With whom do you trade? Defensive innovation and the skill-bias

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Abstract. We examine whether increased trade with countries with ineffective protection of intellectual property has contributed to the skill-deepening of the 1980s. We construct an index of effective protection of intellectual property at the country level, combining data on protection of patents and rule of law. Next, we construct an industry-specific version of this index, using as weights each country's trade share in the total trade of the industry. We find a decline in this trade-weighted index, owing to a rise in trade with countries with low effective protection of intellectual property, which explains 29% of the rise in within-industry skill-intensity. JEL classification: F14, F16, J31

Avec qui commercez-vous? Innovation défensive et la tendance à la qualification du travail. On se demande si un commerce accru avec des pays qui ont une protection inefficace de leur propriété intellectuelle a contribué à une demande de travail qualifié accrue dans les années 1980. On construit un indice de la protection effective de la propriété intellectuelle au niveau du pays, combinant des données sur la protection des brevets et l'état de droit. Ensuite, on construit une version de cet indice au niveau des industries spécifiques, utilisant comme pondération les parts du commerce de chaque pays dans le commerce total de l'industrie. On note un déclin dans cet indice pondéré par l'importance du commerce international (attribuable à un accroissement du commerce avec les pays qui ont une protection effectivement faible de la propriété intellectuelle) qui explique 29% de l'accroissement dans l'intensité du travail qualifié à l'intérieur de l'industrie.

1. Introduction

Since the late 1970s, we have witnessed a shift in the demand for labour 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.

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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, not through the expansion of skill-intensive industries (Berman, Bound, and Griliches 1994). Meanwhile, the within-industry rise in the demand for skilled labour (henceforth addressed as skill-deepening), and the corresponding rise in the skill-premium, have been blamed on skill-biased technological change (Baldwin and Cain 2000), as well as on rising outsourcing (Feenstra and Hanson 1999). However, a number of authors, starting with Wood (1995, 1998), have argued that this skill-biased technological change itself may be attributed to globalization and the rise of trade.

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. 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.

The importance that the US government attaches to the threat of technological leapfrogging via imitation can be seen in a series of recent initiatives launched to counteract intellectual property right (IPR) violations. These include the National Intellectual Property Law Enforcement Coordination Council created by President Clinton in 1999; the Strategy Targeting Organized Piracy (STOP!) initiative by President Bush that brings together six US government departments; ‘IP toolkits’ to guide businesses through securing and enforcing their rights in key markets such as China, Russia, India, Mexico, Korea, Malaysia, and Taiwan; pushing for greater IPR protection through regional trade agreements; stationing IP attachés in embassies around the world. Further, these initiatives are explicitly

1 Consensual estimates show that the expansion of skill-intensive sectors explains less than a third of the rising demand for skills (Berman, Bound, and Griliches 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 labour 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.

3 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.
linked to the rise in trade and globalization. For instance, the US government’s export portal explicitly states that ‘Globalization and the rapid proliferation of technology have elevated the importance of intellectual property protection.’ 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, firms clearly have incentives to invest in hard-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; 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 (ICRGRGLW). 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, owing 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.4

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 because of a fall

4 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.
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. 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 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 imitation capabilities, such as the share of the population with higher education, magnify the impact of low IEPIPs as inducers of defensive innovation by US firms.

Several other authors have looked at the implications of trade phenomena for skill-intensity at the level of the strategies of the firm. 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, Garcia 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, owing to the fears of competitive imitation. They too present supportive evidence.

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5 Our preferred regression includes controls that confirm the role of changes in industry-level Outsourcing (Feenstra and Hanson 1999) and Computer Investment (Berman, Bound, and Griliches 1994).
2. 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 labour, and the production workers group for unskilled labour, 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 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 labour, 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 labour ($q$), we obtain the compensated demand for skilled labour ($H_j$). After straightforward manipulation, this yields the following expression for skill-intensity (the share of non-production workers in the wage bill, $S_j$)

$$S_{jt} = \frac{q_{jt}H_{jt}}{C_{jt}} = \alpha_j + \gamma_j(ln q_{jt} - \ln w_{jt}) + \phi_{kj} ln K_{jt} + \phi_{yj} ln Y_{jt} + \beta_{xzj} + \beta_{zdj}d_j.$$  

(1)

The parameters $\alpha_j, \gamma_j, and \phi_q$ arise directly from the translog specification, and $\beta_j$ captures the impact of structural variables. Assuming that the elasticity of substitution between skilled and unskilled labour is larger than one, $\gamma_j$ is negative.\(^6\) Meanwhile, $\phi_k$ is positive, assuming that capital and skilled labour are complements. Note that the effects of changes in the supply of skilled labour 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

$$\Delta S_j = \beta_z \Delta z_j + \beta_k \Delta k_j + \beta_y \Delta y_j + \beta_0,$$

(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) $\beta_0 = \gamma \Delta (\ln q - \ln w)$ is a constant that emerges from ignoring the

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\(^6\) 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.’
industry-variation in factor prices. $\Delta S_j$ is the skill-deepening in industry $j$, that is, the industry-specific rise in skill-intensity.

With the inclusion of an error term, (2) can be estimated with different sets of structural variables ($z_i$), 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 labour 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 we examine the role of IP protection for skill-deepening at the industry level.

3. Measuring the threat of competitive imitation

3.1. 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.

We use data from the International Country Risk Guide to measure the rule of law ($ICGRGLW$) 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 $ICGRGLW$ 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 and higher numbers indicate 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

7 Here we follow Berman, Bound, and Griliches (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 price do not affect the cost function. Meanwhile the economy-wide factor prices is subsumed in the constant term, after first-differences are taken.
source have 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, 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 0.4—relatively high number, showing that countries with higher protection of IPR also have a strong rule of law. There are, nevertheless, some remarkable outliers, such as Nigeria, Ghana, and Zambia, where the statutory protection of patents is relatively high, owing to the similarity of patent laws with the former European colonizers, but where the rule of law is weak. In contrast, countries such as Venezuela, Papua New Guinea, Madagascar, and 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 1980s, 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. For ICRGRLW, the mean also barely changed between 1982, the first year that data are available, and 1990, when 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 (an average rise of 0.79), and 25 (26%) saw a decline (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 1980s was statistically independent.

8 Note that the dramatic changes in intellectual property brought about by the Uruguay round are not covered in the period of the data.
3.1.1. The index of effectiveness of protection of intellectual property (IEPIP)
Since the threat of competitive imitation depends on both the legal environment and the enforcement, we define our Index of Effectiveness of Protection of Intellectual Property (IEPIP), for country \( i \) at time \( t \) as

\[
IEPIP_{it} = IGPP_{it} \times ICRGRLW_{it}.
\]

(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 is stricter. On the other hand, \( IEPIP \) is zero if either \( IGPP \) or \( ICRGRLW \) is zero.

We computed the IEPIP for 1980, using the data for \( ICRGRLW \) in 1982 and for \( IGPP \) in 1980. Data for 1990 are 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 countries (25%). 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 better or for worse, have done so mostly because of changes in the rule of law.

In sum, while the average index for the effectiveness of patent protection barely changed during the 1980s, there were some changes across different countries. From the perspective of US firms and industries, the effects of the IEPIP may arise because of 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 \( j - IEPIP_{j,t} \), is constructed as follows:

\[
IEPIP_{j,t} = \sum_i e_{ij} IEPIP_{it}, \quad e_{ij} = \frac{Exp_{jt} + Imp_{jt}}{\sum_i Exp_{jt} + \sum_i Imp_{jt}},
\]

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 IEPIPs, where each country’s weight is equal to its share in the total trade of industry \( j \).\(^9\) 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

\(^9\) 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.
index, at the level of countries, or to changes in the direction of trade flows of US industries.

The industry data on $\text{Exp}_{it}$ and $\text{Imp}_{it}$ for each of these measures are obtained from the NBER Trade Database (Feenstra 1996, 1997), which provides data on US 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 $\text{IEPIP}$ for the trading partners of US industries barely changed during the 1980s, there was a substantial decline of the industry-specific index for most industries. The unweighted mean of the $\text{IEPIP}$ across countries ($\text{IEPIP}_{i,t}$) increased by 0.5%, while the cross-industry average of the trade weighted index ($\text{IEPIP}_{i,t}$) fell by 5.4%. Figure 1 shows a histogram of the change in $\text{IEPIP}$ between 1979 and 1990 across industries. We see a decline in $\text{IEPIP}$ 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 1 summarizes, for the 418 industries for which data are available, the cross-industry distribution of the changes in the $\text{IEPIP}$. For comparison, we also calculated similar, industry-specific measures for the rule of law ($\text{ICRGRLW}_{jt}$) and the patent protection ($\text{IGPP}_{jt}$) for the early and late 1980s, and provide data

![FIGURE 1 Change in index of effective protection of intellectual property between 1979 and 1990](image-url)
<table>
<thead>
<tr>
<th></th>
<th>Std. Dev.</th>
<th>Imitation threat</th>
<th>Patent protection</th>
<th>Rule of law</th>
<th>Schooling</th>
<th>Openness</th>
<th>Income</th>
<th>$\Delta \ln(K/Y)$</th>
<th>$\Delta \ln(Y)$ (narrow)</th>
<th>Outsourcing (narrow)</th>
<th>Outsourcing (other)</th>
<th>Computer investment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index of effectiveness of protection of intellectual property (IEPP)</td>
<td>-0.40</td>
<td>0.60</td>
<td>1</td>
<td></td>
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<td></td>
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<tr>
<td>Index of global patent protection (IGPP)</td>
<td>-0.25</td>
<td>0.84</td>
<td>0.67**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Rule of law (ICRGLRW)</td>
<td>-0.43</td>
<td>0.70</td>
<td>0.81**</td>
<td>0.26**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Schooling (ability to imitate)</td>
<td>-2.14</td>
<td>1.58</td>
<td>0.10*</td>
<td>0.07</td>
<td>0.02</td>
<td>1</td>
<td></td>
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<tr>
<td>Openness</td>
<td>4.92</td>
<td>5.40</td>
<td>-0.11*</td>
<td>0.07</td>
<td>-0.25**</td>
<td>-0.11*</td>
<td>1</td>
<td></td>
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<tr>
<td>Income</td>
<td>-0.14</td>
<td>0.74</td>
<td>0.75**</td>
<td>0.42**</td>
<td>0.67**</td>
<td>0.44**</td>
<td>-0.21**</td>
<td>1</td>
<td></td>
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<tr>
<td>$\Delta \ln(K/Y)$</td>
<td>0.16</td>
<td>0.48</td>
<td>0.14**</td>
<td>0.10</td>
<td>0.06</td>
<td>-0.02</td>
<td>0.17**</td>
<td>0.07</td>
<td></td>
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<tr>
<td>$\Delta \ln(Y)$</td>
<td>0.21</td>
<td>0.34</td>
<td>-0.03</td>
<td>-0.08</td>
<td>0.05</td>
<td>0.03</td>
<td>-0.22**</td>
<td>0.02</td>
<td></td>
<td></td>
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<tr>
<td>Outsourcing (narrow)</td>
<td>5.61</td>
<td>5.52</td>
<td>-0.05</td>
<td>0.03</td>
<td>-0.09</td>
<td>0.04</td>
<td>0.10*</td>
<td>-0.07</td>
<td>0.14**</td>
<td>-0.10</td>
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<tr>
<td>Outsourcing (other)</td>
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<td>3.12</td>
<td>-0.08</td>
<td>0.06</td>
<td>-0.18**</td>
<td>0.05</td>
<td>0.20**</td>
<td>-0.06</td>
<td>0.00</td>
<td>0.05</td>
<td>-0.06</td>
<td>1</td>
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<td>Computer investment</td>
<td>0.35</td>
<td>3.75</td>
<td>0.03</td>
<td>0.11*</td>
<td>-0.03</td>
<td>0.14**</td>
<td>0.02</td>
<td>0.05</td>
<td>0.09</td>
<td>0.07</td>
<td>0.18**</td>
<td>0.20**</td>
</tr>
</tbody>
</table>

**NOTES:** Number of observations = 418; ** significant at 1%; * significant at 5%
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. 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 \((z_i)\) 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 because of 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. Next we address the additional controls, which include previously established drivers of the US skill-deepening of the 1980s or potential correlates whose omission might bias the coefficient of IEPIP.

3.2. Controls

3.2.1. 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 4-digit input industry, and they multiply it by the share of imports in consumption in the industry, to arrive at imported intermediate inputs. Their ‘narrow’ measure of outsourcing looks at the sum over the input industries in the same 2-digit SIC code as the using industry, as a share of total expenditure on non-energy intermediates. According to the authors, when averaged over ‘using’ industries, this measure grew from 3.1% in 1979 to 5.7% in 1990. They also compute a ‘broad’ measure of outsourcing that sums imported intermediate inputs over input industries, as a share of total expenditure on non-energy intermediates. The difference between the broad and narrow measures of outsourcing, termed ‘outsourcing (other)’ represents the intermediate inputs from outside the 2-digit purchasing industry that are sourced from abroad. We use both their ‘narrow’ and ‘other’ outsourcing measures in our regression.

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10 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.
3.2.2. Per capita income
Because developing countries exhibit ineffective protection of IPR and are relatively abundant in unskilled labour, the effects of the IEPIP may capture the impact of unskilled labour abundance in trading partners on the skill-deepening, through comparative advantage and specialization effects (see, e.g., Bernard, Jensen, and Schott 2006). To control for this, we use income per capita of an industry’s trading partners (income) as a proxy for abundance in unskilled labour, 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’ were obtained from the Penn World Tables Version 6.1.

3.2.3. 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, Machin, and Van Reenen 1997). 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.

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

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11 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.


13 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, because of changes in trading partners and/or patterns.
3.2.4. Computer investment
We account for the possibility that innovation in the 1980s 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 the 1980s - the time period covered by our study. Industry data for Computer Investment in the 1980s are from Berman, Bound, and Griliches (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 1 provides summary statistics and correlations for all variables.

3.3. 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 $e_{ij}$ 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). 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

\[
XX_{IEPIP_j} = \sum_i e_{ij}^{XX} IEPIP_{it}
\]

where

\[
e_{ij}^{XX} = \frac{1}{I} \sum_i e_{ij} X_{ij} \quad \text{and} \quad \bar{e}_j = \frac{1}{I} \sum_i e_{ij}
\]

with \( XX = MD, UT \) and \( SX \).

Similar instruments are computed for \( INC_j \).

These instruments are to be used in first-differences; that is, we use changes in \( UT_{IEPIP_j} \) and \( MD_{IEPIP_j} \) and \( SX_{IEPIP_j} \) between 1979 and 1990 to instrument for the changes in \( IEPIP_j \) in (2). Hence changes in the weights \( e_{ij}^{UT} \), \( e_{ij}^{MD} \) and \( e_{ij}^{SX} \) are instruments for changes in the weights in \( IEPIP_j(e_{ij}) \). Take \( e_{ij}^{UT} \) 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 \( UT_{ij} \), keeping constant all other \( UT_{ij'}(i' \neq i) \), changes the weight of country \( i \) in the total trade of industry \( j \) (\( e_{ij} \)). Meanwhile, the country-weights \( \bar{e}_j \) 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 \( e_{ij}^{UT} \) (and \( e_{ij}^{MD} \) and \( e_{ij}^{SX} \)) should capture the effects of changes in the country partners on \( e_{ij} \), and be uncorrelated with changes in skill-intensity at the industry level.

4. Results

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

\[
\Delta S_j = \beta_p \Delta IEPIP_j + \beta_1 \Delta INC_j + \beta_0 \Delta OPEN_j + \beta_S \Delta OUTS_j + \beta_C \Delta COMP_j + \beta_k \Delta k_j + \beta_r \Delta r_j + \beta_0,
\]

14 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 these data to calculate each trading partner’s export share. The data at 3-digit ISIC rev. 2 were assigned by authors to the 4-digit ISIC72 classification of the NBER Trade Database. In some cases, we used export and import shares instead of total exposure.
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 $\beta_O$ Thoenig and Verdier (2003) see a more nuanced role. That is, it is the composition of trading partners captured via $\beta_P$ rather than the overall volume of trade that matters. However, an insignificant coefficient on $\beta_O$ is certainly compatible with their theory.

Table 2a 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 2b 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 2a), and expressing the result as a proportion of the dependent variable.\textsuperscript{15}

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 show that trading volumes, in terms of sheer size are irrelevant – the coefficient on Openness is insignificant. Moreover, its

\textsuperscript{15} These means differ from those in table 1, which are unweighted. Table 2a 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 2a) confirm that our instruments are valid, that is, they are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.
TABLE 2a
Effect of change in effectiveness of protection of intellectual property of trading partners on change in non-production wage share (1979-90)

<table>
<thead>
<tr>
<th>Effectiveness of protection of intellectual property (ΔIEPIP)</th>
<th>Mean</th>
<th>(1) OLS</th>
<th>(2) IV</th>
<th>(3) IV</th>
<th>(4) IV</th>
<th>(5) IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(K/Y)</td>
<td>0.669</td>
<td>0.046***</td>
<td>0.075***</td>
<td>0.051***</td>
<td>0.049***</td>
<td>0.051***</td>
</tr>
<tr>
<td>ln(Y)</td>
<td>1.429</td>
<td>0.024***</td>
<td>0.043***</td>
<td>0.021**</td>
<td>0.021**</td>
<td>0.024**</td>
</tr>
<tr>
<td>Outsourcing (narrow)</td>
<td>0.405</td>
<td>0.263***</td>
<td>0.270***</td>
<td>0.195***</td>
<td>0.186***</td>
<td>0.198***</td>
</tr>
<tr>
<td>Outsourcing (other)</td>
<td>0.196</td>
<td>0.086</td>
<td>0.044</td>
<td>-0.086</td>
<td>-0.093</td>
<td>-0.106</td>
</tr>
<tr>
<td>Computer investment</td>
<td>6.173</td>
<td>0.024***</td>
<td>0.024***</td>
<td>0.025***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Openness</td>
<td>4.132</td>
<td>0.003</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>-0.046</td>
<td></td>
<td></td>
<td>-0.170</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTES: * Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions and means are computed over 418 4-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.

inclusion does not affect the coefficients 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.16 Finally, column 5 adds as an additional control, the income of trading partners – this

16 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
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, because of a 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.

### 5. Decomposing changes in *IEPIP*

#### 5.1. 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 1) raises difficulties in the significance of our estimates, due to multicollinearity. Moreover, the endogeneity concerns raised above with *ΔIEPIP*, should extend to its components, namely, *ΔIGPP* and *ΔICRGRLW*, and we have obtained appropriate instruments using the methodology introduced in (5).

openness fails to be significant. Our empirical methodology also captures within effects, albeit at the industry level.
### TABLE 3
Decomposing change in effectiveness of protection of intellectual property (1979–90)

<table>
<thead>
<tr>
<th></th>
<th>(1) IV</th>
<th>(2) IV</th>
<th>(3) IV</th>
<th>(4) IV</th>
<th>(5) IV</th>
<th>(6) IV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Effectiveness of protection of intellectual property</strong> ((\Delta IEPIP))</td>
<td>-0.400**</td>
<td>-0.384*</td>
<td>-0.280</td>
<td>-0.174</td>
<td>0.278</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>(0.230)</td>
<td>(0.178)</td>
<td>(0.169)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Index of global patent protection</strong> ((\Delta IGPP))</td>
<td>-0.384*</td>
<td>-0.280</td>
<td>-0.174</td>
<td>0.278</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Rule of law ((\Delta ICGRGLW))</strong></td>
<td>-0.017</td>
<td>-0.003</td>
<td>0.027**</td>
<td>0.28**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.072)</td>
<td>(0.075)</td>
<td>(0.075)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(\Delta \ln (K/Y))</strong></td>
<td>0.051***</td>
<td>0.058***</td>
<td>0.030**</td>
<td>0.050***</td>
<td>0.061***</td>
<td>0.063***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td><strong>(\Delta \ln (Y))</strong></td>
<td>0.021**</td>
<td>0.024*</td>
<td>0.009</td>
<td>0.020*</td>
<td>0.027**</td>
<td>0.028**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td><strong>Outsourcing (narrow)</strong></td>
<td>0.195***</td>
<td>0.217***</td>
<td>0.195***</td>
<td>0.211***</td>
<td>0.204***</td>
<td>0.208***</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.056)</td>
<td>(0.050)</td>
<td>(0.060)</td>
<td>(0.060)</td>
<td>(0.061)</td>
</tr>
<tr>
<td><strong>Outsourcing (other)</strong></td>
<td>-0.086</td>
<td>-0.041</td>
<td>-0.047</td>
<td>-0.043</td>
<td>-0.080</td>
<td>-0.067</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.071)</td>
<td>(0.063)</td>
<td>(0.069)</td>
<td>(0.075)</td>
<td>(0.075)</td>
</tr>
<tr>
<td><strong>Computer investment</strong></td>
<td>0.024***</td>
<td>0.026***</td>
<td>0.022***</td>
<td>0.025***</td>
<td>0.026***</td>
<td>0.025***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.030</td>
<td>0.046</td>
<td>0.176***</td>
<td>0.082</td>
<td>-0.012</td>
<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.088)</td>
<td>(0.037)</td>
<td>(0.073)</td>
<td>(0.085)</td>
<td>(0.112)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
</tr>
<tr>
<td><strong>Overall model test</strong></td>
<td>16.78***</td>
<td>14.86***</td>
<td>19.46***</td>
<td>14.27***</td>
<td>12.72***</td>
<td>12.26***</td>
</tr>
<tr>
<td><strong>OID test p-value</strong></td>
<td>0.42</td>
<td>0.69</td>
<td>0.23</td>
<td>0.14</td>
<td>0.67</td>
<td>0.14</td>
</tr>
</tbody>
</table>

**NOTES:** *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions and means are computed over 418 4-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, outsourcing and computer investment variables are measured by interactions. 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 overidentifiability test.

The individual significance tests in columns 2–6 of table 3 clearly show the complementarity between the coverage and enforcement of patent protection. When it is entered separately, we find that \(IGPP\) is only marginally significant at the 10% level (column 2), while \(ICGRGLW\) is not statistically significant (column 3). Moreover, neither of these are statistically significant when entered in conjunction (column 4), or in addition to \(IEPIP\) (columns 5 and 6). In sum, only in product form (shown in column 1) are coverage and enforcement of patent protection laws significant drivers of skill-bias.

5.2. 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 the 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 toward countries with lower IEPIP. Therefore, we decompose the change in the IEPIP (ΔIEPIP) into two components. The first component (Δ,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 (Δ,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:

$$\Delta,IEPIP_j = \sum_i \bar{e}_g \Delta IEPIP_i$$

$$\Delta,IEPIP_j = \sum_i \Delta e_i,IEPIP_i,$$

where $e_g$ 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 ΔIEPIP is approximately equal to the sum of Δ,IEPIP and Δ,IEPIP.

Columns 1–3 in table 4 assess the role of the two components for the rise in skill-intensity. The previous discussion on the issues of endogeneity implies the need to instrument Δ,IEPIP, which captures the changes in the country-weights. In contrast, Δ,IEPIP, which captures changes in IPR protection in trading partners, is assumed to be independent of changes in the skill-intensity of US industries.

Accordingly, column 1 presents OLS results, while in columns 2 and 3 we instrument Δ,IEPIP in the same way as before. In column 1, we find that the variable Δ,IEPIP does not influence skill-deepening. In contrast, column 2 shows that Δ,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 toward 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.

6. 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 imitate has been widely discussed in the literature (Grossman and Helpman 1991) and is well established empirically (Engelbrecht 1997). Our hypothesis is that the threat of imitation under a weak IP regime is magnified under the presence of an enabling skilled work force.
TABLE 4
Decomposing effectiveness of protection of intellectual property; ability to imitate and its interaction with effectiveness of protection of intellectual property

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) IV</th>
<th>(3) IV</th>
<th>(4) IV</th>
<th>(5) IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta_{IEPIP} )</td>
<td>(-0.077)</td>
<td>0.148</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.194)</td>
<td>(0.273)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta_{IEPIP} )</td>
<td>(-0.623^{**})</td>
<td>(-0.702^{**})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.286)</td>
<td>(0.319)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effectiveness of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>protection of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>intellectual</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>property ((\Delta_{IEPIP}))</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Schooling (ability</td>
<td>0.034(^{**})</td>
<td>0.496</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>to imitate)</td>
<td>(0.016)</td>
<td>(0.318)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effectiveness of</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>protection of</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>intellectual</td>
<td></td>
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</tr>
<tr>
<td>property +</td>
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</tr>
<tr>
<td>schooling</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>( \Delta \ln (K/Y) )</td>
<td>(0.030^{**})</td>
<td>(0.063^{***})</td>
<td>(0.067^{***})</td>
<td>(0.045^{***})</td>
<td>(0.054^{***})</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.013)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>( \Delta \ln (Y) )</td>
<td>(0.008)</td>
<td>(0.029^{**})</td>
<td>(0.031^{**})</td>
<td>(0.016^{*})</td>
<td>(0.021^{**})</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.009)</td>
<td>(0.010)</td>
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<tr>
<td>Outsourcing (narrow)</td>
<td>(0.196)</td>
<td>(0.195^{***})</td>
<td>(0.195^{***})</td>
<td>(0.176^{***})</td>
<td>(0.194^{***})</td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.061)</td>
<td>(0.064)</td>
<td>(0.054)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Outsourcing (other)</td>
<td>(-0.042)</td>
<td>(-0.129)</td>
<td>(-0.144)</td>
<td>(-0.066)</td>
<td>(-0.084)</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.084)</td>
<td>(0.091)</td>
<td>(0.067)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>Computer investment</td>
<td>(0.022^{***})</td>
<td>(0.026^{**})</td>
<td>(0.027^{***})</td>
<td>(0.023^{***})</td>
<td>(0.024^{***})</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Constant</td>
<td>(0.163^{***})</td>
<td>(0.093^{*})</td>
<td>0.118</td>
<td>0.165</td>
<td>0.040</td>
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<tr>
<td></td>
<td>(0.059)</td>
<td>(0.054)</td>
<td>(0.075)</td>
<td>(0.085)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>Observations</td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
</tr>
<tr>
<td>Overall model test</td>
<td>(8.31^{***})</td>
<td>(13.83^{***})</td>
<td>(11.01^{***})</td>
<td>(16.52^{***})</td>
<td>(11.32^{***})</td>
</tr>
<tr>
<td>OID test p-value</td>
<td>0.55</td>
<td>0.51</td>
<td>0.25</td>
<td>0.18</td>
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</table>

NOTES: *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions and means are computed over 418 4-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. \( \sum_{j} \hat{c}_j IEPIP_j \) allows for time-variation in \( IEPIP \) but uses constant trade weights for each sector; \( \sum_{j} \hat{c}_j IEPIP_j \) allows for time-variation in sectoral trade weights \( (\epsilon_{ij}) \) but uses constant country-specific \( IEPIP \). Ability to imitate is captured in terms of percentage of population with higher secondary education from Barro-Lee.

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

\[
\Delta S_j = \beta_p \Delta IEPIP_j + \beta_{PS} (IEPIP_j \ast SCHOOL_j) + \beta_S \Delta SCHOOL_j + \\
\beta_I \Delta INC_j + \beta_S \Delta OUTS_j + \beta_k \Delta k_j + \beta y_j + \beta_0,
\] (7)
where \( \Delta S_{\text{CHOOL}j} \) and \( \Delta (\text{IEPI}_j \times S_{\text{CHOOL}j}) \) are industry-specific variables that aggregate the level of schooling in trading partners and its interaction with \( \text{IEPI}_j \). Schooling in each trading partner is captured by the percentage of population older than 25 who have attained high-school education. Using the procedure in (4), we construct a weighted average of the schooling of trading partners, for each industry/year. As before, the weights can be instrumented using the exogenous measures of exposure in trading partners.

Column 4 in table 4 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 \( \Delta \text{IEPI}_j \). 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 skill-intensity. Next, in column 5, we find that the sign of the interaction term is in accordance with our hypothesis of complementarity, but is statistically insignificant. However, failure to find significant results may simply be due to data limitations, and the fact, that there is strong correlation between \( \Delta S_{\text{CHOOL}j} \) and \( \Delta \text{IEPI}_j \). The change in schooling and in \( \text{IEPI}_j \) are mostly driven by the changes in trade-weights (see section 5.2), resulting in multicollinearity. Insufficient variation in the data over this time period implies that this is a weak and perhaps inconclusive test of complementarity. However, the overall IP regime matters, even when we allow for differences in the ability to imitate.

7. Conclusion

This paper provides support for 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 labour demand. This argument was first advanced 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 adopting 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 toward 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.

17 The data on schooling are from Barro and Lee (2000) and are available at five-year intervals from 1960 to 1999. We get very similar results if we use the percentage of population who have completed high-school.
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.

References


