \(\omega_k\) as a function of technology parameters and relative wages. SBTC, i.e., a rise in \(\delta_k\), raises \(\omega_k\), ceteris paribus. Equation (5) adds capital to equation (2') and allows more than two sectors. Our model had only two factors and two sectors because this was sufficient to identify the link from sector bias to factor prices. Other researchers (e.g., Leamer, 1998) have demonstrated that the key intuition of sector bias (i.e., relative profitability across sectors) holds in higher dimensions. Accordingly, we include the regressor \((K/Y)_k\) to capture any capital-skill complementarity. In addition, because we have data on many more than two sectors we use this information rather than aggregate it away. Finally, note that (5) has a translog functional form, unlike the CES form in (2'). CES was sufficient to present the sector-bias theory. But for our empirical work we prefer translog because it imposes fewer restrictions on factor substitutability and because it has been used in many recent empirical studies of SBTC.

Equation (6) follows Lawrence and Slaughter (1993), who measured the sector bias of product-price changes by regressing sector price changes on \((S/U)_k\). Higher values of \((S/U)_k\) are interpreted to indicate greater skill-intensity of sectors, following the definition of skill intensity.
in a 2x2 model. With more than two factors sector factor intensity is more difficult to define. But the results we report are robust to an unreported alternative specification of equation (6) that measures factor intensity accounting for capital and intermediate inputs as well, as has been done in many recent empirical studies of the Stolper-Samuelson theorem.\footnote{For the United States and United Kingdom, Haskel and Slaughter (1998) report results for an alternative specification of equation (6) in which the regressors are the shares of skilled labor, unskilled labor, and capital in total industry costs. Baldwin and Cain (1997), Feenstra and Hanson (1999), Leamer (1998), and Haskel and Slaughter (2000) all use this approach (although they do not focus on SBTC). This specification follows from differentiating zero-profit conditions for all sectors which are assumed to hold at each point in time. This generates an estimating model in which product-price changes and/or TFP changes are regressed on factor-cost shares. We followed this general methodology with the innovation of using SBTC as the regressand. We interpreted the difference between the coefficient estimates for the skilled and unskilled cost shares as indicating the sector bias of SBTC. Overall, this approach has the advantage of explicitly accounting for capital and intermediate inputs. For brevity we do not report results from this alternative specification because they are qualitatively the same as the results reported here. Thus, we regard (6) as a useful "shorthand" for this more-structural specification: empirically, our regressor in (6) is a good summary statistic of the sector-bias information contained in the full set of factor-cost shares.} Also, like equation (5), equation (6) is estimated on as many sectors as data permit.

Because the estimates of $\beta_{bias}$ are central to our empirical analysis, it is important to consider our interpretation of the link between $\beta_{bias}$ and observed skill-premia changes. One possibility is that our correlations between $\beta_{bias}$ and wage changes might be driven by factors other than SBTC. For example, consider either product-price changes or factor-neutral TC biased towards skilled-labor-intensive sectors. From (4), these changes raise the skill premium, and from (2') this rise tends to increase $\omega_k$ (if $\sigma < 1$)---more so in the skill-intensive sectors. If we then estimate equation (6) measuring SBTC as $\Delta \omega_k$, we get a positive $\beta_{bias}$. From this we might incorrectly conclude that SBTC had contributed to a rise in the skill premium.

Forces other than SBTC can generate these spurious correlations via changes in the skill premium. But equation (5) directly controls for these wage changes. By estimating SBTC conditional on wage changes (measured either as data, the constant term, or industry dummies) we try to "strip out" of our SBTC measures variation in $\omega_k$ caused by wage variation.

\textit{3b Data, Measurement, and Econometrics}

We require sector-level data on capital stocks, output, computer use, and employment and wages for both skilled and unskilled workers. In principle these data should span all tradable sectors, but we have data for manufacturing sectors only.
For our ten-country panel we use the United Nations (U.N.) General Industrial Data Base. It contains all required information except computerization and, for three of our countries, capital stocks. In these data sectors are defined at the three-digit ISIC level, so for each country-decade we have approximately 28 manufacturing sectors. For the United States we also use the National Bureau of Economic Research’s Productivity Data Base, an industry-year panel of 450 four-digit U.S. SIC sectors. Our U.S. computerization measure comes from the U.S. Census of Manufactures. For the United Kingdom we also use a sector-year panel of 125 three-digit sectors based on the U.K. Census of Production compiled by Oulton and O’Mahoney (1994). Our U.K. computerization measure comes from the U.K. ARD data base, the establishment-level data set that underlies the U.K. Census.16

All of our data classify employees as either nonproduction or production workers. Following the precedent of a number of studies, we define the former to be skilled and the latter to be unskilled.17 We construct $\omega_k$ as the nonproduction wage bill divided by total wage bill of production and nonproduction workers. We construct $w_{sk}$ as total nonproduction wage bill divided by total nonproduction employment; $w_{uk}$ is constructed analogously for production workers. In our data $K_k$ is measured as property, plant, and equipment. Because value-added price deflators are generally not available, we measure $Y_k$ as real value of shipments. We have sufficient sector detail to construct industry dummy variables only for the detailed U.S. and U.K. data. For both countries we report results using two-digit industry dummies (20 for the U.S. data and 17 for the U.K. data). Our U.S. computerization measure is the share of computer investment in total investment averaged for the two years 1982 and 1987. The U.K. measure is constructed analogously from 1986 and 1988 data. For both the U.S. and the U.K. we have

16 We are very grateful to Nick Oulton for providing us with the U.K. panel data. The Oulton/O’Mahoney data runs 1954 to 1986 at 5 year intervals. We use their data for the 1970s and Census data for the 1980s described in Haskel (1999) (the 1980s data contain fewer sectors because of a major classification change in 1980, but we use these data because they extend to 1989). For providing us with the U.N. data and the U.S. computerization data we are extremely grateful to Eli Berman.

17 Berman, et al (1994) document for the United States that employment trends for this job-classification measure track quite closely employment trends measured by the white-collar/blue-collar job classification—which in turn closely reflects the college/high-school classification.
computerization data spanning (at least part of) the 1980s only, so we use these data in these countries’ 1980s regressions only.

In summary, for each country-decade we measure SBTC using equation (5) and its variations. We then use these measures as regressands to estimate sector bias using equation (6). All regressions use weighted least squares with sector employment averaged over the decade as weights. Also, in equation (6) the errors $u_k$ are correlated across observations for cases where the regressand was calculated using regression coefficients from equation (5). We correct our standard errors for the $\beta_{\text{bias}}$ estimates following the methodology in Feenstra and Hanson (1999).

3c Empirical Results

Using our U.N. data, Table 1 reports the wage facts we aim to help explain. The table lists for ten countries changes over the 1970s and 1980s in skill premia measured as the manufacturing-wide average annual nonproduction/production earnings ratio. As the table shows, Denmark, the United Kingdom, and the United States all experienced falls in the skill premium over the 1970s and increases in the 1980s. Ireland, Japan, and Portugal all experienced rising skill premia during the 1980s as well. Australia (Aus) and Finland had falling and then flat premia; in Austria (Au) the skill premium rises in both periods. Sweden is an interesting exception: its skill premium rose in the 1970s and fell in the 1980s. These trends generally match the evidence from other data sources.\textsuperscript{18}

We start our analysis using the detailed data for the United States and United Kingdom. In both countries the skill premium fell during the 1970s and then rose sharply during the 1980s. By our sector-bias hypothesis, in both countries we should find SBTC concentrated in unskill-intensive sectors during the 1970s, skill-intensive sectors during the 1980s.

\textsuperscript{18}To try to minimize data-quality problems we focus on developed countries. Data problems included no employment breakdown between skill levels and excessively few industries with reported data. We tried to sensibly “clean” the data we decided to use. This included omitting sectors with negative relative wages, relative employment, or relative wages above 8.5. By narrowing this set of countries based on incomplete and/or poor quality data we obtained our ten countries. For Ireland, Japan, and Portugal we use only the 1980s because of 1970s data problems; for the remaining countries we use both decades.
To examine this, Figure 3 plots SBTC (measured simply as $\Delta \omega_k$) over the 1970s and 1980s against start-of-decade skill intensity for 17 two-digit sectors defined congruently across the two countries (i.e., the graphical equivalent of (6)). In all four country-decades the lines of best fit ($\beta_{bias}$ multiplied by skill intensity) support the sector-bias hypothesis.

Table 2 confirms the message of Figure 3 more formally by using the fully-disaggregated data and using several SBTC measures. For each country, each column in Table 2 uses a different SBTC measure obtained from a different specification of equation (5). The top row in Table 2 reports estimates of $\beta_{bias}$ (and t-statistics) for the 1970s; the second row for the 1980s. The significantly negative estimates in the first row indicate that in both countries SBTC was concentrated in unskill-intensive sectors in the 1970s. The significantly positive estimates in the next row indicate that SBTC was concentrated in skill-intensive sectors in the 1980s. The last row of Table 3 reports chi-squared test statistics confirming that each country had a significantly different sector bias of SBTC across the two decades. Overall, the evidence suggests that the sector bias of SBTC contributed to U.S. and U.K. wage trends.19

For a broader consistency check of our sector-bias hypothesis, we estimate equation (6) on each of our ten countries in each decade. Table 3 reports the results using SBTC measured as $\Delta \omega_k$. The key message of Table 3 is that the sector bias of SBTC varies over both countries and decades. The 1970s parameter estimates (significance aside) indicate three countries with SBTC concentrated in unskilled-labor-intensive sectors and four in skilled-labor-intensive sectors. In the 1980s the analogous breakdown is three countries and seven countries. Across the two decades, every country except Austria experienced a statistically significant change in its sector bias.

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19 In Table 2 each U.S. regression contains 444 sectors. Each U.K. regression contains 122 sectors in the 1970s and 80 in the 1980s. The U.S. regressions omit sectors SIC # 2026, 2086, 2711, 2721, 2731, and 3761. All these sectors had (S/U)k greater than 1.5, more than three standard deviations from the mean. U.K. regressions omit shipbuilding, automobiles, aerospace, and iron and steel since all these sectors were publicly owned for at least part of the sample period. Our results are robust to including these omitted sectors. They are also robust to several other checks including weighting all sectors equally, dating the two decades differently (subject to data limitations), and aggregating sectors more broadly (as demonstrated by Figure 3). In unreported results we also modified equation (6) by pooling both countries to test whether within each decade the two countries had different sector biases to SBTC. We found no significant differences, consistent with the countries’ similar wage trends.
bias of SBTC between the 1970s and the 1980s. These results are robust to alternative SBTC measures based on estimates of equation (5).  

By combining the skill-premium data from Table 1 with the $\beta_{\text{bias}}$ estimates from Table 3, we can check whether country-decades with rising skill premia had SBTC biased towards the skilled-labor-intensive sectors, and similarly whether country-decades with falling skill premia had SBTC biased towards the unskilled-labor-intensive sectors. We test this in Figure 4 for the 1970s and Figure 5 for the 1980s. In each figure the horizontal axis plots each country-decade’s estimated $\beta_{\text{bias}}$ and the vertical axis plots each country-decade’s observed skill-premium change. The sector-bias hypothesis makes two predictions. First, if the sector bias of SBTC were the only force affecting skill premia then all country-decade observations should lie either in the upper-right or lower-left quadrant. Second, country-decades with larger estimates of $\beta_{\text{bias}}$ should have larger observed changes in skill premia.

Figures 4 and 5 support the sector-bias hypothesis. The majority of country-decade observations lie in the lower-left or upper-right quadrants (five out of seven in Figure 4 and seven out of ten in Figure 5). The fact that not every observation lies in a "correct" quadrant suggests that forces other than SBTC also affected skill premia. In addition, the observations generally slope upward, suggesting that country-decades with greater degrees of sector bias of SBTC tended to experience greater changes in skill premia. Overall, the patterns in Figures 4 and 5 suggest differences in the sector bias of SBTC are an important explanation for cross-country and cross-decade differences in skill premia.

3d Discussion of Empirical Results

To properly interpret the our empirical results, there are five issues to emphasize.

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20 We report results measuring SBTC as $\Delta \omega_k$ to maximize country coverage. Because of missing capital-stock data our preferred translog SBTC measure can be constructed for only seven countries. The translog results from estimating equation (5) are qualitatively identical to the results in Table 3. Since $\Delta \omega_k$ can be affected by labor hoarding we try to start and end decades at like points in the business cycle. Table 3 reports years used. To test formally for cross-country differences in sector biases within decades, we modified equation (6) by pooling all countries together and then estimated all countries together using a full set of country dummy variables for interactions. The parameter estimates for 64% of the country pairs were significantly different at the 5% significance level (71% at the 10% level).
i. Other Kinds of TC. We have examined the sector bias of SBTC only, not of other kinds of TC as well. In principle, one could measure the sector bias of all kinds of TC, as summarized by TFP growth. In practice, we focus on SBTC for two reasons. One is the large empirical literature documenting that an important aspect of recent TC has been its skill-biased nature in many countries. We think that our empirical approach is an important first step linking this literature with the idea of sector bias. The second is that our data are simply not detailed enough to calculate TFP growth for any countries other than the United States and United Kingdom.

A few papers have considered the sector bias of U.S. and U.K. TFP growth. For the U.S., Leamer (1998) estimates that the sector bias of TFP growth raised the U.S. skill premium during the 1970s and lowered it during the 1980s. Kahn and Lim (1998) also find that during the 1970s U.S. TFP growth was more concentrated in skilled-labor-intensive industries. For the U.K., Haskel and Slaughter (2000) find that TFP growth had no significant sector bias in the 1970s or 1980s. The contrast between our SBTC results and these TFP results highlight that TFP is a combination of factor-biased and factor-neutral TC (Berndt and Wood, 1982), and so SBTC and TFP growth need not have the same sector bias. Feenstra and Hanson (1999) decompose U.S. TFP into parts attributable to computerization and outsourcing. They then estimate wage changes caused by each of these two forces. Our measure of SBTC as skill upgrading related to computerization (Table 2) qualitatively match their results: a mandated rise in skill premia.

ii. Cost Reductions. Given our focus on just SBTC, a second important issue is that we have not estimated any link from sectoral SBTC to sectoral cost reductions and subsequent wage changes. Accordingly, as explained in section 2b, our results should be interpreted as a suggestive consistency check, where sectors with greater skill upgrading enjoy greater cost reductions.21

21 Our empirical focus on decades makes it less likely that observed SBTC was increasing unit costs, a possibility we had assumed away in Section 2. Even if SBTC does not reduce firms’ unit costs in the short run (e.g., because of learning), over longer time horizons it seems more plausible that observed SBTC lowers costs. In theory, one can decompose observed TFP growth, the dual of unit-cost reductions, into portions attributable to factor-biased and factor-neutral innovations (see, e.g., Berndt and Wood, 1982). In practice, this decomposition requires far more data than we have, even for the United States and United Kingdom (e.g., real quantities of intermediate inputs and industry prices for all inputs in levels, not indices). Without the necessary data, econometric attempts at this decomposition can suffer biases from omitted variables and endogeneity.
An important aspect of not evaluating SBTC’s cost reductions is that we do not try to measure any indirect product-price responses from SBTC. As shown in Figure 1, measuring world product-price responses to TC would require data on world tastes, technology, and endowments. This is clearly beyond the scope of this paper (and has not been attempted in any empirical study of trade, technology, and wages that we know of).22

How important might this indirect product-price effect be? Three points are worth noting. First, in theory the indirect effect applies only to countries large enough to have their TC affect world prices. Many countries in our data (e.g., Ireland and Portugal) are probably not far from the baseline small-country assumption for many industries. Second, theory predicts the nontraded sector can dampen any price impacts of TC in tradables by absorbing displaced workers. In recent decades many OECD countries have seen employment declines in manufacturing offset by employment gains in services, which suggests this dampening mechanism may be important. Third, for the countries for which we have comprehensive price data, the U.S. and the U.K., SBTC does not seem to have been the main force behind price changes. For example, over the 1980s there was no clear sector bias to changes in U.S. product prices (Lawrence and Slaughter, 1993; Baldwin and Cain, 1997; Leamer, 1998) while U.K. product prices grew significantly more in skill-intensive sectors (Haskel and Slaughter, 2000). Yet in both countries over the 1980s, SBTC was concentrated in the skill-intensive sectors. If this SBTC had driven price changes in these countries, then the relative price of skill-intensive products would likely have fallen (recall from Section 2c that different cases are possible here). That this did not happen in either case suggests SBTC was not driving observed price changes.

iii. Factor Supplies. Our analysis has not considered the possible wage impacts of changes in a country’s factor supplies. If FPI holds then there are no wage impacts from factor-supply changes, just Rybczynski output-mix impacts. But FPI depends on two key assumptions. One is the small-country assumption: output changes cannot trigger Stolper-Samuelson wage changes.

22Feenstra and Hanson (1999) is the only study we are aware of estimating the empirical link from TC (in this study TFP) to product-price reductions for a single country (the United States).
The other is the “constant cone” assumption: factor-supply changes must be small enough that the country does not switch its produced sectors (i.e., its cone of diversification) and thereby switch the zero-profit conditions that govern wages.

How are our SBTC results affected by not examining factor-supply changes? Regarding the small-country assumption, in recent decades most developed countries have seen their relative supply of skilled labor increase. This might tend to lower the price of skill-intensive goods as their output expands, and thereby lower the skill premium. But as discussed above, U.S. and U.K. prices did not move like this over the 1980s, a decade of rising skill premia for both. Regarding cones, because our data measure the same set of industries in all years, our analysis implicitly assumes that each country-decade produces an unchanging set of sectors throughout, i.e., that no country switches cones in any decade. This is a maintained assumption of every HO empirical study of trade and/or technology’s effect on wages that we know of. Our data support this assumption in that no industry had zero production in any year.\footnote{Of course, one may argue the industries in are too aggregated to show true cone switches occurring at finer industry levels.} We know of no empirical research in the recent trade-and-wages literature to test for cone switches (this would require extensive data on national factor supplies and outputs).

iv. \textit{Comparison with the One-Sector Model.} It is instructive to contrast our multi-sector treatment of factor-supply changes with the one-sector treatment. In both frameworks, equation (2) describes relative labor demand for any sector with positive production. But in the one-sector framework, (2) also describes relative labor demand for the entire country. Thus (2) leads directly to the equation for the one-sector national wage premium in (3), where changes in relative factor supplies have to be absorbed by changes in wages. Many studies (e.g., Katz and Murphy, 1992) map labor-supply changes into wage changes via equation (3).

In the multi-sector framework, national relative labor demand is \textit{not} described by equation (2). Instead, it is a weighted average of the \( k \) equations in (2), where the weights are the endogenously determined sectoral shares of total employment. As in Section 2b, this framework is closed by assuming zero profits in all \( k \) sectors, yielding equation (4) when \( k = 2 \). FPI holds
when changes in relative factor supply are completely absorbed by changes the $k$ employment shares, the output consequences of which are described by the Rybczynski theorem.

Clearly, a helpful exercise to weigh these two frameworks would be to analyze changes in product prices, output mix, and (as just discussed) possibly cones. This is a very important research question, but is beyond the scope of this paper.

v. Relation to SBTC Studies. Finally, it is important to relate our results to a few other studies of SBTC. Berman, et al (1998) argue there is similar SBTC within sectors across countries. We are interested in SBTC within countries across sectors. If SBTC were exactly the same within each sector across all countries, then there would be no difference across countries in the sector bias of SBTC. But Berman, et al report that only 13 of 36 country-pairs in their sample have statistically significantly correlated within-sector SBTC (measured by $\Delta \omega_k$) over the 1980s. This seems consistent with sufficient differences in the extent of SBTC within sectors across countries to allow for important differences across countries in the sector bias of SBTC, which is what we find. Notably, Berman, et al, find Sweden is significantly correlated with no county but Finland.

Many studies (e.g., Berman, et al, 1994, and Autor, et al, 1998) document that most skill upgrading manufacturing-wide is accounted for by within-sector skill upgrading rather than between-sector shifts towards more skill-intensive sectors. The relatively small between-sector shifts are sometimes interpreted as support for the hypothesis that SBTC explains rising inequality. In our framework, by definition SBTC generates within-sector shifts. But SBTC can also generates between-sector shifts of factors in response to shifts in relative profitability. So our sector-bias hypothesis predicts both within and between-sector shifts. Without further assumptions, our model does not predict the relative importance of these two shifts.

4 Conclusion

This paper has shown that the sector bias of skill-biased technical change (SBTC) can help explain changing skill premia within countries in recent decades. First, using a two-factor, two-sector, two-country model we demonstrated that in many cases it is the sector bias of SBTC that
determines SBTC’s effect on relative factor prices, not its factor bias. Rising skill premia are caused by more extensive SBTC in skill-intensive sectors, falling skill premia by more extensive SBTC in unskill-intensive sectors. Second, we tested the sector-bias hypothesis on ten OECD countries over the 1970s and 1980s. Ours is the first empirical study of the sector bias of SBTC, and the data are consistent with it being important. In countries when skill premia were falling we find that SBTC was generally concentrated in unskill-intensive sectors. In contrast, when skill premia were rising SBTC was generally concentrated in skill-intensive sectors.

Our findings raise a number of issues for future work. We have not attempted to link SBTC and TFP to determine the cost reductions induced by SBTC. We have also not explored why different country-decades have different sector biases of SBTC.\textsuperscript{24} We regard issues like these to be important areas for future research.

\textsuperscript{24}Our results are consistent with the hypothesis that countries do not share identical production technologies. This hypothesis is supported by Trefler (1995), Davis, et al (1997), and Harrigan (1997b), all of whom find that cross-country technology differences help explain patterns in national production and/or international trade. It is also supported by Harrigan (1997a), who calculates significant cross-country differences in industry TFP levels.
References


Table 1: Changes In Skill Premia Across Ten Countries

<table>
<thead>
<tr>
<th>Country</th>
<th>1970s % Change in Skill Premium</th>
<th>1980s % Change in Skill Premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>-16.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Austria</td>
<td>4.8</td>
<td>6.1</td>
</tr>
<tr>
<td>Denmark</td>
<td>-14.9</td>
<td>6.1</td>
</tr>
<tr>
<td>Finland</td>
<td>-16.5</td>
<td>-1.3</td>
</tr>
<tr>
<td>Ireland</td>
<td>N.A.</td>
<td>3.9</td>
</tr>
<tr>
<td>Japan</td>
<td>N.A.</td>
<td>2.2</td>
</tr>
<tr>
<td>Portugal</td>
<td>N.A.</td>
<td>14.5</td>
</tr>
<tr>
<td>Sweden</td>
<td>3.4</td>
<td>-3.1</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>-2.7</td>
<td>12.0</td>
</tr>
<tr>
<td>United States</td>
<td>-2.5</td>
<td>7.6</td>
</tr>
</tbody>
</table>

Notes: Changes in skill premia measured as the manufacturing-wide average annual nonproduction earnings relative to the average annual production earnings. "N.A." indicates wage changes not available because of data-quality problems.
Sources: United Nations General Industrial Data Base.

Table 2
U.S. and U.K. Sector Bias of SBTC

<table>
<thead>
<tr>
<th></th>
<th>United States</th>
<th>United Kingdom</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SBTC1</td>
<td>SBTC2</td>
</tr>
<tr>
<td>1970s $\beta_{bias}$</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(-5.56)</td>
<td>(-3.44)</td>
</tr>
<tr>
<td>1980s $\beta_{bias}$</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(8.18)</td>
<td>(6.19)</td>
</tr>
<tr>
<td>Test Statistic</td>
<td>94.22</td>
<td>45.66</td>
</tr>
</tbody>
</table>

Notes: Each column reports estimation of equation (6) for a different measure of SBTC derived from estimating a different variation of equation (5). SBTC1 comes directly from equation (5). SBTC2 drops the wage regressor. SBTC3 drops the wage regressor and includes two-digit industry dummy variables. SBTC4 includes the computerization regressor. See text for details on these measures. T-statistics are reported in parentheses, and are based on standard errors adjusted for correlation across errors $u_k$ in equation (6) induced by using SBTC regressands that are calculated using regression coefficients from equation (5). All equations are estimated separately for each decade by weighted least squares using sector employment averaged over the decade as weights. Each U.S. regression contains 444 sectors; each U.K. regression 122 sectors in the 1970s and 80 in the 1980s. U.S. time periods are 1970 to 1980 and 1980 to 1990. U.K. time periods are 1968 to 1978 and 1980 to 1989. The test statistic is distributed chi-squared with a 5% critical value at 3.84.
Sources: U.S. data are NBER Productivity Data Base, U.K. data are Oulton and O'Mahoney (1994) panel.
Table 3
The Sector Bias of SBTC In Ten Countries

<table>
<thead>
<tr>
<th>Country</th>
<th>Aus</th>
<th>Au</th>
<th>Den</th>
<th>Fin</th>
<th>Ire</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970s $\beta_{bias}$</td>
<td>-0.09</td>
<td>0.09</td>
<td>-0.02</td>
<td>0.02</td>
<td>N.A.</td>
</tr>
<tr>
<td>Test Statistic 1970s=1980s?</td>
<td>(-3.03)</td>
<td>(2.24)</td>
<td>(-0.68)</td>
<td>(0.26)</td>
<td>N.A.</td>
</tr>
<tr>
<td>R²</td>
<td>0.37</td>
<td>0.56</td>
<td>0.38</td>
<td>0.65</td>
<td>0.47</td>
</tr>
<tr>
<td># obs</td>
<td>27, 26</td>
<td>28, 26</td>
<td>26, 26</td>
<td>28, 28</td>
<td>N.A., 24</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Country</th>
<th>Jap</th>
<th>Por</th>
<th>Swe</th>
<th>UK</th>
<th>US</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970s $\beta_{bias}$</td>
<td>N.A.</td>
<td>N.A.</td>
<td>0.06</td>
<td>0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>Test Statistic 1970s=1980s?</td>
<td>(-0.43)</td>
<td>(1.72)</td>
<td>(2.17)</td>
<td>(2.99)</td>
<td>(2.04)</td>
</tr>
<tr>
<td>R²</td>
<td>0.79</td>
<td>0.63</td>
<td>0.45</td>
<td>0.78</td>
<td>0.75</td>
</tr>
<tr>
<td># obs per dec</td>
<td>N.A., 10</td>
<td>N.A., 27</td>
<td>28, 28</td>
<td>28, 28</td>
<td>28, 28</td>
</tr>
</tbody>
</table>

Notes: Each column reports estimation results for equation (6) with SBTC measured as $\Delta w_k$. T-statistics and F-statistics are reported in parentheses, and are based on White’s heteroskedasticity-robust standard errors. All equations estimated by weighted least squares using sector employment averaged over the decade as weights. The test statistic is distributed chi-squared. "N.A." means estimates not available due to data limitations.

Sources: United Nations General Industrial Data Base.
Notes: This figure presents the qualitative wage effects of technological change in a two-sector economy with flexible product prices, as discussed in Section 2c. In the left panel the SS curve relates a country’s skill premium to its product prices for given technology. The right panel shows how world supply and demand determine these product prices. At initial product prices, technological change shifts the SS curve either left or right: this is the “direct” wage effect, as shown by the D arrows. This technological change may alter world prices by altering world relative supply; in turn, this feeds back to a country’s skill premium along the relevant new SS curve: this is the “indirect” wage effect, as shown by the I’ and I’” arrows. The net wage effect of any technological change is the sum of the direct and indirect effects.

Figure 2
Summary of the Effects of Technological Change on the Skill Premium:
Two-Sector Economy With Fixed Product Prices or Small Indirect Product Price Effects

<table>
<thead>
<tr>
<th>Types of Technological Change</th>
<th>Column (1)</th>
<th>Column (2)</th>
<th>Column (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor-Neutral (change in $A_k$)</td>
<td>Rise</td>
<td>Fall</td>
<td>Rise if Machinery-Biased, Fall if Apparel-Biased</td>
</tr>
<tr>
<td>Skill-Biased (change in $\delta_k$)</td>
<td>Rise</td>
<td>Fall</td>
<td>Rise if Machinery-Biased, Fall if Apparel-Biased</td>
</tr>
</tbody>
</table>

Notes: This figure presents the wage effects summarized in Section 2d. In this framework, machinery is the skill-intensive sector and apparel the unskill-intensive sector. The rows cover alternative factor biases to technological change: either factor-neutral or skill-biased. The columns cover alternative sector biases to technological change: occurring just in machinery, i.e., machinery-biased; occurring just in apparel, i.e., apparel-biased; or occurring in both sectors, i.e., sector-pervasive. Each cell reports the effect of that cell’s technological change on the country’s skill premium, with either fixed product prices or flexible product prices where the indirect effect of price changes is smaller than the direct effect at constant prices. All these terms are defined in detail in the text.
Figure 3
U.K. and U.S. Sector Bias of SBTC During the 1970s and 1980s

Notes: Each circle is a sector; circle size reflects sector size (measured by employment). The y axis measures SBTC as $\Delta \omega_k$; the x axis measures skill intensity as each sector’s start-of-decade skilled/unkilled employment ratio; and the regression line comes from estimation of equation (6) on 17 sectors defined congruently across the two countries. For both countries the 1970s covers 1968-1978 and the 1980s 1978-1988.
Sources: U.S. data are NBER Productivity Data Base, U.K. data are Oulton and O’Mahoney (1994) panel.
Figure 4
The Sector Bias of SBTC and Changing Skill Premia in the 1970s

Sector Bias of SBTC

Notes: In each diagram the x axis measures the sector bias of SBTC taken from the estimates in Table 3, and the y axis measures changes in the skill premium as reported in Table 1.