With Whom do You Trade?

Defensive Innovation and the Skill-bias

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Abstract

This paper tests the hypothesis that increased trade with countries with weak or ineffective protection of intellectual property has contributed to the skill deepening of the 1980s. We draw on Thoenig and Verdier's (2003) theory that the threat of competitive imitation from countries where the protection of intellectual property rights (IPR) is low promotes skill-biased strategies and technologies, which are less likely to be imitated. We first construct an index of effective protection of intellectual property at the country level, combining data on the statutory protection of patents and the rule of law (as a proxy for enforcement). Next we construct an industry-specific version of this index, using as weights each country's trade share in the total trade of industry. We find an important and pervasive decline in this trade weighted index, due to a rise in trade with countries with a low effective protection of intellectual property, which explains 29% of the rise in within-industry skill intensity.

Keywords: Trade and Wages, Skill Bias, Defensive Innovation,
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1 Introduction

Since the late 1970s, we have witnessed a shift in the demand for labor toward more-skilled workers in many industrialized nations, and a consequent worsening in the economic position of low-skilled workers relative to high-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 (e.g. the increased use of computers), as well as on rising outsourcing (Feenstra and Hanson, 1999). However, a number of authors, starting with Wood (1995), have made the argument that skill-biased strategic and technological options of US firms, themselves, might itself be a consequence of trade related phenomena.

Recently, based on the notion that more skill-intensive technologies might emerge as "defensive innovation" to protect against the threat of competitive imitation, Thoenig and Verdier (2003) have suggested that globalization might have contributed to the skill-deepening by heightening this threat.[2] In particular, they argue that trade with countries with weak IPR regimes, where firms find it easy to engage in competitive imitation, is a strong inducer of "defensive", skill-biased innovation by home firms. This paper explores the extent to which an increased threat of competitive imitation due to trade with countries with weak IPR protection has contributed to the skill-deepening of the 1980's, in the United States.

[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.

[2] Thoenig and Verdier (2003) argue that skill-intensive technologies feature tacit knowledge and non-codified know-how, which, by reducing informational leakages and spillovers, lessen the chances of being imitated and provide a more lasting, knowledge-based competitive advantage.

The extent of the rising threat competitive innovation to US firms is explicitly acknowledged in the US government's export portal, which states that "globalization and the rapid proliferation of technology have elevated the importance of intellectual property protection." Its efforts to contain it include initiatives such as the "IP toolkits" provided to US companies in markets like China, Russia, India, Mexico, Korea, Malaysia, and Taiwan or the diplomatic push for stronger IPR protection in regional trade agreements. Despite such initiatives, the U.S. Trade Representative Office calculates that fake products - such as CDs, DVDs, software, electronic equipment, clothing, pharmaceutical products, and auto parts - account for an estimated 5 to 7% of global trade and expose US firms to billions of dollars worth of losses. In such an environment, US firms trading with these countries clearly have incentives to further protect themselves by investing in harder-to-imitate skill-biased technologies.

To measure the effectiveness of the protection of intellectual property in the trading partners of US industries, we take into account the extent to which the protection of intellectual property is codified into law and the degree to which the (intellectual property) law is enforced. We capture these two components using, respectively, the Index of Global Patent Protection ($IGPP$) (Ginarte and Park, 1997 and Mahadevanvijaya and Park, 1999), which measures the coverage of legal patent protection in national laws, and the Rule of Law measure from the International Country Risk Guide ($ICRGRLW$). We construct an index for the effectiveness of protection of intellectual property ($IEPIP$), for the trading partners of US manufacturing industries, as the product of the country indices for Global Patent Protection and ICRG's Rule of Law.

In their model, Thoenig and Verdier (2003) show that the emergence of trade with a country where firms represent a stronger potential for competitive imitation, due to the ineffective protection of IPRs, leads to the adoption of more skill-intensive technologies by the home firm. A straightforward implication is that the lower is the $IEPIP$ in a trading partner, the stronger is the skill-deepening caused by "defensive innovation". In this paper, we posit that, in a world with many trading partners with varying degrees of IPR protection, the threat of competitive imitation faced by a home firm can be captured by averaging the $IEPIP$ across trading partners, using bilateral trade volumes as weights. Hence we establish the notion that the IPR protection in major trading partners is more relevant for the "defensiveness" decision of home firms, than the conditions in less significant partners. An important implication is that shifts in trading patterns that increase the relative weight of countries with ineffective IPR regimes heighten the threat of competitive imitation and contribute to skill-deepening.[3]

Our analysis takes place at the industry-level. For each industry, $IEPIP$ is calculated as a weighted average of the $IEPIP$ of each trading partner, using as weights the share of bilateral trade with the country. Our proposition is that industries that experience a stronger decline in their $IEPIP$, either due to a fall in the effectiveness of IPR protection in trading partners or because the pattern of trade has shifted to increase the weight of countries with lower IPR protection, should experience a more pronounced skill-deepening. To enable a comparison with existing studies, we use the well-established empirical framework of Berman, Bound and Griliches (1994) and Feenstra and Hanson (1996, 1999), which we extend to assess the role of changes in the industry-level $IEPIP$ for the skill-deepening.

Our results show that the decline in $IEPIP$ is a statistically significant driver of the skill-deepening, explaining 29% of the rise in skill-intensity, when measured against the variables previously addressed in the literature.[4] The result holds even when we control for income per head, showing that the $IEPIP$ does not just capture the level of development of trading partners. We also test two decompositions of the changes in the $IEPIP$. First, we show that our index performs much better than its individual components (i.e. the rule of law and the coverage of patent law) by themselves, highlighting the complementary of the individual components. Second, we find that

[3] In their model, Thoenig and Verdier (2003) argue that the volume of trade does not matter for the threat of competitive imitation from a given country. Our results confirm that the volume of trade is not a significant driver of the skill-deepening. However, this paper implies a more nuanced interpretation where an exogenous rise in the relative weight of a given trading partner enhances the relevance of its institutional environment for the decision of home firms, at the expense of those countries whose trade weights decline.

[4] Our preferred regression includes controls that confirms the role of changes in industry-level Outsourcing (Feenstra and Hanson, 1999) and Computer Investment (Berman, Bound and Griliches, 1994).

changes in trade weights toward low $IEPIP$ countries are much more important in explaining the skill-deepening than changes in country-specific $IEPIP$ in each trading partner. Finally, we fail to find conclusive evidence that country-specific enablers of competitive innovation, such as the share of the population with higher education, magnify the impact of low $IEPIP$'s as inducers of defensive innovation by US firms.

2 Trade and Skill-Biased Innovation

The rise in the wage-skill gap of the 1980s coincided with a dramatic growth of trade, particularly with developing nations. Therefore, the effort to investigate the causal relationship between these two phenomena and identify its drivers has attracted an extensive literature. For most authors, the industry-wide skill-deepening undermined the role of Stolper-Samuelson effects, making skill-biased innovation, not trade-driven effects, the main culprit. Recently, however, researchers have begun to argue that trade may have played an indirect role by fostering the skill-deepening through skill-biased innovation.

Wood (1995) was the first to stress that technical change could be biased towards skilled labor as an endogenous reaction of developed country firms to trade with low-wage countries.[5] First, 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". Second, Wood (1998) also made the case 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.[6] Paradoxically, as a first-order

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

[6] 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)

effect, this implies an expansion of these industries, which should increase the demand for unskilled workers and contribute to a decline in the skill-premium. The possibility that a perverse price-effect - due to an inelastic demand for less skill-intensive goods - would reduce profitability of less skill-intensive industries 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.

Recently, Thoenig and Verdier (2003) have provided the underpinnings for a theory of *factor-biased* defensive innovation. They argue that some technologies feature tacit knowledge and non-codified know-how, which, by reducing informational leakages and spillovers, lessen the chances of being imitated. These include technological developments that make reverse engineering more difficult, but also investments in marketing, branding or certification that differentiate products from those of imitators. These "defensive" strategies have in common, a strong need for highly skilled engineers, marketers or developers, i.e. they are skill-biased in nature. In their model, home firms react by engaging in "defensive", skill-biased innovation strategies to protect their knowledge advantages, when faced with an increased threat of competitive imitation, arising, for example, from increased trade. Although competitive imitation is ultimately determined by the actions of firms in foreign countries, they argue that the weakness of the protection of intellectual property in trading partners is an enabler of these actions, and enough to encourage skill-biased innovation. It could actually be argued that the threat of imitation implicit in the institutional environment in trading partners is likely to trigger preemptive skill-biased defensive innovation, even before competitive imitation by local firms occurs. The emergence and/or rise in trade with a country where the protection of IPR is ineffective increases the risk of imitation. This, in turn, may induce skill-biased, "defensive" innovation, with a concomitant rise in the demand for skilled

for the US; Cortes and Jean (2000) for the US, France and Germany; Haskel and Slaughter (2001), for the UK.

workers and increasing skill-intensity over time in each industry. Our paper tests this skill-biased, “defensive” innovation as a reduced-form relationship and assesses its relevance in explaining the skill-deepening during the 1980’s in the United States.[7]

In a related paper, Bernard, Jensen and Schott (2006) show that increased import-penetration from developing countries (those with less than 5% of US per capita GDP) raises the probability of death (more than import-penetration from other nations), and that this effect is stronger in less skill-intensive plants. Relying on the notion that more skill-intensive plants produce more skill-intensive products, the authors draw on comparative advantage theory to explain their findings. An alternative explanation, closer to this paper, is that the stronger survival rate of skill-intensive plants is part of a strategy by firms to deter competitive imitation. This might explain the authors’ additional finding that industry-switchers move to higher and lower skill-intensity sectors with statistically indistinguishable odds. In another related paper, Gancia and Bonfiglioli (2008) argue that US industries experiencing increased import-penetration from low-wage, low IPR countries will see a decline in R&D and in innovation, due to the fears of competitive imitation. They too present supportive evidence.

3 Empirical Strategy

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 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 (Feenstra, 2003).

The starting point in this methodology is to consider a short-run cost function, which is the

[7] Thoenig and Verdier (2003) also show, in their model, that increased technological competition due to trade with other technologically leading countries should foster skill-biased innovation, because skill-intensive technologies are harder to imitate and less likely to be leapfrogged. Addressing this link is beyond the scope of our paper and remains a challenge for future work. Moreover, since these effects are not dependent on the effectiveness of IPR protection in trading partners, they are unlikely to bias our results.

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 with respect 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)

$$S_{jt} \equiv \frac{q_{jt}H_{jt}}{C_{jt}} = \alpha_j + \gamma_j(\ln q_{jt} - \ln w_{jt}) + \phi_{kj} \ln K_{jt} + \phi_{yj} \ln Y_{jt} + \beta_{zj} z_{jt} + \beta_{dj} d_j \tag{1}$$

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.[8] 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 (1) is often estimated from data on a panel of industries. We can eliminate the industry fixed-effect (d_j) and simplify the estimation, by taking the first-difference of (1). Since this yields a cross-sectional data set, we can drop the time subscript and write:

$$\Delta S_j = \beta_z \Delta z_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0 \tag{2}$$

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) $\beta_0 = \gamma\Delta(\ln q - \ln w)$

[8] 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".

is a constant that emerges from ignoring the industry-variation in factor prices.[9] 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, (2) can be estimated with different sets of structural variables (z_j), including an industry measure of the aggregate threat of competitive imitation from trading partners. S_j, 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). Data on the industries' value-added and capital stock were also obtained from this database. Following Feenstra and Hanson (1996, 1999), we use the average annual changes for all variables between 1979 and 1990, which coincides with two peaks of the business cycle, and estimate the resulting cross-industry regression. Overall, we use exactly their specification and variables as the baseline specification, and examine the role of IP protection for skill-deepening at the industry level.

4 Measuring the Threat of Competitive Imitation

4.1 Patent laws and Enforcement

We capture the threat of competitive imitation, by constructing an index of effective protection of IPR. Our index encompasses two complementary components: first, the existence of a legal framework for the protection of intellectual property and, second, the effective and affordable implementation of such legal framework by the authorities, in what is often addressed as the rule of law (Grossman and Lai, 2004). Each element, may be necessary, but is not sufficient to ensure US firms against the threat of competitive imitation. In essence, the threatened firm must know that there is a law it can turn to, and that law will be implemented fairly and at an appropriate cost. On its own, neither of these components will make a difference: if there is no legal protection, there is no law to reach out to; if there is no rule of law, it is simply not enforced.

[9] 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 use data from the International Country Risk Guide to measure the Rule of Law ($ICRGRLW$), and the Index of Global Patent Protection ($IGPP$) from Ginarte and Park (1997) to measure the protection of intellectual property codified in the law. The $ICRGRLW$ constitutes a survey-based measure that captures the strength and impartiality of the enforcement of the legal system in a country, including respect for property rights. The variable is measured on a scale of 0-6 with higher numbers indicating stronger legal institutions. It is available from 1982 onwards. By using this measure, we are assuming that the impartiality and affordability of the enforcement of patent law can be captured by the overall enforcement of the rule of law in the economy. The Rule of Law data and this data source has been used extensively in the literature on the role of institutions in economic development.

The $IGPP$ (Ginarte and Park, 1997) was constructed by examining national patent laws. The index ranges from 0 to 5, with higher numbers reflecting stronger protection levels. The value of the index is obtained (per country, per time period) by aggregating scores in five equally-weighted categories: (1) extent of coverage, (2) membership in international patent agreements, (3) provisions against loss of protection, (4) enforcement mechanisms, and (5) duration. This index is available from 1960 to 1995, at five year intervals. Previous empirical work has made use of the $IGPP$ index to examine the characteristics of patent protection (Lerner, 2002), the effect of IPR rules on FDI (Javorcik, 2004), on sectoral growth across countries (Claessens and Laeven, 2003), on firm size (Kumar, Rajan and Zingales, 2004), and patent rules as barrier to exports (Smith, 1999).

The cross-country correlation coefficient between both indices is around 0.41 - a relatively high number, showing that countries with higher protection of IPR also have a strong rule of law. There are, nevertheless, some remarkable outliers, like Nigeria, Ghana or Zambia, where the statutory protection of patents is relatively high, due to the similarity of patent laws with the former European colonizers, but where the rule of law is weak. In contrast, countries like Venezuela, Papua New Guinea, Madagascar, or Mexico show levels of Rule of Law that are considerably above average, whereas their Patent Protection is relatively low. Our proposition states that, for different reasons, all these countries fail to qualify for the effective protection of intellectual property, and should represent focal points in the threat of competitive imitation for US firms trading with them.

Our analysis focuses on the 1980's, which was the period of acceleration of skill-deepening by US manufacturing industries. During this period, the mean $IGPP$ grew only slightly from 2.38 in 1980 to 2.43 in 1990 (a rise of only 2%). In our sample, 16 countries (17%) saw an increase in the $IGPP$ (with an average rise of 0.39), while 4 (4%) saw a decline in their rating (with an average fall of -0.24). In sum, there was only a minor and not very pervasive rise in the protection of patents around the world in the 1980s.[10] For $ICRGRLW$, the mean also barely changed between 1982, the first year when data is available, and 1990 - it declined 3% from 3.08 to 2.99. However, the changes were more varied across countries. In this period, 18 countries (19%) saw an increase in the Rule of Law (with an average rise of 0.79), and 25 (26%) saw a decline (with an average of fall -0.93). Finally, the cross-country correlation between the changes in the $IGPP$ (1980-1990) and the $ICRGRLW$ (1984-1990) was -0.1, showing that the evolution of both variables across countries in the 1980's was statistically independent.

4.1.1 The Index of Effectiveness of Protection of Intellectual Property (*IEPIP*)

Since the threat of competitive imitation depends on the both legal environment and the enforcement, we define our Index of Effectiveness of Protection of Intellectual Property ($IEPIP$), for country i at time t as:

$$IEPIP_{it} = IGPP_{it} * ICRGRLW_{it} \tag{3}$$

This formulation captures the complementarity described above. It implies that an increase in the strictness of the law (captured by the $IGPP$) has a stronger effect, if the rule of law ($ICRGRLW$) is stronger; while an increase in the rule of law, has a stronger effect when the protection of patents

[10] Note that the dramatic changes in intellectual property brought about by the Uruguay round are not covered in the period of the data.

is stricter. On the other hand, $IEPIP$ is zero if either $IGPP$ or $ICRGRLW$ are zero.

We computed the $IEPIP$ for 1980, using the data for $ICRGRLW$ in 1982, and for $IGPP$ in 1980. Data for 1990 is available for both measures. The mean $IEPIP$ has increased negligibly from 7.96 to 8.00. It has risen for 28 countries (30%) and fallen for 23 (25%) others. The correlation coefficient between changes in the $IEPIP$ and changes in $ICRGRLW$ is 0.85, whereas the correlation with changes in $IGPP$ is 0.19. This implies that countries that have changed their potential for competitive imitation of US firms, for the better or for the worse, have done so mostly due to changes in the rule of law.

In sum, while the average index for the effectiveness of patent protection has barely changed during the 1980s, there are some changes across different countries. From the perspective of US firms and industries, the effects of the $IEPIP$ may arise due to changes in patterns of trade across trading partners or because the trading partners themselves change their IPR environment.

Next, we move to the industry level and calculate an industry-specific measure of $IEPIP$. This industry-specific variable for the representative trading partner of industry j - $IEPIP_j$, is constructed as follows:

$$IEPIP_{jt} = \sum_i e_{ijt} IEPIP_{it} \qquad e_{ijt} = \frac{\mathrm{Exp}_{ijt} + \mathrm{Imp}_{ijt}}{\sum_i \mathrm{Exp}_{ijt} + \sum_i \mathrm{Imp}_{ijt}} \tag{4}$$

where as before i is an index for country and t for time. That is, for each industry we construct a weighted average of the country-specific $IEPIP's$ with each country's weight equal to its share in the total trade of industry j.[11] Note that differences in the country-weights generate industry-specific variables. Moreover, changes in each industry-specific index can now be due to changes in the original index, at the level of countries, or to changes in the direction of trade flows of US industries.

[11] 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 industry data on Exp_{ijt} and Imp_{ijt} for each of these measures are obtained from 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.

While the mean $IEPIP$ for the trading partners of US industries barely changed during the 1980's, there was a substantial decline of the industry-specific index for most industries. The un-weighted mean of the $IEPIP$ across countries ($IEPIP_{it}$) increased by 0.5%, while the cross-industry average of the trade weighted index ($IEPIP_{jt}$) fell by 5.4%. Figure 1 shows a histogram of the change in $IEPIP$ between 1979 and 1990 across industries. We see a decline in $IEPIP$ for almost all industries at the 4-digit SIC code (it declined for 80% of US industries). This clearly points to an increased role of trade with countries with weaker effectiveness of IP protection.

Table 2 summarizes, for the 418 industries for which data is available, the cross-industry distribution of the changes in the $IEPIP$. For comparison, we also calculated similar, industry-specific measures for the rule of law ($ICRGRLW_{jt}$) and the patent protection ($IGPP_{jt}$), for the early and late 1980's, and provide data on the changes in these variables, as well as on their correlation. For all indices, there has been a decline in the cross-industry mean. This is due to an increase in trade with countries with lower indices for US manufacturing industries, since, at the country level, the indices have increased, even if only slightly, on average. The actual magnitude of the decline is similar across the three indices.[12] This trend captures a shift in the pattern of trade of US industries toward developing countries.

Our empirical strategy is to include $IEPIP$ among sets of structural variables (z_j) in (2), to capture the threat of competitive imitation from an industry's trading partners. Our proposition is that industries that experience a stronger decline in their $IEPIP$, either due to a fall in the

[12] An online appendix available at http://faculty.insead.edu/dutt/imitate/ provides more details on the construction of these indices, including summary statistics and country coverage of the individual measures.

effectiveness of IPR protection in trading partners or because the pattern of trade has shifted to increase the weight of countries with lower IPR protection, should experience a more pronounced skill-deepening. Next we address the additional controls, which include previously established drivers of the US skill-deepening of the 1980's or potential correlates whose omission might bias the coefficient of $IEPIP$.

4.2 Controls

4.2.1 Outsourcing

Feenstra and Hanson (1999) have shown that trade in intermediate goods, has affected the skill-intensity within industries. Therefore, we include their measure of outsourcing (OUTS) in our estimates. 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 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.[13] According to the authors, when averaged over 'using' industries, this measure grew from 3.1% in 1979 to 5.7% in 1990.

4.2.2 Per Capita Income

Because developing countries exhibit ineffective protection of IPR[14] and are relatively abundant in unskilled labor, the effects of the $IEPIP$ may capture the impact of unskilled labor abundance in trading partners on the skill deepening, through comparative advantage and specialization effects (see, for example, Bernard, Jensen and Schott, 2006). To control for this, we use income per

[13] They compute also a broad measure of outsourcing that looks at the sum over all input industries, as a share of total expenditure on non-energy intermediates. We use both their 'narrow' and 'other' outsourcing measure in our regression.

[14] Lerner (2002) 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.

capita of an industry's trading partners (*income*) as a proxy for abundance in unskilled labor, as often assumed in the literature. Following the weighting procedure identical to (4), we construct an industry-specific measure of income per capita as a weighted average of the income per capita of trading partners. If an industry has suffered an increase in skill-intensity because of a relative shift toward unskilled abundant partners, this should be captured by our income variable. Data on 'Real Per Capita GDP' was obtained from the Penn World Tables Version 6.1.

4.2.3 Openness

Previous efforts to look at the role of trade variables for the factor-bias of technological change have focused on the effect of trading volumes. Most studies have found that measures of trade intensity (openness, export-intensity, import-penetration), on aggregate, with developing countries, or even with subsets of this group, fail to explain the change in skill-intensity (Lawrence, 2000; Desjonqueres et al. 1997).[15] Thoenig and Verdier (2003) argue, 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.[16]

To keep in line with the literature, we add to our benchmark specification, a measure of log-openness of the industries, defined as the log of exports-plus-imports divided by shipments. Openness is also computed from the NBER Trade database, using measures of total industry exports, imports, and shipments. This measure can be obtained as an overall index, that includes all trading partners of US industries, or for specific groups, such as OECD and developing countries.

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

[16] 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.

We expect the significance of these measures of openness to be low, in line with previous literature.

4.2.4 Computer Investment

We account for the possibility that innovation in the 1980's has been inherently skill-biased, particularly in the wake of increased automation and computer intensity. This view has been pervasive in the literature, which has used a measure of computer investment to control for the role of technological change as a driver of the skill-bias (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 non-production 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. Industry data for Computer Investment in the 1980's is from Berman et al. (1994).

According to our theory, rising Computer Investment can emerge endogenously as a form of defensive innovation. As a result, accounting for the impact of Computer Investment is likely to reduce the size of the coefficients of the IPR variables, which now capture their impact on defensive innovation through strategies other than rising computer intensity.

Table 2 provides summary statistics and correlations for all variables.

4.3 Endogeneity and Instruments

While the institutional environment of each trading partner is likely to be exogenous, a worrying possibility is that an industry's trade patterns may be affected by its skill intensity. In other words, the weights e_{ijt} used in the construction of the industry-specific $IEPIP_j$ may be endogenous to the skill intensity in industry j. In particular, it can be argued that industries with a higher skill-intensity, producing more high-tech, knowledge intensive goods, are more likely to trade with countries with a high $IEPIP$, to prevent their knowledge advantages from being squandered. From this perspective, an increase in skill-intensity leads to a shift in trading patterns that raises the industry's $IEPIP_j$. This would bias our estimates of the impact of $IEPIP_j$ on skill-intensity upward. Similarly, high skill-intensity industries, producing knowledge intensive goods are prone to trade with higher income countries, where demand for these products is stronger. As a result, our estimates of the impact of INC_j on skill-intensity may also be biased upward.

We use instrumental variables estimation to address these concerns. To construct appropriate instruments, we pursue 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. We use three measures of a trading partner's exposure as instruments: total import duties collected as a percentage of total imports from the World Development Indicators (MD), the un-weighted average external tariff data from the World Bank (UT) and the share of global exports of the trading partner, available at the industry level from UNIDO (SX).[17]

To obtain operational instruments, we construct industry-specific variables, using the three measures of exposure of trading partners mentioned before. Hence we derive three instruments for each of the industry-specific aggregate variables. Using $IEPIP_j$ as an example, we obtain:

$$\begin{aligned} XX\_IEPIP_{jt} &= \sum_i e_{ijt}^{XX} IEPIP_{it} \qquad (5) \\ \text{where} \quad e_{ijt}^{XX} &= \frac{\bar{e}_{ij} XX_{ijt}}{\frac{1}{I}\sum_i \bar{e}_{ij} XX_{ijt}} \qquad \text{and } \bar{e}_{ij} = \frac{1}{T}\sum_t e_{ijt} \\ \text{with } XX &= MD, UT \text{ and } SX \end{aligned}$$

Similar instruments are computed for INC_j.

These instruments are to be used in first-differences, i.e. we use changes in UT_IEPIP_{jt} and MD_IEPIP_{jt} and SX_IEPIP_{jt} between 1979 and 1990 to instrument for the changes in

[17] Note that, unlike the other two instruments, the share of global exports is an industry-country-specific variable. The data are from the UNIDO database which provides annual data on exports for 28 manufacturing sectors for 183 countries over the time period 1979-2001. We used this data to calculate each trading partner's export share. The data at 3-digit ISIC rev. 2 was assigned by authors to the 4-digit SIC72 classification of the NBER Trade Database.

$IEPIP_{jt}$ in (2). Hence changes in the weights e_{ijt}^{UT}, e_{ijt}^{MD} and e_{ijt}^{SX} are instruments for changes in the weights in $IEPIP_{jt}$ (e_{ijt}). Take e_{ijt}^{UT} as an example: for industry j, it computes the tariff of trading partner i relative to that of the representative trading partner of the industry. The fundamental principle is that changes in UT_{it}, keeping constant all other $UT_{i't}$ ($i' \neq i$), changes 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 the tariff 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}^{UT} (and e_{ijt}^{MD} and e_{ijt}^{SX}) should capture the effects of changes in the country partners on e_{ijt}, and be uncorrelated with changes in skill-intensity at the industry level.

5 Results

Given the econometric framework developed, and the variables outlined, we estimate variations of the following specification

$$\Delta S_j = \beta_P \Delta IEPIP_j + \beta_I \Delta INC_j + \beta_O \Delta OPEN_j + \beta_S \Delta OUTS_j + \beta_C \Delta COMP_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0 \tag{6}$$

using weighted instrumental variables techniques, with the instruments as discussed above and weights as the average (for 1979-1990) of the industry's share in the manufacturing wage bill. According to our discussion, the expected signs for the main coefficients are: $\beta_P < 0$ - capturing the threat of competitive imitation, , $\beta_S > 0$ and $\beta_I < 0$ - capturing the impact of the outsourcing of unskilled intensives elements of the value chain and trade with low-income countries, and $\beta_C > 0$ - capturing the role of computer investment. For β_O Thoenig and Verdier (2003) see a more nuanced role. That is, it is the composition of trading partners captured via β_P rather than the overall volume of trade that matters. However, an insignificant coefficient on β_O is certainly compatible with their theory.

Table 3a shows the weighted mean of the change in each variable (in the first column) and the regression results for the OLS and IV estimates, while Table 3b reports the economic significance of these estimates, obtained as the predicted contribution of the changes in each variable to the change in the dependent variable. The latter is obtained by multiplying the regression coefficients by the weighted mean for each independent variable (both in Table 3a), and expressing the result as a proportion of the dependent variable.[18]

Column 1 presents the OLS estimates. The coefficient on $\Delta IEPIP$ is positive, but statistically insignificant. Recognizing that the endogeneity of each industry's trade patterns may bias the OLS coefficient upward, column 2 instruments $\Delta IEPIP$ using the three instruments listed in the previous section. The IV regressions confirm our predictions. Now, the coefficient on $\Delta IEPIP$ is negative and significant. Given the presence of a clear bias in the OLS estimates, henceforth we will present and discuss only IV estimates. This result implies that industries that experienced a rise in trade with countries with weaker IP regimes ($\Delta IEPIP_j < 0$) exhibited a more significant rise in skill-intensity, as predicted by the arguments in Thoenig and Verdier (2003).

In column 3, with the introduction of Computer Investment, the coefficient of $\Delta IEPIP$ declines, as expected, but continues to remain negative and significant. The contribution of $IEPIP$ is quite important, reaching 29%, even when Computer Investments is introduced. As in Feenstra and Hanson (1999) narrow outsourcing contributes to skill deepening. The contribution of Outsourcing (around 20%) is lower than the contribution of $IEPIP$, and lower than the original contribution estimated by Feenstra and Hanson (1999), although the significance of our estimates is considerably higher than theirs.

Next, the results in column 4 shows that trading volumes, in terms of sheer size are irrelevant - the coefficient on Openness is insignificant. Moreover, its inclusion does not affect the coefficients

[18] These means differ from those in Table 2, which are unweighted. Table 3a also reports the F-test of excluded instruments for the corresponding first-stage regression. The F-statistic is close to or exceeds 10 as recommended by Staiger and Stock (1997). Hansen-Sargan tests of overidentifying restrictions (the p-value of this is reported on the last row of Table 3a) confirm that our instruments are valid, i.e., they are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.

or significance of other variables. We also experimented with measures of openness to subsets of countries, such as OECD countries and the developing countries, with the same results. This result confirms our prediction that what matters for the burgeoning wage-skill gap is not the overall volume of trade in an industry but with whom it trades.[19] Finally, column 5 adds as an additional control, the income of trading partners - this variable is not significant, and its inclusion does not affect the coefficient of our variable of interest. In other words, IPR variables are not simply capturing the rising role of poor, developing countries in US trade.

Overall, our results show that a decline in the $IEPIP$ at the level of US manufacturing sectors, driven fundamentally by a change in their trade patterns, has been an important force in driving the rise in skill-intensity across industries. Our results support the notion that US industries have increased skill-intensity to safeguard their intellectual property, due to rise in trade with countries where the effective protection of such intellectual property cannot be taken for granted (Thoenig and Verdier, 2003). The results suggest also that this effect is an additional driver of the rise in skill-intensity, since the established role of Outsourcing is not undermined by this new explanation.

6 Decomposing changes in *IEPIP*

6.1 Rule of Law vs. Patent Laws

This section tries to assess how the $IEPIP$ performs against alternative combinations of its components: the $IGPP$ (coverage of patent laws) and the $ICRGRLW$ (rule of law). The aim is to test the complementarity between the coverage and enforcement of the law as captured in the $IEPIP$. The high correlation between the three measures (see Table 2) raises difficulties in the significance of our estimates, due to multicollinearity. Moreover, the endogeneity concerns raised above with $\Delta IEPIP_j$ should extend to its components, namely $\Delta IGPP_j$ and $\Delta ICRGRLW_j$,

[19] Thoenig and Verdier (2003) use a similar measure of openness and find that it is a significant variable in explaining skill-deepening at the firm level. However, they acknowledge that their empirical implementation is not a direct test of their theory and that what they show is simply a high correlation between skill-intensity and openness. Further, they acknowledge that this correlation may be explained by other theories Moreover, in their empirical implementation, the specification that includes firm fixed-effects and looks at changes *within* firms, the coefficient on openness fails to be significant. Our empirical methodology also captures *within* effects, albeit at the industry level.

and we have obtained appropriate instruments using the methodology introduced in (5).

The individual significance tests in columns 2-6 of Table 4 clearly show the complementarity between the coverage and enforcement of patent protection, which are significant drivers of the skill bias only their product is used.[20] When entered separately, we find that $IGPP$ is only marginally significant at the 10% level (Column 2), while $ICRGRLW$ is not statistically significant (Column 3). Moreover, neither of these are statistically significant when entered in conjunction (Column 4) or in addition to the $IEPIP$ (Columns 5 and 6). In sum, only in product form (replicated in Column 1) are coverage and enforcement of patent protection laws significant drivers of the skill bias.

6.2 Changes in Partners' *IEPIP* vs. Changes in Trade Weights

The decline in the $IEPIP$ for US manufacturing industries over time can emerge from two sources: on one hand, with unchanged trade shares, $IEPIP$ in trading partners of US industries might have declined; on the other, while the IPR regime may be unchanged within each trading partner, the trade shares of each industry may have witnessed a shift towards countries with lower $IEPIP$. Therefore, we decompose the change in the $IEPIP$ ($\Delta IEPIP$) into two components. The first component ($\Delta_c IEPIP$) aggregates the changes in the $IEPIP$ of the trading partners using the mean of each industry's weights in 1979 and 1990. The second component ($\Delta_e IEPIP$) assesses the changes in the trade weights of each industry's trading partner, and uses these to aggregate the mean of the $IEPIP$ of trading partners in 1979 and 1990.

$$\begin{aligned}
\Delta_c IEPIP_j &= \sum_i \overline{e_{ij}} \Delta IEPIP_i \\
\Delta_e IEPIP_j &= \sum_i \Delta e_{ij} \overline{IEPIP}_i
\end{aligned}$$

where e_{ij} are shown in (4) and the upper-bar captures the mean for the values of the variable in 1979 and 1990. It can be shown that $\Delta IEPIP$ is approximately equal to the sum of $\Delta_c IEPIP_j$ and $\Delta_e IEPIP_j$.

[20] Column 1 in Table 4 simply replicates column 3 in Table 3a for purpose of comparison.

Columns 1-3 in Table 5 assess the role of the two components for the rise in skill-intensity. The previous discussion on the issues of endogeneity imply here the need to instrument for $\Delta_e IEPIP_j$, which captures the changes in the country-weights. In contrast, $\Delta_c IEPIP_j$, which relies on changes in IPR protection in trading partners, is assumed to be independent of exogenous changes the skill-intensity of US industries.

Accordingly, Column 1 presents OLS results while in Columns 2 and 3 we instrument $\Delta_e IEPIP_j$ in the same way as before. In Column 1, we find that the variable $\Delta_c IEPIP$ does not influence skill-deepening. In contrast, Column 2 shows that $\Delta_e IEPIP$ is a significant driver of changes in skill-intensity. Our conclusion is that, for the US manufacturing sector, the shift in trade weights over time towards countries with weak IPR regimes is a key driver of the rise in skill-intensity, while the changes in the IPR of trading partners have played a minor role.

7 Education as an Enabler

Finally, we look at the role education as an enabler of the threat of competitive imitation. The role of educational achievement as a determinant of capacity to undertake deliberate, resource-consuming imitation has been widely assumed in the literature (Grossman and Helpman, 1992) and is well established empirically (Engelbrecht, 1997). Our hypothesis is that foreign firms in countries with weak protection of IPRs are more likely to constitute an imitative threat, if these countries posses a suitably skilled domestic labor force. Moreover, the two may be complementary in the sense that the threat of imitation under a weak IP regime is magnified since the presence of a skilled work force enables and facilitates this imitation.

To test this complementarity, we modify our benchmark specification in (6) as follows:

$$\begin{aligned} \Delta S_j \quad = \quad & \beta_P \Delta IEPIP_j + \beta_{PS} \Delta (IEPIP_j * SCHOOL_j) + \beta_S \Delta SCHOOL_j \\ & + \beta_I \Delta INC_j + \beta_S \Delta OUTS_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0 \end{aligned} \tag{7}$$

where $\Delta SCHOOL_j$ and $\Delta (IEPIP_j * SCHOOL_j)$ are industry-specific variables that aggregate the level of Schooling in trading partners and its interaction with $IEPIP$. Schooling in each trading partner is captured by the percentage of population older than 25 who have attained high-school education.[21] The data on schooling are from Barro and Lee (2000) and are available at 5 year intervals from 1960-1999. Again, we follow the weighting procedure in (4) to construct an industry-specific measure of schooling as a weighted average of the schooling of trading partners. Similar to the procedures outlined in the main section, these weights can be instrumented using the exogenous measures of exposure in trading partners.

Column 4 in Table 5 shows that sectors that have experienced an increase in trade with countries with higher levels of schooling also exhibit rising levels of skill-intensity. At the same time, the IP regime continues to matter for skill-deepening - we obtain a negative and significant coefficient on $\Delta IEPI\dot{P}$. This suggests that even when we control for the ability to imitate as measured by the presence of a skilled work-force, weakness in the IP regime affects the skill-intensity. Next, in Column 5 we find that although the interaction term has the predicted sign (negative for complementarity), it is statistically insignificant. In other words, there is no evidence that the ability to imitate complements the effect of a weak IP regime. To summarize, the overall IP regime matters even when we allow for differences in the ability to imitate. The capacity to imitate, as measured by the availability of a skilled labor force, matters for still intensity – sectors that experience a rise in trade with countries that have a higher capacity to imitate, also exhibit higher skill intensity. Finally, there is no evidence that the ability to imitate magnifies or diminishes the effect of a weak IP regime.

8 Conclusion

This paper provides support to the notion that the rise in US trade with countries where the protection of intellectual property is weak or has weakened during the 1980s, has contributed to the rise in skill-intensity and to the skill-bias of labor demand. This argument was first advanced

[21] We get very similar results if we use the percentage of population who have completed high-school.

by Thoenig and Verdier (2003), who suggested that lower patent protection in trading partners facilitates the activities of competitive imitation by foreign firms, and that US firms would react to this threat by engaging in skill-intensive technologies and strategies, because the latter have non-codified know-how and tacit knowledge that are less likely to be imitated. Our results suggest that both the coverage and the enforcement of patent protection law matter in a complementary relationship, to define the effectiveness of IPR protection. We also show that the decline in the average effectiveness of IPR protection in the trading partners of US industries, is mainly due to a shift in trade patterns towards developing countries, with less weaker IPR regimes and that this explains 29% of the rise in the skill-intensity across US industries in the 1980s.

Our results highlight the role of rising trade with countries where weak protection of intellectual property, which creates the threat of imitation by foreign firms. From a policy perspective, our paper suggests that pressure for a more effective enforcement of IPR protection in trading partners may, in the long-run, help slow the skill-deepening and the rise in the relative demand for skilled workers. Although we stress the role of the patent law environment, the ultimate threat of competitive imitation depends on the actual activities of foreign firms. From this perspective, it would be important to find measures of the threat of competitive imitation that capture the actual strategies of a trading partner's firms. Such measures would allow a more direct and complete test of the theories of "defensive" innovation suggested in Thoenig and Verdier (2003), possibly using firm-level data. This remains a challenge for future research.

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Figure 1

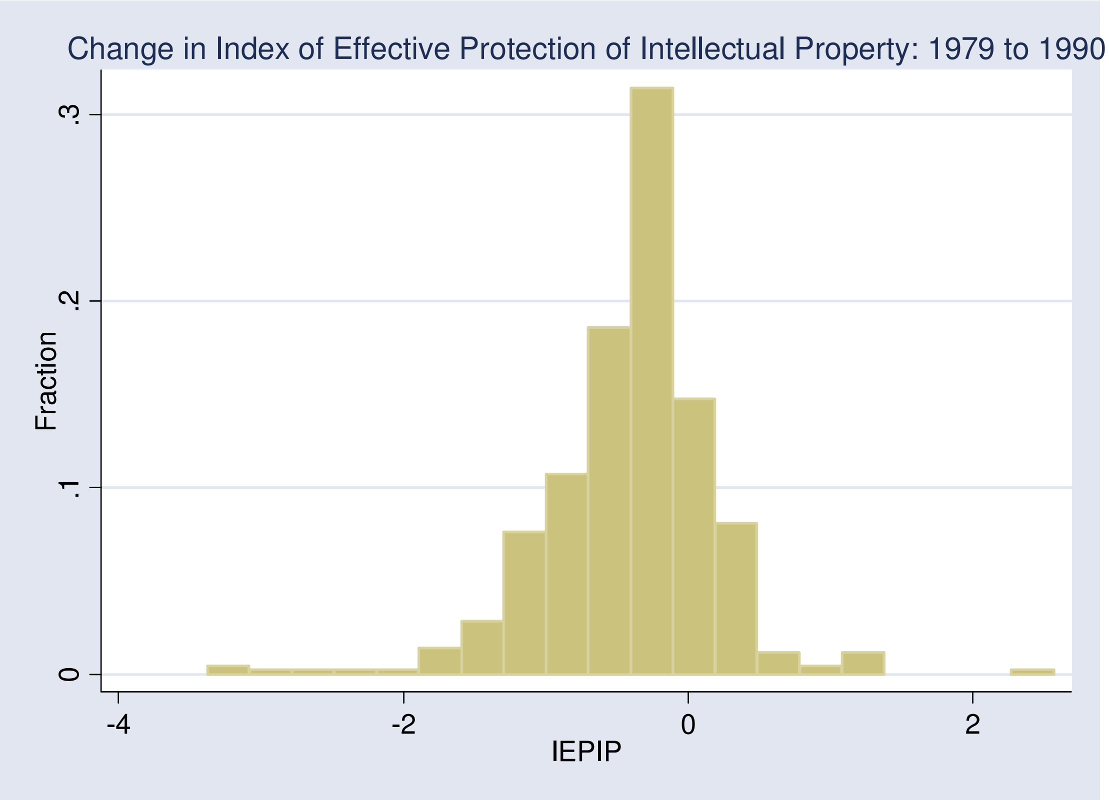
Change in Index of Effective Protection of Intellectual Property: 1979 to 1990
Fraction
0
.1
.2
.3
-4
-2
0
2
IEPIP

Table 2: Summary Statistics and Correlations of Unweighted Variables (first-differences)

	Mean	*Std. Dev.*	*imitation threat*	*patent protection*	*rule of law*	*schooling*	*openness*	*income*	*Δln(K/Y)*	*Δln(Y)*	*outsourcing (narrow)*	*outsourcing (other)*	*computer investment*
index of effectiveness of protection of intellectual property (IEPIP)	-0.40	0.60	1										
index of global patent protection (IGPP)	-0.25	0.84	0.67**	1									
rule of law (ICRGRLW)	-0.43	0.70	0.81**	0.26**	1								
schooling (ability to imitate)	-2.14	1.58	0.10*	0.07	0.02	1							
openness	4.92	5.40	-0.11*	0.07	-0.25**	-0.11*	1						
income	-0.14	0.74	0.75**	0.42**	0.67**	0.44**	-0.21**	1					
Δln(K/Y)	0.16	0.48	0.14**	0.10	0.06	-0.02	0.17**	0.07	1				
Δln(Y)	0.21	0.34	-0.03	-0.08	0.05	0.03	-0.22**	0.02	-0.71**	1			
outsourcing (narrow)	5.61	5.52	-0.05	0.03	-0.09	0.04	0.10*	-0.07	0.14**	-0.10	1		
outsourcing (other)	0.53	3.12	-0.08	0.06	-0.18**	0.05	0.20**	-0.06	0.00	0.05	-0.06	1	
computer investment	0.35	3.75	0.03	0.11*	-0.03	0.14**	0.02	0.05	0.09	0.07	0.18**	0.20**	1

Number of observations = 418**;** ** *significant at* 1%; * *significant at* 5%

Table 3a: Effect of Change in Effectiveness of Protection of Intellectual Property of Trading Partners on Change in Nonproduction Wage Share (1979-90)

	Mean	(1)	(2)	(3)	(4)	(5)
		OLS	IV	IV	IV	IV
effectiveness of protection of intellectual property (Δ*IEPIP*)	-0.270	0.075	-0.447**	-0.400**	-0.359*	-0.227*
		(0.048)	(0.181)	(0.168)	(0.187)	(0.136)
$\Delta ln(K/Y)$	0.669	0.046***	0.075***	0.051***	0.049***	0.051***
		(0.010)	(0.015)	(0.014)	(0.014)	(0.014)
$\Delta ln(Y)$	1.429	0.024***	0.043***	0.021**	0.021**	0.024**
		(0.007)	(0.010)	(0.009)	(0.009)	(0.010)
outsourcing (narrow)	0.405	0.263***	0.270***	0.195***	0.186***	0.198***
		(0.051)	(0.058)	(0.056)	(0.057)	(0.056)
outsourcing (other)	0.196	0.086	0.044	-0.086	-0.093	-0.106
		(0.060)	(0.069)	(0.070)	(0.069)	(0.074)
computer investment	6.173			0.024***	0.024***	0.025***
				(0.004)	(0.004)	(0.004)
openness	4.132				0.003	
					(0.006)	
income	-0.046					-0.170
						(0.123)
Constant		0.273***	0.082	0.030	0.034	0.068
		(0.034)	(0.074)	(0.072)	(0.069)	(0.062)
Observations		418	418	418	418	418
Overall model test		15.56***	12.97***	16.78***	15.10***	14.14***
F-Test of excluded			13.59***	13.95***	11.14***	14.11***
OID test p-value			0.24	0.42	0.45	0.52

* significant at 10%; ** significant at 5%; *** significant at 1%.

All regressions and means are computed over 418 four-digit SIC industries and are weighted by the average industry share of the manufacturing wage bill. Δln (K/Y) is the average annual change in the log capital-shipments ratio, and Δln (Y) is the average annual change in log real shipments. The imitation threat, outsourcing variables, income and openness measures are in annual changes. The instruments are based on trading partners' tariffs, import duties, and sectoral export share in world exports. The last row reports the *p*-value for the Sargan overidentification test.

Table 3b: Contribution to Change in Nonproduction Wage Share

	(2)	(3)	(4)	(5)
effectiveness of protection of intellectual property ($\Delta IEPIP$)	0.32	0.29	0.26	0.16
$\Delta ln(K/Y)$	0.13	0.09	0.09	0.09
$\Delta ln(Y)$	0.16	0.08	0.08	0.09
outsourcing (narrow)	0.29	0.21	0.20	0.21
outsourcing (other)	0.02	-0.04	-0.05	-0.06
computer investment		0.40	0.40	0.41
openness			0.03	
income				0.02

The contribution by each variable to change in nonproduction wage share is calculated by multiplying the regression coefficients by the mean values in table 3a and expressing it as a proportion of the mean of the dependent variable. The mean of the dependent variable equals 0.375.

Table 4: Decomposing Change in Effectiveness of Protection of Intellectual Property (1979-90)

	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
effectiveness of protection of intellectual property ($\Delta IEPIP$)	-0.400**				-0.349*	-0.797*
	(0.168)				(0.186)	(0.440)
index of global patent protection ($\Delta IGPP$)		-0.384*		-0.280	-0.174	
		(0.230)		(0.178)	(0.169)	
rule of law ($\Delta ICRGRLW$)			-0.017	-0.003		0.278
			(0.068)	(0.072)		(0.207)
$\Delta \ln(K/Y)$	0.051***	0.058***	0.030***	0.050***	0.061***	0.063***
	(0.014)	(0.020)	(0.010)	(0.017)	(0.017)	(0.021)
$\Delta \ln(Y)$	0.021**	0.024*	0.009	0.020*	0.027**	0.028**
	(0.009)	(0.012)	(0.007)	(0.011)	(0.011)	(0.013)
outsourcing (narrow)	0.195***	0.217***	0.195***	0.211***	0.204***	0.208***
	(0.056)	(0.060)	(0.050)	(0.056)	(0.060)	(0.061)
outsourcing (other)	-0.086	-0.041	-0.047	-0.043	-0.080	-0.067
	(0.070)	(0.071)	(0.063)	(0.069)	(0.075)	(0.075)
computer investment	0.024***	0.026***	0.022***	0.025***	0.026***	0.025***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Constant	0.030	0.046	0.176***	0.082	-0.012	-0.028
	(0.072)	(0.088)	(0.037)	(0.073)	(0.085)	(0.112)
Observations	418	418	418	418	418	418
Overall model test	16.78***	14.86***	19.46***	14.27***	12.72***	12.26***
OID test p-value	0.42	0.69	0.23	0.14	0.67	0.14

* significant at 10%; ** significant at 5%; *** significant at 1%.

All regressions and means are computed over 418 four-digit SIC industries and are weighted by the average industry share of the manufacturing wage bill. Δln (K/Y) is the average annual change in the log capital-shipments ratio, and Δln (Y) is the average annual change in log real shipments. The imitation threat, outsourcing variables and openness measures are in annual changes. The instruments are based on trading partners' tariffs, import duties, and sectoral export share in world exports. The last row reports the p-value for the Sargan overidentification test.

Table 5: Decomposing Effectiveness of Protection of Intellectual Property; Ability to Imitate and its Interaction with Effectiveness of Protection of Intellectual Property

	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	IV
$\Delta_c IEPIP = \sum_i \bar{e}_{ij} \Delta IEPIP_i$	-0.077		0.148		
	(0.194)		(0.273)		
$\Delta_e IEPIP = \sum_i \Delta e_{ij} \overline{IEPIP}_i$		-0.623**	-0.702**		
		(0.286)	(0.319)		
effectiveness of protection of intellectual property ($\Delta IEPIP$)				-0.279*	-0.420**
				(0.154)	(0.193)
schooling (ability to imitate)				0.034**	0.496
				(0.016)	(0.318)
*effectiveness of protection of intellectual property*schooling*					-0.524
					(0.351)
$\Delta \ln(K/Y)$	0.030**	0.063***	0.067***	0.045***	0.054***
	(0.012)	(0.019)	(0.021)	(0.013)	(0.016)
$\Delta \ln(Y)$	0.008	0.029**	0.031**	0.016*	0.021**
	(0.009)	(0.013)	(0.014)	(0.009)	(0.010)
outsourcing (narrow)	0.196	0.195***	0.195***	0.176***	0.194***
	(0.157)	(0.061)	(0.064)	(0.054)	(0.061)
outsourcing (other)	-0.042	-0.129	-0.144	-0.066	-0.084
	(0.065)	(0.084)	(0.091)	(0.067)	(0.075)
computer investment	0.022***	0.026***	0.027***	0.023***	0.024***
	(0.008)	(0.005)	(0.005)	(0.004)	(0.005)
Constant	0.163***	0.093*	0.118	0.165*	0.040
	(0.059)	(0.054)	(0.075)	(0.085)	(0.107)
Observations	418	418	418	418	418
Overall model test	8.31***	13.83***	11.01***	16.52***	11.32***
OID test p-value		0.55	0.51	0.25	0.18

* significant at 10%; ** significant at 5%; *** significant at 1%.

All regressions and means are computed over 418 four-digit SIC industries and are weighted by the average industry share of the manufacturing wage bill. $\Delta \ln (K/Y)$ is the average annual change in the log capital-shipments ratio, and $\Delta \ln (Y)$ is the average annual change in log real shipments. The imitation threat and outsourcing variables are in annual changes. The instruments for the IV regressions are based on trading partners' tariffs, import duties, and sectoral export share in world exports. The last row reports the *p*-value for the Sargan overidentification test. $\sum_j \bar{e}_{ij} IEPIP_{it}$ allows for time-variation in *IEPIP* but uses constant trade weights for each sector *j*; $\sum_j e_{ijt} \overline{IEPIP}_i$ allows for time-variation in sectoral trade weights (e_{ijt}) but uses constant country-specific *IEPIP*. Ability to imitate is captured in terms of percentage of population with higher secondary education from Barro-Lee.