DISCUSSION PAPER SERIES

No. 5263

TRADE AND THE SKILL-BIAS - IT'S NOT HOW MUCH, BUT WITH WHOM YOU TRADE

Pushan Dutt and Daniel A. Traca

INTERNATIONAL TRADE

Centre for Economic Policy Research

www.cepr.org

Available online at: **www.cepr.org/pubs/dps/DP5263.asp**

ISSN 0265-8003

TRADE AND THE SKILL-BIAS - IT'S NOT HOW MUCH, BUT WITH WHOM YOU TRADE

Pushan Dutt, INSEAD
Daniel A. Traca, Solvay Business School and CEPR

Discussion Paper No. 5263
October 2005

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR, UK
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 5263

October 2005

ABSTRACT

Trade and the Skill-Bias - It's Not How Much, But With Whom You Trade*

This paper explores the hypothesis that changes in trading patterns and partners of US industries have contributed to skill deepening through defensive, skill-biased innovation. It draws on Thoenig and Verdier's (2003) assertion that, since skill-intensive technologies are less likely to be imitated, increased exposure to international competition promotes skill-biased innovation, due to the rise in the intensity of imitation by foreign firms. Our main proposition is that the rate of growth of a trading partner is related to the intensity of imitation from firms operating in that country, implying that an increase in the rate of growth of an industry's representative trading partner should contribute to the rise in its skill-intensity. We find empirical evidence in support of this notion, showing that the rise in the average growth rate of the trading partners has contributed to about 20% of the skill-deepening within US industries. By contrast, we find evidence that measures of the volume of trade do not matter significantly for the rise in skill-intensity, in line with existing literature.

JEL Classification: F14, F16 and J31
Keywords: defensive innovation, skill bias and trade and wages

Pushan Dutt
INSEAD
1 Ayer Rajah Avenue
Singapore, 138676
SINGAPORE

Tel: (65) 6799 5498
Email: Pushan.Dutt@insead.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=163271

Daniel A. Traca
Université Libre de Bruxelles
Solvay Business School
ULB - CP 145/01
1050 Brussels
BELGIUM
Tel: (32 2) 650 6599
Fax: (32 2) 650 4188
Email: daniel.traca@ulb.ac.be

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=137283

Submitted 08 September 2005

1 Introduction

It is well known that the economic position of low-skilled workers relative to high-skilled workers has worsened in many industrialized nations since the late 1970s, due to a shift in the demand for labor toward more-skilled workers. Over the last decade, the role of Stolper-Samuelson effects has been dismissed, based on counterfactual data on prices (see Feenstra and Hanson, 2001 for a survey) and evidence that the bulk of the increase in skill-intensity occurred within manufacturing industries, and not through the expansion of skill-intensive industries (Berman, Bound and Griliches, 1994).[1] Meanwhile, the within-industry rise in the demand for skilled labor (henceforth addressed as skill-deepening), and the corresponding rise in the skill-premium, have been blamed on skill-biased technological change (SBTC) (e.g. the increased use of computers), as well as on rising outsourcing (Feenstra and Hanson, 1999). Recently, however, a number of authors, starting with Wood (1995), have made the argument that SBTC might itself be a consequence of trade related phenomena.

This paper empirically explores the hypothesis that changes in the trading patterns and partners of US industries have contributed to the skill-deepening, by encouraging defensive skill-biased innovation. It draws on Thoenig and Verdier's (2003) argument that skill-intensive technologies are more robust to imitation, providing a more lasting competitive advantage. They conclude, as a result, that rising trade exposure to countries whose firms constitute a stronger danger of competitive imitation causes skill-biased innovation, as domestic firms 'defend' from the increased threat to their knowledge advantages.

Our proposition is that the rate of growth of a trading partner is related to the threat of competitive imitation from firms operating in that country. Motivated by the literature on the role of knowledge transfers for productivity convergence and economic growth, we argue that

[1] Consensual estimates show that the expansion of skill-intensive sectors explains less than a third of the rising demand for skills (Berman et al., 1994; Feenstra and Hanson, 2001). At the same time Lawrence and Slaughter (1993) show that the relative price of skill-intensive goods did not increase in the 1980s. On the other hand, the rise in the relative supply of skilled labor might explain the skill-deepening, but has the counterfactual implication of reducing the wage-skill gap.

a trading partner's rate of productivity growth depicts, in large part, the extent of knowledge absorption that emerges from the activities of competitive imitation by the country's firms. For example, Grossman and Helpman (1992) show that countries that imitate from technological leaders, such as the US, will enjoy higher rates of productivity and economic growth, at least until they reach the frontier.

Hence, a country's high growth *reveals* the dynamism of its firms at taking advantage of 'unprotected' know-how to turn it into a competitive weapon against original US innovators. In this sense, the rate of growth summarizes, in reduced form, many factors that influence the extent of imitation, such as: the weak protection of intellectual property, the incentives and strategies of firms in a given trading partner to take advantage of imitation possibilities, or these firms' willingness to compete with US firms in domestic and foreign markets. Consequently, US firms operating in industries trading with countries with higher growth rates are more likely to engage in defensive, skill-biased innovation to protect their knowledge-based advantages.

Using the NBER trade and manufacturing database, we construct a industry-year series for GROWTH, depicting the long-run rate of growth of GDP per capita of an industry's average trading partner, weighted by the industry's bilateral trade (imports+exports).[2] Then, we look at the contribution of changes in GROWTH for the changes in skill-intensity (i.e. the 'share of non-production wages') in US industries.

To account for the possibility that the pattern of trade, which determines the weight of each trading partner in GROWTH, is affected by autonomous changes in the skill-intensity of an industry, we correct for endogeneity. We construct instruments based on the measures of exposure to globalization of the trading partners, following the principle that the rises in an industry's openness that are driven by increased exposure (e.g. trade liberalization) in its trading partners are independent of changes in that industry's skill-intensity.

[2] The long-run rate of growth of a trading partner is the five-year moving average of the growth of GDP per capita.

We find empirical support for the proposition that changes the average trading partner's GROWTH are associated with the rise in skill-intensity for US industries. Overall, an increase in the trading partner's rate of growth explains around 20% of the rise in skill-intensity, at the industry-level. This result is robust to the inclusion of several additional controls, discussed below.

First, we include a control for changes in industry-level Outsourcing, using the data in Feenstra and Hanson (1999). We find that the role of Outsourcing declines slightly relative to the estimates obtained by Feenstra and Hanson (1999), once changes in GROWTH are taken into account. Meanwhile, the economic and statistical significance of GROWTH is only marginally affected by the inclusion of Outsourcing.

Second, we include also the most widely used set of regressors in this literature, namely the volume of trade in the industry (see Wood, 1998, for a survey). Interestingly, the notion that rising trade volumes matter for skill-intensity is challenged by Thoenig and Verdier (2003). They argue that what triggers defensive innovation (in their model) "is not the importance of trade volumes or variations in goods prices but the degree of transferability of information across firms and the intensity of imitation or technological competition". Hence, once a firm is in an international environment, what matters is whether competitors will imitate it, and this is independent of how much the firm is selling in international markets.

The fundamental implication is that trade volumes do not matter. We address it statistically, by looking at the role of changes in various measures of an industry's degree of openness (henceforth OPENNESS) for the changes in skill-intensity. We find that changes in OPENNESS are an insignificant predictor of skill-deepening, and consistently appear with a negative sign.[3] This "irrelevance result" is in accordance with other studies that find no association between the skill-deepening and changes in import-penetration, even if they focus on imports from developing countries (e.g. Freeman and Revenga, 1999; Lawrence, 2000; Desjonqueres et al, 1999). It confirms

[3] We experiment with measures of aggregate openness, as well as focusing on specific regions and country-groups. The "irrelevance" of OPENNESS emerges in OLS and IV estimation methods.

the hypothesis of the irrelevance of trade volumes.

Finally, we control for the role of proxies for the institutional protection of intellectual property (IP) in trading partners, such as its rule of law index or its income per capita. We construct industry-level measures of the INCOME and RULEOFLAW of the representative trading partner for each US industry. By themselves, changes in these variables are negatively correlated with the rise in skill-intensity, showing that industries that shifted trading patterns or partners to countries with weaker IP protection engaged in stronger defensive innovation. However, these variables become insignificant, when the rate of GROWTH is introduced. We speculate that, to a large extent, GROWTH, as a reduced-form measure of the pro-imitation environment, already captures the extent of IP protection in trading partners.

We close our paper by examining the relationship between investments in computers - one of the key technological drivers of SBTC - and our trading partner variables. Our results show that the above-mentioned impact of changes in trading partners of US firms on the skill-deepening is mediated by their implications for computer investments. However, we find also a role for our variables that is independent of computer investments, which captures other dimensions of the skill-bias. In fact, SBTC may include investments in tacit knowledge, through the increased complexity of products and production processes, which are independent of changes in computer investments (Thoenig and Verdier, 2003).

This paper shows that we would be remiss in discounting the role of international trade as a driver of SBTC and the widening wage-skill gap, based on the established results (which we confirm) that the growth of the volume of trade does not play an important role in the skill deepening. Instead, our results imply that what matters is not the volume of trade in an industry, but, rather, with whom the industry trades and the changes therein over time. Our paper suggests that SBTC is driven in part by an increase in the average GROWTH rate of trading partners of US industries, which, we argue, are associated with an increase in the intensity of competitive imitation. We find also a role for the INCOME level and RULE OF LAW index of trading partners,

which we relate to the protection of IP. The role of GROWTH for SBTC has operated through increased use of computers and IT, but also through alternative, unidentified channels, possibly related to tacit knowledge.

2 Trading Partners and Skill-Biased Innovation

2.1 Trade, Defensive Innovation and the Skill-Bias

Wood (1995) was the first to stress that, the well-established notion that international competition stimulates innovation and productivity growth, has implications for the skill-premium.[4] In particular, he argued that "firms faced with import-competition from the South find new ways of producing with fewer unskilled workers, which enables them to fight off the imports, but still reduces their demand for [unskilled] labor". Elsewhere, Wood (1998) argues that "many less skill-intensive industries subject to competition from the South shed unskilled labor by defensive innovation [experiencing higher TFP growth] (and so experienced little rise in imports)".

The widespread interpretation has been that import-competition from developing countries induces *sector-biased* innovation, raising TFP growth in less skill-intensive industries.[5] Paradoxically, this implies an expansion of these industries, which should increase the demand for unskilled workers and contribute to a decline in the skill-premium. One possibility is the presence of a perverse price-effect - an inelastic demand for less skill-intensive goods, would reduce profitability of less skill-intensive industries (Acemoglu, 2002). However, this caveat is dismissed by Haskel and Slaughter (2001), who show that sectoral differences in "TFP growth did not have significant wage effects via price changes". Moreover, Acemoglu (2002) argues that trade with developing nations should reduce, not increase, the incentives for productivity growth in less skill-intensive industries, due to the rise in the relative price of skill-intensive goods.

[4] For a discussion of the link between international competition and firm-innovation and productivity growth, see, for example, Traca, (2000).

[5] Evidence in support of the role of 'defensive innovation' in the sector-bias of technological change over the last three decades can be found in several studies showing that rising import-competition, measured by relative import-prices or import-penetration, has contributed to an increase in TFP growth, at the industry level. Moreover, the results are stronger and more significant for import-competition from outside the OECD. See Lawrence (1998) for the US; Cortes and Jean (2000) for the US, France and Germany; Haskel and Slaughter (2001), for the UK.

Alternatively, Thoenig and Verdier (2003) provide the underpinnings of a theory of *factor-biased* defensive innovation, whereby industries facing increased competition from developing nations engage in technological change aimed at replacing unskilled workers with skilled ones. They argue that defensive innovation is driven by the threat of imitation by Southern firms, which undermines the competitive advantage of domestic firms in local and foreign markets. In their model, skill-intensive technologies feature tacit knowledge and non-codified know-how, which, by reducing informational leakages and spillovers, lessen the chances of being imitated. Hence, skill-biased innovation emerges from the efforts by home firms to escape imitation, and intensifies as the opening up of trade (with countries where the protection of intellectual property is ineffectual) expands the intensity of international imitation.[6]

2.2 The Irrelevance of Trading Volumes

From an empirical perspective, several attempts have been made at measuring the role of trade variables for the factor-bias of technological change. These studies look at the drivers of changes in the skill intensity of production (the share of the skilled in the wage bill), at the industry level. Most of them have found that measures of aggregate openness and openness to developing countries, or subsets of this group, fail to explain the change in skill-intensity.

Lawrence (2000) finds that the change in import-penetration from developed and developing countries is not statistically significant for skill-deepening.[7] Desjonqueres et al. (1997), using data for various countries, also find that "in almost all cases, there is a perversely signed negative (although typically statistically insignificant) association between the growth of skilled workers and the rise in imports from LDCs. In contrast, Feenstra and Hanson (1996, 1999) find a strong role for the change in import-shares on the non-production wage share, which they attribute to outsourcing, but the relationship loses significance when a control for Computer Investment is

[6] Thoenig and Verdier (2003) also argue that North-North trade should foster skill-biased innovation, by increasing the likelihood of leapfrogging. They argue that skill-intensive technologies are less likely to be leapfrogged. However, it is unclear what the difference between foreign and domestic competition is, in this case.

[7] Lawrence (2000) does find a role for the initial import-penetration from developed countries. However, this disappears once the variable is instrumented.

introduced (Autor et al., 1998). Finally, Bernard and Jensen (1997) and Autor et al. (1998) find a strong association with exporting, but do not correct for endogeneity. [8]

However, the lack of association between trade volumes and changes in skill intensity does not imply that international trade has had no role to play. Thoenig and Verdier (2003) show, in the context of their model, that what triggers defensive innovation "is not the magnitude of trade volumes or variations in goods prices but the degree of transferability of information across firms and the intensity of imitation or technological competition". Hence, once a firm is in an international environment, what is critical is the threat of competitive imitation that it faces rather than the volume of its international sales. The fundamental implication is that trade volumes do not matter.

As Thoenig and Verdier (2003) point out, this challenges the critique by Krugman (2000) that the role of trade for the rising skill-premium is bounded by the small magnitude of trade flows with developing nations. In fact, low volumes of trade, namely with developing countries, are not an impediment for an important role in the demand for skills, provided there is a rise in the intensity of international imitation, due to changes in trading partners and/or patterns.

2.3 Growth in Trade Partners and Competitive Imitation by their Firms

Instead of volumes, the key question is whether a trading partner has an environment conducive to competitive imitation, which induces defensive, skill-biased innovation by US firms. The main hypothesis of this paper is that a trading partner's rate of economic growth is related to the threat of competitive imitation by firms operating in that country.

Our working assumption is that a country's economic growth is related to the increase in total factor productivity arising, to a large extent, from the effort of its firms to imitate foreign, more advanced know-how. This idea, developed in theoretical models of knowledge-based endogenous growth (e.g. Grossman and Helpman, 1992), is confirmed in Easterly and Levine (2001), who show

[8] Actually, other than Lawrence (2000), all others ignore the potential for endogeneity of trade variables. This is particularly important, when import- and export-intensity are addressed separately.

that differences in rates of TFP growth, not capital accumulation, are the main determinant of variations in economic growth, across countries and over time. The implication is that foreign firms from high growth countries are *revealed* to be more dynamic at taking advantage of 'unprotected' know-how and turning it into a competitive weapon against US innovators.

There are many factors driving the strength of competitive imitation by these foreign firms. For example, to the extent that high rates of growth are associated with countries with dynamic firms as well as wages that are lower than in the United States, the payoff of aggressive imitation strategies is higher: firms in these countries can easily undermine the competitive advantage of US firms, once they rob them of their knowledge advantages. On the other hand, the protection of intellectual property is likely to be weak, as the level of development in their countries is lower. Finally, if the imitation is to represent a threat to US firms, the foreign firms must be willing to compete with US firms in US and foreign markets, highlighting the role of international trade.

In sum, we argue that the rate of economic growth is highly correlated with the extent of international imitation undertaken by a country' firms, summarizing, in reduced-form, the relevant country characteristics, and, therefore, is a good measure of the threat of competitive imitation to US firms trading with that country. Consequently, US firms operating in industries trading with countries with higher growth rates are more likely to engage in defensive, skill-biased innovation to protect their knowledge-based advantages.

An appropriate proxy for the competitive pressure would be the growth of Total Factor Productivity, which is related to the extent of knowledge absorption by the firms in the country. However, given the difficulty to obtain reliable cross-country data over time on this variable that encompasses all the trading partners of US industries, we have chosen to use, as a proxy, the rate of GDP per capita growth. To focus on sustained growth rates and abstract from fluctuations associated with the economic cycle, we use the five-year moving average of the growth rate.

We construct an industry-specific variable for the representative trading partner's rate of eco-

nomic growth, henceforth addressed as GROWTH, $GRTH_{jt}$, as follows:

$$\text{GROWTH:} \qquad GRTH_{jt} = \sum_i e_{ijt} \frac{g_{it}}{g_{ust}} \qquad e_{ijt} = \frac{\text{Exp}_{ijt} + \text{Imp}_{ijt}}{\sum_i \text{Exp}_{ijt} + \sum_i \text{Imp}_{ijt}} \tag{1}$$

where g_{it} is the rate of growth of GDP per capita in country i at time t and g_{ust} is the rate for the United States, and e_{ijt} are the country-weights. The country-weight, e_{ijt}, is the share of trade with country i in the total trade of industry j. As Thoenig and Verdier (2003) suggest, in most instances, it is the competitive pressure of trade and globalization that produces the incentives for the skill-bias, rather than whether the battleground is the home or the foreign market, indicating that imports and exports ought to contribute jointly to the skill-bias. Hence, for each industry, we express the weight of each trading partner using the aggregate trade (imports + exports) of the industry to the respective country.

The series obtained shows an increase in the dispersion of the average trading partner GROWTH across industries after the 1980's, captured by the widening of the 95% confidence interval, while the mean shows no discernible trend. In other words, the experience of US industries across this dimension has varied considerably; while those trading with low growth countries have seen a decline in the growth of trading partners from the late 1980's, those trading with high-growth countries have seen an increase in their growth rates.

2.4 IP protection: Income levels and Imitation Deterrence

Another factor influencing the threat of imitation is the institutional development of the trading partner, particularly with regard to the existence and effectiveness of the protection of intellectual property. Following Thoenig and Verdier's (2003), firms operating in countries with weaker protection of intellectual property are more likely to engage in competitive imitation, thus encouraging the adoption of skill-intensive technologies.

Of course, the protection of intellectual property means nothing unless there are firms capable of taking advantage of the permissive institutional environment. From this perspective, to the

extent that it captures the result of the activity of dynamic firms raising productivity and inflicting market pressure on US firms through competitive imitation, the GROWTH variable discussed above already captures the effects of the relatively weaker institutional protection of intellectual property in high growth countries.

Nevertheless, we introduce an additional control that proxies the effectiveness of IP protection in trading partners. Since direct data on IP protection, extending to the period and countries in our sample, was not available at the time of this paper, we consider a country's level of income as a proxy. It is widely recognized that the protection of IP is negatively correlated with a country's level of economic and institutional development. For example, Lerner (2000) shows that wealthier countries have more stringent patent protection, allow patentees a longer time to put their patents into practice, and ratify international treaties guaranteeing intellectual protection to patentees in other nations.[9] Hence, like before, we construct the industry-specific variable INCOME, INC_{jt}, which measures the relative GDP per capita of industry $j's$ representative trading partner at time t, as follows

$$\text{INCOME:} \qquad INC_{jt} = \sum_i e_{ijt} \frac{y_{it}}{y_{ust}} \tag{2}$$

In the expression, y_{it} is the GDP per capita in country i at time t and y_{ust} is the GDP per capita in the United States. The data show that the INCOME per capita of trading partners has declined, between 1979 and 1990, for US industries across the board. This captures the increased role of developing nations as trading partners of US industries.

For robustness, we compute another proxy of the effectiveness of IP protection, based on the general level of institutional development depicted by the "Rule of Law", from the International Country Risk Guide.[10] In fact, the high correlation of institutional variables in several databases is a well-established result in the 'institutions' literature. We constructed the variable RULE-

[9] There are several factors that contribute to this: first, economic development creates the funds, skills and institutional maturity needed for effective IPR protection; second, demand for IPR protection is also likely to rise, as innovation becomes a more important driver of economic growth.

[10] The "Rule of Law" variable, is a survey based measure that captures the strength and impartiality of the legal system of a country including respect for property rights.

OFLAW, $RLAW_{jt}$, measuring the relative relative "Rule of Law" of industry $j's$ representative trading partner similarly to (2), substituting a country's "Rule of Law" indicator for y_{it} and y_{ust}, respectively.

3 Econometric Framework

3.1 Skill-intensity in the Short-Run

We adopt the methodology developed in Berman, Bound and Grilliches (1994), to obtain an estimable equation for an industry's skill-intensity. Following the literature, we will take the non-production workers group as a proxy for skilled labor, and the production workers group for unskilled labor, and use the terms interchangeably. Skill-intensity is captured by the share of non-production workers on the industry's wage bill (see also Feenstra, 2003).

The starting point in this methodology is to consider a short-run cost function, which is the dual to the production function, and includes as arguments the structural variables of interest that shift the production function and therefore affect costs. Let the short-run variable cost function in industry j be written as $C_j(w_j, q_j, K_j, Y_j|z_j, d_j)$, where Y_j is value-added; K_j is the capital stock, taken as fixed in the short-run; w_j and q_j are the industry factor-prices for production and non-production labor, respectively; and, z_j and d_j are, respectively, a vector of structural variables and an industry-specific dummy that shift the cost function.

Assuming a translog cost function and taking the derivative wrt to the price of skilled labor (q), we obtain the compensated demand for skilled-labor (H_j). After straightforward manipulation, this yields the following expression for skill-intensity (the share of non-production workers in the wage bill), S_j:

$$S_{jt} \equiv \frac{q_{jt}H_{jt}}{C_{jt}} = \alpha_j + \gamma_j(\ln q_{jt} - \ln w_{jt}) + \phi_{kj} \ln K_{jt} + \phi_{yj} \ln Y_{jt} + \beta_{zj} z_{jt} + \beta_{dj} d_j \tag{3}$$

The parameters α_j, γ_j and ϕ_{ij} arise directly from the translog specification, and β_j captures the impact of structural variables. Assuming that the elasticity of substitution between skilled

and unskilled labor is larger than one, γ_j is negative.[11] Meanwhile, ϕ_k is positive, assuming that capital and skilled labor are complements. Note that the effects of changes in the supply of skilled labor are captured by the changes in factor prices. Following the literature, we assume also that the cost-functions are identical across industries ($C_j = C, \forall j$) and drop the j subscripts from the coefficients.

Equation (3) is often estimated from data on a panel of industries with observations for two periods coinciding with peak to peak of the business cycle (Feenstra and Hanson, 1996, 1999). We can eliminate the industry fixed-effect (d_j) and simplify the estimation, by taking the first-difference of (3). Since this yields a cross-sectional dataset, we can drop the time subscript and write:

$$\Delta S_j = \beta_z \Delta z_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0 \tag{4}$$

where (i) $k_j = \ln K_j/Y_j$ and $\beta_k = \phi_k$; (ii) $y_j = \ln Y_j$ and $\beta_y = \phi_k + \phi_y$; and (iii) $\beta_0 = \gamma\Delta(\ln q - \ln w)$ is a constant that emerges from ignoring the industry-variation in factor prices.[12]

ΔS_j is the skill-deepening in industry j, i.e. the industry-specific rise in skill-intensity. With the inclusion of an error term, (4) can be estimated with different sets of structural variables (z_j). Among the structural variables (z_j) we are particularly interested in are the characteristics of an industry's representative trading partner, introduced in the previous section, namely GROWTH, and INCOME. The previous discussion has argued that they matter for the defensive, skill-biased innovation in the industry. The corollary for (4) is that industries experiencing stronger increases in its relative GROWTH rate and/or declines in the relative INCOME of the representative trading partner, should witness a stronger increase skill-intensity. We also use RULEOFLAW instead of INCOME as a robustness check.

[11] Acemoglu (2002) argues that "there is a relatively widespread consensus that it is greater than 1, most likely greater than 1.4, and perhaps as large as 2".

[12] Here we follow Berman et al. (1994) and Feenstra and Hanson (1999), who argue that, since the variation in wages across industries is related to the different skill mixes, changes in the industry-specific component of factor prices do not affect the cost function. Meanwhile the economy-wide factor prices is subsumed in the constant term, after taking first-differences.

We include two additional structural variables. First, following Feenstra and Hanson (1996, 1999), we include a control for outsourcing (OUTS), obtained directly from these authors' dataset. Second, to test the idea introduced in the previous section that trade volumes do not matter, we include in the regression measures of the OPENNESS ($OPEN_{jt}$) of the industries to various subsets of trading partners, defined as

$$\text{OPENNESS:} \qquad OPEN_{jt} = \ln \frac{\text{Exp}_{jt} + \text{Imp}_{jt}}{\text{Ship}_{jt}} \tag{5}$$

where Exp_{jt} and Imp_{jt} are exports and imports of industry j, respectively. We have looked at overall openness (to the set of all trading partners), as well as openness to specific groups, such as OECD and developing countries. Our expectation is that the significance of these measures of openness is likely to be low. Our data shows a steady and across-the-board rise in the openness of US industries, between 1979 and 1990.

In sum, we estimate variations of the following specification

$$\Delta S_j = \beta_G \Delta GRTH_j + \beta_I \Delta INC_j + \beta_O \Delta OPEN_j + \beta_S \Delta OUTS_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0 \tag{6}$$

where, we expect: $\beta_G > 0, \beta_I < 0, \ , \beta_O \approx 0, \beta_S > 0$. The contribution to skill-deepening of the structural variables introduced here (GROWTH, INCOME, and OPENNESS) capture their effects, or lack thereof, for the *factor-bias* of technological change.

3.2 Endogeneity and Instruments

Next, we address the possibility that the variables GROWTH, INCOME, and OPENNESS may be endogenous to changes in skill-intensity, at the industry level, which would bias our estimates. Thoenig and Verdier (2003), themselves, raise the possibility that an industry's OPENNESS may be affected by its skill intensity. They argue that the introduction of a new, skilled-biased technology will increase average productivity and the competitiveness of the sector, and consequently the industry's openness would be affected. In this case, the estimated coefficient on openness will be biased upwards.

Moreover, since the weights used to compute the variables depicting the characteristics of trading partners, GROWTH and INCOME, are based on the industry's openness to each country, the endogeneity concern extends also to these variables. For example, it can be argued that industries with a higher skill-intensity, producing more high-tech goods, are more likely to trade with other industrialized countries. As a result, an industry's skill intensity has implications for its country-weights, which, in turn, will affect the variables.

We use instrumental variables estimation to address these concerns. We instrument for the openness of an industry, both on aggregate and relative to a specific partner, using the exposure to international trade of the countries it trades with. The fundamental principle is that the rises in an industry's openness that are driven by increased exposure of its trading partners are independent of changes in the industry's skill-intensity. Note that, for clarity, we use the term **exposure** to address the openness to trade of the trading partners (countries), whereas the term **openness** is reserved for the trade flows at the industry level. We use two measures of a trading partner's exposure as instruments: total import duties collected as a percentage of total imports (MD) and the magnitude of its trade flows (XM), defined as the sum of imports and exports relative to GDP. Hence we obtain two instruments for each variable, which allows us to verify the quality of our instruments using tests of overidentification.

To obtain operational instruments, we must construct industry-specific variables, from the trading partner's measures of exposure. We do this by weighting each of the measures of the exposure of each partner by its industry-specific country-weight. We construct the instruments for OPENNESS, as follows:

$$\begin{aligned} XM\_OP_{jt} &= \sum_i \frac{\bar{e}_{ij} XM_{it}}{\sum_i \bar{e}_{ij}} \qquad MD\_OP_{jt} = \sum_i \frac{\bar{e}_{ij} MD_{it}}{\sum_i \bar{e}_{ij}} \\ \text{where } \bar{e}_{ij} &= \frac{1}{T} \sum_t e_{ijt} \qquad e_{ijt} = \frac{\text{Exp}_{ijt} + \text{Imp}_{ijt}}{\sum_i \text{Exp}_{ijt} + \sum_i \text{Imp}_{ijt}} \end{aligned} \tag{7}$$

where e_{ijt} is as defined in (2). These variables are good instruments for OPENNESS (see eq. 5), since they capture the increased exposure of an industry's representative trading partner, which

should affect trade flows in the industry and be independent of its skill-intensity.

To understand why we use the average weights ($\bar{e}_{ij}$), note that, given the econometric model in (4), the relevant endogeneity concerns the first-differences in the variables. We are concerned that changes in an industry's skill-intensity generate changes in its OPENNESS, and NOT that the skill-intensity is correlated with OPENNESS across-industries. Using a constant (average) country-weight, implies that changes in the country-weights (caused by skill-deepening) are NOT causing changes in XM_OP_{jt} and MD_OP_{jt}, which implies that the first-differences in these instruments are uncorrelated with the first-differences in S_{jt} (ΔS).

This manipulation also allows us to compute instruments for GROWTH and INCOME. As discussed above, the key reason for endogeneity in these variables are the country-weights used to aggregate the trading partners, e_{ijt}. We fear that changes in skill-intensity will lead to a change in trade patterns that affect the country-weights, at the industry level. To construct appropriate instruments, we follow the notion that changes in the weight of country i in industry j's openness (e_{ij}) can be instrumented by the change in the exposure of country i relative to the average exposure of all of industry j's partners. When a trading partner's exposure rises, relative to all others, the country-weight of that partner should also rise, for reasons that are orthogonal to the changes in the industry's skill intensity.

Using the two measures of country exposure mentioned before, we obtain two instruments for each of the two partner variables: GROWTH and INCOME, as follows:

$$\begin{aligned} XM\_GRTH_{jt} &= \sum_i e_{ijt}^{XM} \frac{g_{it}}{g_{ust}} \qquad MD\_GRTH_{jt} = \sum_i e_{ijt}^{MD} \frac{g_{it}}{g_{ust}} \\ XM\_INC_{jt} &= \sum_i e_{ijt}^{XM} \frac{y_{it}}{y_{ust}} \qquad MD\_INC_{jt} = \sum_i e_{ijt}^{MD} \frac{y_{it}}{y_{ust}} \\ \text{where} \qquad e_{ijt}^{XM} &= \frac{\bar{e}_{ij} XM_{it}}{\frac{1}{I}\sum_i \bar{e}_{ij} XM_{it}} \qquad e_{ijt}^{MD} = \frac{\bar{e}_{ij} MD_{it}}{\frac{1}{I}\sum_i \bar{e}_{ij} MD_{it}} \end{aligned} \tag{8}$$

where $\bar{e}_{ij}$ was introduced in (7).

These instruments are to be used in first-differences. Hence changes in the weights e_{ijt}^{XM} and e_{ijt}^{MD} are instruments for changes in the weights in GROWTH and INCOME (e_{ijt}). Take e_{ijt}^{XM} as

an example: for industry j, it computes the exposure of trading partner i relative to that of the representative trading partner of the industry. The fundamental principle is that changes in XM_{it}, keeping constant all other $XM_{i't}$ ($i' \neq i$), cause changes in the weight of country i in the total trade of industry j (e_{ijt}). Meanwhile, the country-weights $\bar{e}_{ij}$ capture the notion that a rise in exposure of country i should have an effect on industry j that is proportional to the role of country i in that industry. Note that, since we are using time-independent weights for each country, we avoid the problem of having changes in skill-intensity affect the instruments. Hence changes in e_{ijt}^{XM} (and e_{ijt}^{MD}) should capture the effects of changes in the relative exposure of country partners on e_{ijt}, and be uncorrelated with changes in skill-intensity at the industry level.

The correlation of our constructed instruments with the GROWTH and INCOME variables range from 0.2 (for INCOME) to 0.8 (for GROWTH).

4 Econometric Results

4.1 Data

Following Feenstra and Hanson (1999), we use the average annual changes for all variables between 1979 and 1990, which coincides with two peaks of the business cycle. This period also coincides with the bulk of the rise in the wage-skill gap. The skilled labor-share, our measure of skill-intensity, was computed as the share of non production labor in total wages, obtained from the NBER Productivity Database (Bartelsman and Gray, 1996). This database spans the time period 1972-94 and covers 448 industries in manufacturing. On aggregate, the share of nonproduction labor in wages exhibits a growth rate of 0.38% per year between 1979 and 1990. Data on the industries' value-added and capital stock were also obtained from this database.

Our main data source for constructing our structural variables is the NBER Trade Database (Feenstra, 1996, 1997), which provides data on U.S. export and import values for the period 1972-94, at the 4-digit SIC level, on an aggregate as well as a bilateral basis. In the bilateral trade data, imports and exports of each industry are disaggregated by the source countries for imports

and destination countries for exports. This allows us to calculate the share of each country i in the openness of industry j at time t to be used as country-weight (e_{ijt}). GROWTH and INCOME were computed by combining these weights with country-data on 'GDP Per Capita Growth' and 'Real Per Capita GDP,' respectively, obtained from the Penn World Tables Version 6.1. The GDP growth measure was smoothed using a five-year moving average. Note that differences in the country weights generate industry-specific partner variables. We computed OPENNESS using measures of total industry exports, imports and shipments. Finally, for the instruments, country-level data on total import duties collected as a percentage of total imports (MD) and the country exposure (XM), was obtained from the World Development Indicators and the Penn World Tables, respectively.

"Rule of Law" was obtained from the International Country Risk Guide. The variable is measured on a scale of 0-6 with higher numbers indicating stronger legal institutions. It is available from 1984 onwards. However, given the slow process of institutional change, we used the 1984 value for the 1979-83 period.

Additional controls include measures of narrow outsourcing (OUTSNRW) and broad outsourcing (OUTSBRD) from Feenstra and Hanson (1999). They measure outsourcing by combining data on imports of final goods with data on total input purchases. They use data from the Census of Manufactures to obtain the value of intermediate inputs for each four-digit input industry, and multiply it by the share of imports in consumption in the input industry, to arrive at imported intermediate inputs. The broad measure of outsourcing looks at the sum over all input industries, as a share of total expenditure on non-energy intermediates. The narrow measure of outsourcing looks at the sum over the input industries in the same two-digit SIC code as the using industry, as a share of total expenditure on non-energy intermediates. According to the authors, the broad measure, when averaged over 'using' industries, has increased from 5.3% in 1972, to 7.3% in 1979 and 12.1% in 1990, while the values for narrow measure for the same period were 2.2%, 3.1% and 5.7%.

4.2 Regression Results

In this section, we estimate various versions of (6), using OLS and Instrumental Variables. In Table 1a, we present the summary statistics of the cross-industry distribution of key variables, while Table 1b presents their correlation. None of the correlation coefficients between pairs of independent variables seem particularly high.

Table 2a shows the regression results. All regressions use as weights the average over the period (1979-1990) for the industry's share in the manufacturing wage bill. The first column in the table reports the weighted means of the independent variables for 1979-90.[13] The remaining columns report the coefficients and standard errors, using OLS and IV estimation techniques.[14] Regressions 1-5 look at the role of GROWTH and INCOME, as drivers of skill-biased innovation and rising skill-intensity. Regressions using "Rule of Law" measures for institutional development have been omitted, for reasons of space, but are discussed below. Regressions 6-10 address the role of OPENNESS, testing for the irrelevance of trade volumes.

In Table 2b, we report the economic significance of our estimates, corresponding to each of the regressions in table 2a. For each regression, we compute the predicted contribution of the changes in each independent variable for the actual change in the non-production workers' wage share. This is obtained by multiplying the regression coefficients with the weighted mean for each independent variable (in the first column of Table 2a), and expressing the result as a proportion of the actual yearly change in the non-production workers' wage-share (our dependent variable).

Regressions (1) and (2) in table 2a show that GROWTH is an important contributor to the change in the non-production workers' wage share. The variable is strongly significant and, as expected, has a positive sign, suggesting that industries that have experienced an increase in the growth rate of its representative trading partner have seen a significant rise in skill-intensity.

[13] These means differ from those in Table 1, which are unweighted.

[14] For all instrumented variables, F-statistics of first-stage regressions are significant at 1% margin. These tables are available from the authors, upon request.

The coefficients obtained are also very significant, from an economic perspective, with the rise in growth rates of trading partners explaining around 20% of the increase in the non-production workers' wage share (see table 2b). The Hansen overidentification tests (p-value is reported), in the last row, fail to reject the hypothesis of overidentifying restrictions, confirming the validity of our instruments.

Comparing regressions (3) and (4), we see that the sign on relative INCOME of the representative trading partner on skill intensity changes from positive to negative when instrumental variables techniques are used. This suggests that OLS estimates are biased upward, as rises in skill-intensity cause an increase in the relative INCOME of the representative trading partner. In the IV estimates (regression 4), where this bias is corrected, the sign of the coefficient is negative, as predicted, suggesting that declines in the income of the representative partner have contributed to skill-deepening. However, the relationship is not statistically significant. This is also true when we include both GROWTH and INCOME, as shown in regression (5). Here, while we obtain a positive coefficient on GROWTH and a negative one on INCOME, only the coefficient on GROWTH is significant; moreover, the decline in INCOME of trading partners of US industries explains only 9% of the rise in skill-intensity, while the increase in GROWTH accounts for 20.5%. Hansen overidentification tests once again confirm the validity of our instruments. The weakening of the statistical and economic significance of INCOME, when GROWTH is included, arises because GROWTH already captures, at least in part, the 'output' of imitation activity by firms from countries with low income and weak IP protection.

Regressions 6-8 in table 2a add OPENNESS as an additional structural variable, where we also instrument for OPENNESS. OPENNESS is consistently non-significant, from a statistical perspective, for both OLS and IV estimation techniques. (We omit the OLS results). The coefficient is consistently negative, when GROWTH is included. We also experimented with measures of openness to subsets of countries, such as OECD countries and the developing countries, with the same results. In keeping with our discussion in the previous sections, our results confirm that

what matters for the burgeoning wage-skill gap is not the volume of trade but whom you trade with; and that it is trade with fast growing countries (such as those in East Asia) that is the main driver for the rise in skill-intensity.

Regressions using the RULE OF LAW proxy for the effectiveness of IP protection (not shown here) closely mimic those we obtained with INCOME. The correlation between the two proxies is 0.73. When RULE OF LAW is the only regressor, it has a negative sign but is not significant. In regressions that include both GROWTH and RULE OF LAW, it is GROWTH which is strongly significant.[15] Once again, trade volumes do not seem to play a significant role.

In terms of our control variables, we find evidence that capital and skilled workers complement one another. The narrow outsourcing variable of Feenstra and Hansen (1996) has a positive impact though its effect is weak in terms of statistical significance - in only one of the regressions is this variable significant. Remaining outsourcing is never significant and frequently has the wrong sign. The low statistical significance of these variables was already present in Feenstra and Hanson (1999). Despite the lack of statistical significance, their economic significance is high: even when GROWTH is included (in regressions 2 and 5) broad outsourcing (narrow plus other) contributes about 18-20% to the actual rise in skill-intensity. However, this value is lower than the original estimates in Feenstra and Hanson (1999). Finally, our model as a whole is very significant and on average explains more than 18% of the variation in the dependent variable.

Overall, the results show that a rising GROWTH rate of the representative trading partner is the key contributor to the rise in the share of nonproduction workers. The declining INCOME has also played a part, although its statistical significance is not very strong. The signs of these variables are in accordance with our hypothesis that US firms and industries, when exposed to the increased role of high-growth countries where aggressive firms benefit from a pro-imitation economic environment, have responded to the threat to their knowledge-based advantages with skill-biased, defensive innovation. They also confirm the prediction that the volume of trade

[15] These results are available from the authors upon request.

is not an important driver of skill-deepening. Meanwhile, the conclusions regarding the role of Outsourcing drawn by Feenstra and Hanson (1999) remain largely unaffected by the introduction of our variables.

4.3 Exports vs. Imports: Robustness

In constructing the GROWTH and INCOME variables, we used as weights each industry's aggregate trade ($exports + imports$) with country i as a share of total trade in that industry. In doing this, we followed Thoenig and Verdier (2003) who argue that imports and exports ought to contribute jointly to the skill-bias. For robustness, we redid our analysis using only exports as weights; and, subsequently, using only imports as weights.

We used both OLS and IV estimates. As instruments, we used variables similar to (8). The only difference was in the use of indicators of country exposure. For the industry-exports weighted regressions, we used the trading partner's volume of imports as a share of GDP and its import-duties as a share of total imports (MD) as indicators of the exposure to imports of its economy. For the industry-imports weighted regressions, the sole instrument used was the trading partner's exports as a share of GDP. For the latter, the system is just-identified so we are unable to evaluate the efficacy of the instruments using overidentification tests.

When partner characteristics are weighted by exports, our results are much stronger than when they are weighted by imports. With exports as weights, GROWTH is strongly significant (p-$value = 0.006$); with imports as weights, it is not statistically significant. In both cases it accounts for about 12% of the skill deepening. Hence, there is evidence that industries who export to rapidly growing countries are more likely to undertake defensive innovation than do industries that import from these rapidly growing economies. This may capture the threat endured by US exporters of knowledge intensive products (the comparative advantage of US firm) that reverse engineering will undermine their competitive position in export markets. On the other hand, regardless of the weights used, the variables capturing the IP protection in trading partners (INCOME and RULE

OF LAW) do not seem to have played an important role and remain insignificant in both the export-weighted and import-weighted regressions, when GROWTH is included.

5 The Role of Computer-intensity

The measure of technical change that has been most frequently used in the literature is investment in computers (see Berman, Bound and Griliches, 1994; Lawrence and Slaughter, 1993; Autor, Katz and Krueger, 1998). Berman et al (1994) attribute 40% of the change in nonproduction wage share to computer investments; Feenstra and Hanson (1999) find that this number drops to 34% once outsourcing is included. In addition, BLS case studies portray the dramatic impact of computers in most major innovations during the decade of 80s - the time period covered by our study. In our regression results in Tables 2a and 2b we did not include any measure of computer investments since investments in computers may itself be endogenous to changes in partner characteristics. In this section we explore this issue in greater detail.

We begin by including a measure of Computer Investment obtained from Berman et al. (1994), henceforth COMPUTERS, in the set of regressions in Table 2a. The results are shown in Table 3a. Even if COMPUTERS is endogenous to INCOME, GROWTH and OPENNESS, this should not bias our estimates. Rather, multicollinearity is more of a concern. Our results do not seem affected to any great extent. As in Table 2a we find that GROWTH has played a significant role in widening the wage skill gap, OPENNESS is insignificant as before, while INCOME has the right sign for the IV regressions but is rarely significant. In line with previous research, we find that COMPUTERS is always highly significant.

Table 3b is analogous to Table 2b and shows the contributions of the various variables to the rise in skill-intensity within-industries, over this time period. We can see that COMPUTERS accounts for 35-45% of the change in skill-intensity gap depending on the specification. Contrasting the coefficients and contributions in Tables 2b and 3b, we see that adding COMPUTERS reduces the contribution of GROWTH from 20% to about 17%, although it does not affect its statistical

significance. This fact, in conjunction with the significant coefficients on GROWTH, suggests that our structural variables have induced technical change partly independent of changes in computer investments. This is not surprising, since rising computer investment is only one of the elements of skill-biased technological change, although not the only one. Other examples include the increased relevance of branding, marketing, design and other components of knowledge management, which are only imperfectly correlated with computer investment. All these are elements that make imitation more difficult and which, as Thoenig and Verdier (2003) stress, gain increased relevance when the intensity of competitive imitation rises. From this perspective, our variables GROWTH and INCOME, should show up as accelerating skill-biased technical change partly through computer investments and partly independent of it.

To see the role of the rise in computer investment as a mediator of the effects of the intensity of international imitation on skill intensity, we use a two-stage approach. First, we regress COMPUTERS on GROWTH and INCOME, and decompose it into the predicted values (PRE-COMP) and the residuals (RES-COMP). Second, we use the two series thus obtained as structural variables in the original specification in (6). Once again, we use OLS and IV estimates in the first stage, using the instruments introduced previously.

The first stage OLS and IV regressions are shown in Table 4a. GROWTH has a positive and significant sign, while the sign on INCOME changes from positive to negative (but is statistically insignificant), once we instrument the variables. These results are in line with those of the previous section. Here, they suggest that industries that experienced an increase in the growth rate or a decline in per capita GDP of its average trading partner, also made greater investments in computers.

In Table 4b, we show the results of the second stage regression, using both the OLS and IV estimates of the first-stage (see table 4a). Our results show that both components of COMPUTERS have significantly contributed to a rise in the wage share of skilled workers. In all specifications, PRE-COMP is strongly significant. This indicates that changes in the relevant features of the

representative trading partners have contributed to an increase in investments in computer equipment, leading to a rise in skill intensity. Further adding the RES-COMP significantly improves the model both in terms of an increase in R^2 and in terms of the overall model test. Therefore, investments in computers have contributed to skill deepening independent of any changes in trading partner characteristics as well.

Our discussion in this section supports a more nuanced and plausible view of the relative importance of trade vs. technology for the skill-bias. First, changes in the GROWTH and INCOME of the representative trading partner have induced skill-biased technological change, partly through its influence in computer investments, but also through investment in other forms of tacit knowledge. Second, the investment in computers has complemented skilled workers and is a big part of the observed shift in skill-intensity, also in ways that are independent of any changes in trading partner characteristics.

6 Conclusion

Our paper argues that changes in trading patterns and partners of US manufacturing industries are an important contributor for the well-documented increase in their skill-intensity, over the 1980's, although we confirm well-established evidence that changes in the volume of trade are irrelevant for this phenomenon.

In particular, we find that industries whose trading partners have experienced a stronger acceleration in rates of economic growth have also suffered a more significant increase in the relative share of skilled-wages (skill-intensity). Controlling for changes in the industry's volume of trade, including trade in intermediate inputs (outsourcing), and for changes in the trading partners' level of development, we find that changes in the growth rates of the representative trading partner have accounted for approximately 20% of rise in skill-intensity, within US manufacturing industries, over 1979-1990. We show also that the changes in growth rates have increased skill intensity partly through increases in computer investments, which complement skilled workers, and partly through

investments in other forms of tacit knowledge that also make greater use of skilled workers.

Our motivation draws on the "theory of defensive innovation," recently developed by Thoenig and Verdier (2003). They argue that, when it raises the threat of competitive imitation, international trade induces skill-biased innovation, since such technologies are less imitation prone. We have argued that the rate of growth in a trading partner measures the actual 'output' of imitation activities by firms operating in that country, which is the key driver of the rise in productivity. Hence, US industries trading with high growth countries endure a stronger threat of competitive imitation from foreign firms, which induces them to engage in skill-biased, defensive innovation to protect their knowledge-based advantages.

7 References

References

Acemoglu, Daron (2002) "Directed Technical Change," *Review of Economic Studies*, volume 69. pp. 781-810.

Autor, David, Lawrence F. Katz, and Alan B. Krueger, "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, v. 113, (1998), 1169–1214.

Baldwin, Robert E., and Glen G. Cain, (2000) "Shifts in Relative U.S. Wages: The Role of Trade, Technology, and Factor Endowments," *Review of Economics and Statistics*, November 2000, v. 82, iss. 4, pp. 105-110.

Bartelsman, Eric J., and Wayne Gray, "The NBER Manufacturing Productivity Database," NBER Technical Working Paper No. 205, 1996.

Berman, Eli, Bound, John, and Zvi Griliches, (1994) "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics*, May 1994, v. 109, iss. 2, pp. 367-38.

Bernard, Andrew and J. Bradford Jensen. 1997. "Exporters, Skill Upgrading, and the Wage Gap," *Journal of International Economics*, v. 42: pp. 3-31.

Cortes O. and Jean S. (2000), "Trade Spurs Productivity," in *Globalisation and EmploymentPatterns*, edited by J. Francois, D. Roland-Holst and D. van der Mensbrugghe, Oxford University Press.

Desjonqueres, Thibaut, Stephen Machin, and John Van Reenen, (1997), "Another Nail in the Coffin? Or Can the Trade Based Explanation of Changing Skill Structures Be Resurrected?" v. 101, iss. 4, pp. 533-554.

Easterly, William and Ross Levine, (2001) "It's Not Factor Accumulation: Stylized Facts and Growth Models" World Bank Economic Review, v 15, N. 2

Feenstra, Robert C. (2003) *Advanced International Trade: Theory and Evidence*, Princeton and Oxford: Princeton University Press, 2004

Feenstra, Robert C. and Gordon Hanson, (2001) "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages", June 2001, in Kwan Choi and James Harrigan, eds., *Handbook of International Trade*, Basil Blackwell.

Feenstra, Robert C., and Gordon H. Hanson, (1999) "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990," *Quarterly Journal of Economics*, August 1999, v. 114, iss. 3 pp. 907-940.

Feenstra, Robert C., and Gordon H. Hanson, (1996) "Globalization, Outsourcing, and Wage Inequality," *American Economic Review*, May 1996, v. 86, iss. 2, pp. 240-245.

Freeman, Richard and Ana Revenga (1999). "How Much Has LDC Trade Affected Western Job Markets?" in Mathias Dewatripont, André Sapir, and Khalid Sekkat, eds. *Trade and Jobs in Europe: Much Ado About Nothing?* Oxford: Oxford University Press.

Grossman, Gene M., and Elhanan Helpman, (1991) *Innovation and Growth in the Global Economy*, Cambridge, Mass. and London: MIT Press, 1991.

Haskel, Jonathan E., and Matthew J. Slaughter, (2002) "Does the Sector Bias of Skill-Biased Technical Change Explain Changing Skill Premia?" *European Economic Review*, December 2002, v. 46, iss. 10, pp. 1757-1783.

Haskel, Jonathan E. and Matthew J. Slaughter, (2001) "Trade, Technology and U.K. Wage Inequality" *Economic Journal*, January 2001, v. 111, iss. 468, pp. pp. 163-187.

Krugman, Paul R. (2000) "Technology, Trade and Factor Prices," *Journal of International Economics*, February 2000, v. 50, iss. 1, pp. 51-71.

Lawrence, Robert Z., (2000)

Lawrence, Robert Z., (1998) *Brookings Trade Forum: 1998* edited by Robert Z. Lawrence, Brookings Institution Press.

Lawrence, Robert Z. and Matthew Slaughter, (1993) "International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup?" *Brookings Papers on Economic Activity*: Microeconomics 2, pp. 161-211.

Lerner, Josh (2002) "150 Years of Patent Protection" *American Economic Review Papers and Proceedings*, May 2002, v. 92, iss. 2, pp. pp. 221-225.

Lerner, Josh, (2000) "150 Years of Patent Protection," NBER Working Papers 7478, National Bureau of Economic Research, Inc

Thoenig, Mathias, and Verdier, Thierry (2003)"A Theory of Defensive Skill-Biased Innovation and Globalization," *American Economic Review*, June 2003, v. 93, iss. 3, pp. 709-728.

Sachs, J.D. and H.J. Shatz, (1994) "Trade and Jobs in U.S. Manufacturing," *Brookings Papers on Economic Activity,* v. 1, pp.1-65.

Wood, Adrian (1995) "How Trade Hurt Unskilled Workers," *Journal of Economic Perspectives*, Summer 1995, v. 9, iss. 3, pp. 57-80.

Wood, Adrian (1998) "Globalisation and the Rise in Labour Market Inequalities" *Economic Journal*, September 1998, v. 108, iss. 450, pp. 1463-1482.

Table 1a: Summary Statistics of Unweighted Variables (first-differences)

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
share of non-production workers in wages	418	0.38	0.48	-1.18	2.97
growth	418	5.10	6.31	-10.80	32.90
income	418	-0.05	0.20	-1.49	0.97
openness	418	4.92	5.40	-25.48	36.37
ln (K/Y)	418	0.53	3.12	-13.03	14.73
ln (Y)	418	0.35	3.75	-13.96	22.53
outsourcing (narrow)	418	0.16	0.48	-4.15	2.73
outsourcing (other)	418	0.21	0.34	-1.76	2.74
computer investments	418	5.61	5.52	0.00	43.48

Table 1b: Cross-industry Correlation of Unweighted Variables (first-differences)

Variable	*share of non-prod workers*	*growth*	*income*	*openness*	ln (K/Y)	ln (Y)	*outsourcing (narrow)*	*outsourcing (other)*
share of non-production workers in wages	1.00							
growth	0.15	1.00						
income	0.07	-0.13	1.00					
openness	0.05	0.18	-0.22	1.00				
ln (K/Y)	0.13	-0.07	0.05	0.17	1.00			
ln (Y)	-0.07	0.06	0.05	-0.22	-0.71	1.00		
outsourcing (narrow)	0.1	0.14	-0.07	0.10	0.14	-0.10	1.00	
outsourcing (other)	0.05	0.13	-0.11	0.20	0.00	0.05	-0.06	1.00
computer investments	0.18	0.25	0.05	0.02	0.09	0.07	0.18	0.20

Table 2a: Change in Nonproduction Wage Share (1979-90)

	Weighted Mean	OLS	IV	OLS	IV	IV	IV	IV	IV
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
growth	4.271	0.014**	0.017**			0.018**	0.018**		0.017**
		(0.007)	(0.009)			(0.01)	(0.009)		(0.009)
income	-0.021			0.168**	-6.162	-1.513		-0.39	-0.428
				(0.095)	(4.464)	(1.078)		(0.954)	(0.703)
openness	4.132						-0.018	0.02	-0.003
							(0.022)	(0.02)	(0.018)
ln (K/Y)	0.669	0.052***	0.053***	0.047***	0.144***	0.076***	0.051***	0.058***	0.059***
		(0.012)	(0.012)	(0.012)	(0.071)	(0.023)	(0.015)	(0.023)	(0.017)
ln (Y)	1.429	0.024***	0.024***	0.024***	0.108**	0.044***	0.019*	0.037***	0.029***
		(0.009)	(0.008)	(0.009)	(0.06)	(0.016)	(0.013)	(0.018)	(0.011)
outsourcing (narrow)	0.405	0.217	0.205	0.265*	0.245	0.196	0.25	0.211	0.211
		(0.158)	(0.162)	(0.173)	(0.227)	(0.166)	(0.224)	(0.178)	(0.198)
outsourcing (other)	0.196	0.051	0.044	0.091**	-0.315	-0.056	0.104	-0.013	0.027
		(0.046)	(0.051)	(0.052)	(0.305)	(0.083)	(0.11)	(0.108)	(0.079)
constant		0.201***	0.191***	0.252***	0.001	0.127*	0.253***	0.159**	0.185***
		(0.05)	(0.054)	(0.032)	(0.19)	(0.086)	(0.101)	(0.093)	(0.08)
N		418	418	418	418	418	418	418	418
Overall model test		14.76***	15.76***	14.22***	1.33	7.04***	14.64***	7.41***	12.03***
R^2		0.18	0.18	0.16	0.001	0.23	0.13	0.1	0.15
OID Test (p-value)			0.43		0.3	0.24	0.26	0.43	0.08

Standard errors in parantheses; *** - significant at 5% level, ** - significant at 10% level * - significant at 15% level

Table 2b: Contribution to Change in Nonproduction Wage Share

	OLS (1)	IV (2)	OLS (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
growth	15.96	19.38			20.52	20.52		19.38
income			-0.96	35.26	8.66		2.23	2.45
openness						-19.85	22.06	-3.31
ln (K/Y)	9.29	9.47	8.40	25.73	13.58	9.11	10.36	10.54
ln (Y)	9.15	9.15	9.15	41.20	16.78	7.25	14.11	11.06
outsourcing (narrow)	23.47	22.17	28.66	26.50	21.20	27.04	22.82	22.82
outsourcing (other)	2.66	2.30	4.75	-16.45	-2.92	5.43	-0.68	1.41
constant								

Table 3a: Change in Nonproduction Wage Share (1979-90)

	Weighted Mean	OLS	IV	OLS	IV	IV	IV	IV	IV
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
growth	4.271	0.012***	0.014***			0.015***	0.015***		0.014***
		(0.005)	(0.005)			(0.006)	(0.005)		(0.005)
income	-0.021			0.114	-4.537*	-0.976		-0.938	-0.518
				(0.089)	(2.88)	(0.800)		(1.098)	(0.659)
openness	4.132						-0.007	0.011	-0.004
							(0.021)	(0.016)	(0.015)
ln (K/Y)	0.669	0.033***	0.033***	0.028**	0.093***	0.047***	0.033***	0.043***	0.041***
		(0.014)	(0.014)	(0.014)	(0.035)	(0.014)	(0.014)	(0.019)	(0.013)
ln (Y)	1.429	0.007	0.007	0.007	0.063***	0.019**	0.006	0.022*	0.013
		(0.011)	(0.011)	(0.012)	(0.03)	(0.01)	(0.012)	(0.014)	(0.01)
outsourcing (narrow)	0.405	0.158	0.15	0.197	0.16	0.141	0.168	0.158	0.157
		(0.152)	(0.153)	(0.164)	(0.205)	(0.155)	(0.203)	(0.168)	(0.184)
outsourcing (other)	0.196	-0.063	-0.067	-0.035	-0.373*	-0.139*	-0.042	-0.153	-0.09
		(0.055)	(0.056)	(0.057)	(0.254)	(0.086)	(0.121)	(0.114)	(0.088)
computer investment	6.173	0.021***	0.021***	0.022***	0.029***	0.023***	0.021***	0.025***	0.022***
		(0.007)	(0.006)	(0.009)	(0.013)	(0.007)	(0.007)	(0.009)	(0.007)
constant		0.147***	0.140	0.187***	-0.018	0.095	0.163*	0.1	0.131**
		(0.049)	(0.049)***	(0.041)	(0.147)	(0.077)	(0.105)	(0.092)	(0.079)
N		418	418	418	418	418	418	418	418
Overall model test		19.81***	20.3***	22.89***	2.24**	13.64***	18.17***	9.11***	15.76***
R^2		0.24	0.24	0.22	0.002	0.23	0.23	0.12	0.21
OID Test (p-value)			0.26		0.49	0.2	0.22	0.54	0.06

Standard errors in parantheses; *** - significant at 5% level, ** - significant at 10% level * - significant at 15% level

Table 3b: Contribution to Change in Nonproduction Wage Share

	OLS (1)	IV (2)	OLS (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
partner growth	13.68	15.96			17.10	17.10		15.96
partner income			-0.65	25.96	5.59		5.37	2.96
exposure						-7.72	12.13	-4.41
ln (K/Y)	5.90	5.90	5.00	16.62	8.40	5.90	7.68	7.33
ln (Y)	2.67	2.67	2.67	24.03	7.25	2.29	8.39	4.96
outsourcing (narrow)	17.09	16.22	21.31	17.31	15.25	18.17	17.09	16.98
outsourcing (other)	-3.29	-3.50	-1.83	-19.48	-7.26	-2.19	-7.99	-4.70
computer	34.60	34.60	36.25	47.78	37.90	34.60	41.19	36.25

Table 4a: Computer Investments

	OLS	IV
	(1)	(2)
growth	0.23***	0.165**
	(0.075)	(0.087)
income	2.232**	-4.0
	(1.158)	(4.499)
constant	4.547***	4.571***
	(0.647)	(0.698)
N	418	418
Overall model test	7.85***	3.79***
R^2	0.07	0.03
OID Test (p-value)		0.19

Standard errors in parantheses

*** - significant at 5% level, ** - significant at 10% level * - significant at 15% level

Table 4b: Change in Nonproduction Wage Share (1979-90)

	Weighted Mean	(1)	(2)	(3)	(4)
ln (K/Y)	0.669	0.05***	0.031***	0.054***	0.034***
		(0.013)	(0.014)	(0.011)	(0.013)
ln (Y)	1.429	0.023***	0.006	0.028***	0.01
		(0.009)	(0.012)	(0.007)	(0.01)
outsourcing (narrow)	0.405	0.217	0.159	0.234	0.17
		(0.158)	(0.152)	(0.164)	(0.156)
outsourcing (other)	0.196	0.059	-0.055	0.049	-0.069
		(0.047)	(0.055)	(0.044)	(0.055)
computer investment (predicted)	5.117	0.06**	0.073***	0.051**	0.068***
		(0.031)	(0.024)	(0.029)	(0.024)
computer investment (residual)	1.057		0.021***		0.022***
			(0.007)		(0.008)
constant		-0.067	-0.082	-0.023	-0.059
		(0.183)	(0.13)	(0.171)	(0.129)
N		418	418	418	418
Overall model test		15.41***	20.18***	11.65***	18.24***
R^2		0.18	0.24	0.17	0.23

Standard errors in parantheses; *** - significant at 5% level, ** - significant at 10% level * - significant at 15% level