HUMAN CAPITAL, THE STRUCTURE OF PRODUCTION, AND GROWTH

Antonio Ciccone and Elias Papaioannou*

Abstract—We document that countries with higher initial education levels experienced faster value-added and employment growth in schooling-intensive industries in the 1980s and 1990s. This effect is robust to controls for other determinants of international specialization and becomes stronger when we focus on economies open to international trade. Our finding is consistent with schooling fostering the adoption of new technologies if such technologies are skilled-labor augmenting, as was the case in the 1980s and the 1990s. In line with international specialization theory, we also find that countries where education levels increased rapidly experienced stronger shifts in production toward schooling-intensive industries.

I. Introduction

Following Barro (1991) and Mankiw, Romer, and Weil (1992), there has been an upsurge of empirical research on human capital and economic growth. The main issue is the strength of the effect of education levels and improvements on output growth. Both effects are often found to be weak (notwithstanding the emphasis on human capital in new growth theories and recent neoclassical growth theories). This could be because of difficulties when specifying cross-country growth regressions (Temple, 1999; Durlauf, Johnson, & Temple, 2005). For example, the limited number of countries forces researchers to use parsimonious specifications. Another reason could be attenuation bias due to mismeasured schooling data (Krueger & Lindahl, 2001; de la Fuente & Domenech, 2001, 2006; Cohen & Soto, 2007). Such attenuation bias could be magnified by multicollinearity, often present in cross-country growth regressions, as high-growth countries tend to have higher rates of human capital accumulation, deeper financial markets, stronger property rights protection, higher savings and investment rates, and so on (Mankiw, 1995; Rajan & Zingales, 1998). Mixed results could also be due to schooling indicators used in empirical work often missing cross-country differences in educational quality (Hanushek & Kimko, 2000).

One way to progress in our understanding of the effects of human capital on growth is to focus on channels through which such effects could work. It is often argued that high levels of human capital facilitate technology adoption (for example, Nelson & Phelps, 1966; Benhabib & Spiegel, 1994, 2005; Acemoglu, 2003a; Caselli & Coleman, 2006). There is a consensus that new technologies becoming available since the 1970s tended to be more skilled-labor augmenting than the technologies of the 1950s and 1960s (for example, Autor, Katz, & Krueger, 1998; Berman, Bound, & Machin, 1998; Berman & Machin, 2000; Caselli & Coleman, 2002). The defining characteristic of skilled-labor-augmenting technologies is that they increase the productivity of workers with higher levels of human capital relative to workers with low human capital. Skilled-labor-augmenting technologies therefore result in faster total factor productivity growth in human-capital-intensive industries (for example, Kahn & Lim, 1998; Klenow, 1998). As a result, countries adopting new technologies quickly should experience fast value-added and employment growth in human-capital-intensive industries once other factors are controlled for. If high levels of human capital facilitate technology adoption, value-added and employment growth in human-capital-intensive industries should be faster in economies with high initial levels of human capital. We therefore test whether countries with higher education levels experienced faster value-added and employment growth in more compared to less schooling-intensive industries in the 1980s and 1990s. Theories of international specialization point to human capital accumulation as another important determinant of growth in human-capital-intensive industries (for example, Ventura, 1997, 2005; Romalis, 2004), Hence, we also examine the link between improvements in schooling and growth in schooling-intensive industries.

Our empirical analysis is based on data for 28 manufacturing industries in a large cross section of countries in the 1980s and 1990s. The approach we take is closely related to the framework of Rajan and Zingales (1998) and subsequent
contributions to the finance and industry growth literature (for example, Beck & Levine, 2002; Claessens & Laeven, 2003; Fisman & Love, 2003, 2007; Guiso et al., 2005). It also relates to recent work using trade data to examine the determinants of international specialization (for example, Romalis, 2004; Levchenko, 2007; Nunn, 2007). One common feature is that limitations of the available international industry-level data are dealt with by using U.S. data to obtain proxies of global industry characteristics. In particular, we use detailed 1980 U.S. Census data to calculate cross-industry indicators of differences in schooling intensity.

We find statistically robust and economically significant support for what we call the human-capital-level effect: countries with higher initial levels of schooling experienced faster growth in more compared to less schooling-intensive industries in the 1980s and 1990s. Our estimates control for country-specific and global industry-specific effects, and also account for other determinants of changes in the production structure (such as physical capital, financial development, rule of law). To get a sense for the size of the human-capital-level effect, consider the annual value-added growth differential between an industry with a schooling intensity at the 75th percentile (electric machinery) and an industry at the 25th percentile (pottery) during the 1980–1999 period. Our estimates imply that this annual growth differential is 0.75%–1.2% higher in a country with initial schooling at the 75th percentile (such as the United Kingdom with 8.17 years of schooling) than in a country with schooling at the 25th percentile (such as Singapore with 3.65 years). This effect is large when compared with the 0.3% cross-country average growth rate of the electric machinery relative to the pottery industry, or the 1.4% median growth differential between these two industries. We also find a robust link between increases in schooling and shifts in production toward schooling-intensive industries. Our results imply that the annual electric machinery–pottery growth differential is 0.5%–1% greater in countries with improvements in average schooling over the 1980–1999 period at the 75th percentile (such as China with an improvement of 2.14 years) than in countries with improvements at the 25th percentile (such as El Salvador with 1.18 years).

Measuring shifts in the production structure using the available international data on industry value added has disadvantages. Most importantly, the data are in nominal terms (following the literature we deflate the original data using the U.S. producer price index, but this has no effect on relative industry growth). Moreover the value-added growth series contain some extreme observations. We therefore also use industry employment growth to measure changes in the production structure. This strengthens our results considerably, in terms of both the robustness and the size of the effects. For example, our estimates yield an annual employment growth differential between the industry at the 75th (electrical machinery) and the 25th (pottery) percentile of schooling intensity that is 1.0%–1.3% higher in a country with initial schooling at the 75th percentile than in a country at the 25th percentile. For comparisons, the average growth differential between electric machinery and pottery is 0.5% and the median growth differential is 0.2%.

The link between increases in schooling and growth of schooling-intensive industries also becomes stronger. Annual employment growth in the industry at the 75th percentile of schooling intensity compared with the industry at the 25th percentile is 0.75%–1.5% greater in countries with schooling improvements at the 75th percentile than in countries at the 25th percentile.

For countries to specialize in production they must be open to international trade. When we limit our empirical analysis to open economies, we find stronger links between initial schooling levels and subsequent shifts of the production structure toward schooling-intensive industries. Focusing on open economies also serves as a robustness check. During the 1980s and especially the 1990s, many countries reduced trade tariffs, quotas, and other trade barriers. Such trade liberalization policies may have allowed human-capital-abundant countries to specialize (further) in human-capital-intensive industries. In this case, the human-capital-level effect could partly reflect adjustments of the pattern of specialization in economies that opened to trade during the 1980–1999 period. We therefore check whether the human-capital-level effect is present in countries that have been open to trade since 1970. Our results show that the effect of initial schooling on growth in schooling-intensive industries is stronger in open economies than in the largest possible sample in all specifications. Hence, there is no evidence that the human-capital-level effect is driven by transitional dynamics in countries that liberalized trade.

The remainder of the paper is structured as follows. Section II presents a model that illustrates the effects of human capital on growth in more compared to less human-capital-intensive industries. Section III explains the sources and main features of our data. Section IV presents our main empirical results. In section V, we provide further evidence and perform robustness checks. Section VI concludes.

II. Theoretical Framework

We now explain how countries’ capacity to adopt new technologies, which following Nelson and Phelps (1966) we take to depend on their human capital, may affect their comparative advantage in human-capital-intensive industries. The two main building blocks of our theoretical framework are (i) a technology adoption function in the spirit of Nelson and Phelps (1966) linking each country’s technology to its initial level of human capital and the world-frontier technology; and (ii) the simplest possible

3 Country-industry-specific deflators are unavailable for most countries in our sample. The industry growth literature refers to the U.S. PPI deflated industry value-added data as real value added.
multicountry general equilibrium model of international specialization. In our framework, a country’s production structure depends on its human capital for two very different reasons: (i) because of the factor supply effect emphasized in the Heckscher-Ohlin model (which ends up being trivial in our model); and (ii) and most importantly, because each country’s level of human capital determines its distance from the world-frontier technology in the steady state, and also how quickly countries converge to steady state. Our main result is that an acceleration of skilled-labor-augmenting efficiency growth at the world frontier leads countries with abundant human capital to specialize further in human-capital-intensive industries. Intuitively, we are trying to capture that faster technology adoption in countries with abundant human capital will lead to more rapid total factor productivity growth in human-capital-intensive industries at times when new technologies are skill-labor augmenting. With free trade, this will lead to shifts in international specialization patterns as countries with higher levels of human capital specialize further in human-capital-intensive industries.

A. Model

The world consists of many open economies, indexed by $c$, that can produce in two industries, indexed by $s = 0, 1$. There are two types of labor, high and low human capital, and we denote their supply in country $c$ at time $t$ by $M_{c,t}$ and $L_{c,t}$ respectively. The efficiency levels $A_{c,t}^L$ and $A_{c,t}^M$ of the two types of labor evolve over time and depend on each country’s capacity to adopt world technologies. Following Nelson and Phelps (1996), we assume efficiency growth $\dot{A}_{c,t}^L = (\partial A_{c,t}^L / \partial t)(A_{c,t}^L / A_{c,t}^M)$ of labor of type $f = L, M$ (hats indicate growth rates) to be increasing in the gap between country efficiency $A_{c,t}^f$ and world-frontier efficiency $A_{w,t}^f$ (W indicates the world frontier),

$$\dot{A}_{c,t}^f = \phi^f (H_{c,t}) \left( \frac{A_{w,t}^f - A_{c,t}^f}{A_{c,t}^f} \right), \quad (1)$$

where $\phi^f (H)$ captures the country’s capacity of technology adoption, which is increasing in its human capital $H = M/L$. The only difference between this framework and that of Nelson and Phelps is that we distinguish between technologies augmenting the efficiency of high and low human capital workers, as in the literature on skill-biased and directed technical change (for example, Acemoglu, 1998, 2003a; Acemoglu & Zilibotti, 2001; Caselli & Coleman, 2002, 2006).4

Output $X_{s,c,t}$ in industry $s$ and country $c$ at time $t$ is produced according to $X_{s,c,t} = D_{s,c,t}E_{s,t}(A_{c,S,t}, L_{c,t})^{1-\gamma}(A_{c,M,t}, M_{c,t})^{\gamma}$ where $D$ captures country-level efficiency and $E$ industry-specific technology. Hence, industry 1 uses only high human capital labor, while industry 0 uses only low human capital labor. This extreme assumption regarding factor intensities simplifies our analysis, but is not necessary for the implications that follow.

To examine how steady-state production levels depend on a country’s capacity to adopt technologies we suppose constant efficiency growth at the world frontier, $\dot{A}_{w,t}^L = g^L$ and $\dot{A}_{w,t}^M = g^M$. Each country’s human capital $H_c$, and hence its capacity to adopt technologies ($\phi^L$ and $\phi^M$), are assumed to be constant in time. In steady state, efficiency in each country grows at the same rate as at the world frontier. Equation (1) therefore implies that the steady-state level of efficiency of labor of type $f = L, M$ in country $c$ is $A_{s,t}^f = \frac{\phi^f (H_c)}{g^f + \phi^f} A_{w,t}^f$ (asterisks denote steady-state values). Hence, the greater the capacity of countries to adopt technologies, the closer their steady-state efficiency levels to the world frontier. It is now immediate to determine steady-state output in sector $s$ in country $c$ as

$$X_{s,c,t}^* = D_{s,c,t}E_{s,t}^*(A_{c,S,t}, L_{c,t})^{1-\gamma}(A_{c,M,t}, M_{c,t})^{\gamma} H_{c,t}, \quad (2)$$

where we have assumed that competitive labor markets ensure full employment. Steady-state production in the high relative to the low human capital industry, $Z_{c,t}^* = X_{1,c,t}^*/X_{0,c,t}^*$, in country $c$ as compared with $q$ is therefore

$$\frac{Z_{c,t}^*}{Z_q^*} = \left[ \frac{H_c}{H_q} \right]^{(\phi^L (H) / \phi^L) \left( \frac{g^L + \phi^L}{g^M + \phi^M} \right)} \left( \frac{\phi^M (H) / \phi^M}{g^L + \phi^L} \right)^{(\phi^L (H) / \phi^L) \left( \frac{g^L + \phi^L}{g^M + \phi^M} \right)} \right]. \quad (3)$$

This expression does not depend on country-level efficiency because we are comparing two industries within each country; it does not depend on industry-level technology because we are comparing the same industries in different countries.

Equation (3) implies that country $c$ ‘s human capital $H_c$ has a factor supply effect and a technology adoption effect on its steady-state production structure as compared with country $q$. The factor supply effect (captured by the first square bracket) is straightforward. An increase in human capital means an increase in the relative supply of the factor used by the human-capital-intensive industry and therefore relatively greater production in the human-capital-intensive industry. The focus of our theoretical framework is on the technology adoption effect (captured by the second square bracket). This effect can reinforce the factor supply effect or work in the opposite direction, depending on whether it is skilled- or unskilled-labor-augmenting technology that is progressing faster at the world frontier. For example, consider the case where human capital has the same impact on

---

4 Acemoglu (2003b) discusses the relationship between the Nelson and Phelps model and the literature on directed technical change.
the capacity to adopt skilled- and unskilled-labor-augmenting technologies, $d^M (H) = d^L (H)$ for all $H$. Suppose first that skilled-labor-augmenting technical progress at the world frontier exceeds unskilled-labor augmenting technical progress, $g^M > g^L$. In this case, a higher level of human capital $H_c$ will translate into more human-capital-intensive production in the long run through the technology adoption effect. This is because human capital facilitates the adoption of all technologies equally and it is skill-augmenting technology that is advancing more rapidly at the frontier. Now suppose instead that $g^L > g^M$. In this scenario it is unskilled-labor-augmenting technology that is progressing faster at the frontier. The technology adoption effect of higher human capital levels will therefore shift production toward the low human capital industry.

We now suppose that skilled-labor-augmenting efficiency growth $g^M$ at the world frontier increases at some time $T$.\(^5\) Equation (3) implies that this acceleration of skilled-labor-augmenting technical change translates into an increase in $Z_c^s / Z_c^u$ if and only if $H_c > H_u$. Countries with high levels of human capital will therefore experience an increase in steady-state production levels in the human-capital-intensive industry relative to countries with low human capital. As a result, they will see relatively faster growth in the human-capital-intensive industry during the transition to the new steady state.\(^6\) Formally, using lowercase variables to denote logs of uppercase variables,

$$\Delta z_c - \Delta z_q \equiv [z_{c,t} - z_{q,t}] - [z_{q,t} - z_{q,t}] = g(h_{c,t}) - g(h_{q,t})$$

for $t > T$, where $g(h)$ is strictly increasing in $h$. Value added in each industry is $Y_{x,t} = P_{x,t}X_{x,t}$ where $P_{x,t}$ denotes international prices. The production function implies that growth of value added between $T$ and $t$ equals $\Delta y_{x,t} = Y_{x,T} - Y_{x,T} = \Delta d_c + \Delta \rho + \Delta s + s \Delta d^M_M + (1 - s) \Delta d^M_M$. Combined with equation (4) this yields

$$\Delta y_{x,t} = [\Delta d_c + \Delta \rho + \Delta s] + \eta + g(h_{c,t})s.$$  \(^{(5)}\)

The country-specific effect $\lambda_c$ captures country-level labor force and total factor productivity growth, while the industry-specific growth effect $\mu_s$ is the sum of price changes and industry-specific technical progress $\eta$ captures unskilled-labor-augmenting technical change. According to equation (5), the impact of initial human capital on growth during the transition is greater in the human-capital-intensive industry.\(^7\) This is what we refer to as the human-capital-level effect on output growth in human-capital-intensive industries.

So far we have assumed that human capital in each country is constant in time. As a result, human capital affects industry output growth only through technology adoption in equation (5). When human capital levels increase in time there is also a factor supply effect.\(^8\) As industries are assumed to be at opposite extremes in terms of their human capital intensity, this effect takes a particularly simple form in our framework. A 1% increase in human capital leads to a one-point output growth differential between the high and the low human capital industry over the same time period. With nonextreme factor intensities, the implied output growth differential would be larger (for example, Ventura, 1997). This is because an increase in human capital would lead to labor moving from the less to the more human-capital-intensive industry (assuming the economy is not fully specialized). We refer to the positive effect of factor supply on output growth in human-capital-intensive industries as the human capital accumulation effect.

### B. Further Remarks

The factor supply effect linking human capital and relative production levels in the human-capital-intensive industry in equation (3) does not carry through to single industry pairs in a neoclassical multi-industry model. It can be shown, however, that human-capital-abundant countries will still specialize in human-capital-intensive industries on average (for example, Deardorff, 1982; Forstner, 1985). Furthermore, as shown by Romalis (2004), the positive effect of human-capital-abundance on relative production levels in human-capital-intensive industries reemerges for single industry pairs once monopolistic competition and transport costs are incorporated into an otherwise standard neoclassical multi-industry model.\(^9\)

---

\(^5\) For evidence that there was such an acceleration sometime around the early 1970s, see Autor, Katz, and Krueger (1998); Berman, Bound, and Machin (1998); Berman and Machin (2000); and Caselli and Coleman (2002). We take this acceleration to be exogenous. See Acemoglu (1998, 2002) and Acemoglu and Zilibotti (2001) for models that endogenize the rate of directed technical change at the technology frontier.

\(^6\) This is because they adopt new skill-augmenting technologies more rapidly. Many of the new technologies becoming available since the 1970s were embodied in computers. Faster technology adoption in countries with high human capital levels should therefore have been accompanied by greater computer imports. This is what Caselli and Coleman (2001) find for the 1970–1990 period.

\(^7\) During the transition, the TFP growth differential between the high and the low human capital industry is greater in a country with high than a country with low human capital. Our framework does not make predictions about whether this TFP growth differential is positive or negative. The evidence on the link between human capital intensity and TFP growth across U.S. industries is mixed. While there appears to be a positive link in the late 1970s and early 1980s (Kahn & Lim, 1998), there is no such relationship over longer periods (Klenow, 1998).

\(^8\) Increases in human capital could also affect industry output growth through technology adoption. Such effects are likely to be small in our empirical application because it takes time for additional human capital to translate into new technologies.

A final note on an alternative theoretical framework that could yield a link between countries’ human capital levels and relative value-added growth in human-capital-intensive industries. Suppose that countries with high human capital have lower efficiency wages for high human capital workers (this requires the absence of conditional factor price equalization). In this case, countries with a greater supply of human capital may end up with a greater ratio of high to low human capital workers in human-capital-intensive industries. This could result in faster total factor productivity growth in human-capital-intensive industries in countries with abundant human capital even if the rate of technology adoption in each industry depended exclusively on the ratio of high to low human capital workers in the industry. We cannot test this alternative view with our data, however, as we do not have industry-level human capital data for a broad cross section of countries.

III. Data

A. Country-Industry

Data on value added and employment at the country-industry level come from the Industrial Statistics of the United Nations Industrial Development Organization (UNIDO). The UNIDO INDSTAT3 database (revision 2) reports value-added and employment data for 28 manufacturing industries at the three-digit International Standard Industrial Classification (ISIC) level for a large number of countries. In our benchmark specifications the dependent variable is the annual logarithmic growth rate of value added (\(VAGR_{t,c}\); the deflator used is the U.S. producer price index) and the annual logarithmic change of employment (\(EMPGR_{t,c}\)) over the 1980–1999 period. We drop countries with data for less than ten industries and also require at least five years of data in the 1980s and in the 1990s for each country-industry. The United States is excluded from the sample because it is used for industry benchmarking. This leaves us with a sample of 44 countries and 1,049 observations for industry value-added growth and a sample of 47 countries and 1,134 observations for industry employment growth.\(^{10}\) The UNIDO database has wider coverage in the 1980s than the 1990s. We therefore also consider two alternative sample periods, the 1980–1989 period (with the widest coverage) and the 1980–1995 period. This enables us to examine industry dynamics in up to 66 countries using up to 1,634 observations at the country-industry level (see the online supplementary appendix table A-I for details on the coverage of different time periods).\(^{11}\)

B. Industry Level

Our measure of human capital intensity at the industry level is based on U.S. data. The limited availability of industry data for most countries makes it necessary to rely on industry human capital intensities from a benchmark country. The U.S. is a natural choice both because of the detail and quality of U.S. statistics and because U.S. labor markets are less regulated than those of other high-income countries for which some industry data are available (Botero et al., 2004). Observed differences in human capital intensities across industries are therefore likely to better reflect technological characteristics of industries. Moreover, as we examine the role of human capital for industry growth jointly with that of finance, physical capital, and property rights it is natural to maintain the same benchmark country as in the finance and industry growth literature and recent empirical work on international specialization (for example, Rajan & Zingales, 1998; Nunn, 2007). Using U.S. data to proxy for differences in human capital intensities across industries in all other countries does have drawbacks. Most importantly, it could lead us to reject our hypotheses linking human capital to growth in human-capital-intensive industries not because they are false but because U.S. data do not yield good proxies for cross-industry differences in human capital intensities in other countries. What matters for avoiding such a false negative is that differences in the human capital intensity across U.S. industries reflect inter-industry differences in human capital intensities in other countries. It is not necessary for industries to use human capital with the same intensity in different countries.

The data source for our industry-level measure of schooling intensity is the 1980 Integrated Public Use Microdata Series. This database contains individual-level data on hours worked by four-digit industry classifications and years of education. This allows us to calculate average years of employee schooling for all industries at the UNIDO three-digit ISIC. We also calculate the share of employees with at least twelve years of education (necessary for completing secondary school in the United States) and at least sixteen years of education (college). Table 1 reports the schooling intensity and descriptive statistics for all 28 industries. The most schooling-intensive industries are petroleum refineries, printing and publishing, and (industrial and other) chemicals, while the least schooling-intensive sectors are leather, apparel, footwear, and textiles.

Table 1 also reports the values of other industry characteristics used in our empirical analysis. The first measure is industry external finance dependence, which Rajan and Zingales (1998) define as the difference between industry investment and industry cash flow relative to industry in-

---

\(^{10}\) These countries are Australia, Austria, Belgium, Bolivia, Cameroon, Canada, Chile, China, Colombia, Costa Rica, Cyprus, Ecuador, Finland, France, Hungary, Indonesia, India, Ireland, Iran, Israel, Italy, Japan, Jordan, Kenya, Korea, Kuwait, Malaysia, Malta, Mexico, the Netherlands, Norway, Panama, Poland, Portugal, Senegal, Singapore, Spain, Sri Lanka, Sweden, Trinidad and Tobago, Turkey, the United Kingdom, Uruguay, South Africa. In the employment models we lose Costa Rica, but also use Argentina, Malawi, New Zealand, and Taiwan.

\(^{11}\) Available at: http://www.antoniociccone.eu.
vestment. To construct industry reliance on external finance, Rajan and Zingales use COMPUSTAT data from large publicly traded U.S. firms over the 1980s at the three- to four-digit ISIC. We obtain this series from Laeven, Klingebiel, & Kroszner (2007), who reconstruct the original Rajan-Zingales measure at the three-digit ISIC level. The data appendix gives details on the construction of the measures and provides exact definitions and sources.

Table 1 reports all industry-level variables used in the analysis for three-digit ISIC (International Standard Industrial Classification) manufacturing industries. HCINT is the average years of schooling of employees in each industry in the United States in 1980. HCINT(SEC) is the ratio of hours worked by employees with at least twelve years of schooling (necessary for completing secondary school) to total hours worked in the United States in 1980. HCINT(COLL) is the ratio of hours worked by employees with at least sixteen years of schooling (college) to total hours worked in the United States in 1980. CONTRACT denotes Rajan and Zingales’s (1998) measure of industry reliance on external finance, defined as 1 minus industry cash flow over industry investment of large publicly traded U.S. firms over the 1980s (taken from Laeven, Klingebiel, & Kroszner, 2007). CONTRA 1 is Nunn’s (2007) measure of industry contract intensity, defined as the cost-weighted proportion of differentiated inputs. The data appendix gives details on the construction of the measures and provides exact definitions and sources.

Table 1.—Industry Characteristics

<table>
<thead>
<tr>
<th>ISIC Code</th>
<th>Industry Name</th>
<th>HCINT</th>
<th>HCINT (SEC)</th>
<th>HCINT (COLL)</th>
<th>CONTRACT</th>
<th>CAPINT</th>
</tr>
</thead>
<tbody>
<tr>
<td>314</td>
<td>Tobacco</td>
<td>11.509</td>
<td>0.660</td>
<td>0.110</td>
<td>−0.450</td>
<td>0.317</td>
</tr>
<tr>
<td>361</td>
<td>Pottery, china, earthenware</td>
<td>13.244</td>
<td>0.650</td>
<td>0.099</td>
<td>−0.150</td>
<td>0.329</td>
</tr>
<tr>
<td>323</td>
<td>Leather products</td>
<td>10.138</td>
<td>0.507</td>
<td>0.071</td>
<td>−0.140</td>
<td>0.571</td>
</tr>
<tr>
<td>324</td>
<td>Footwear, except rubber or plastic</td>
<td>10.259</td>
<td>0.521</td>
<td>0.037</td>
<td>−0.080</td>
<td>0.650</td>
</tr>
<tr>
<td>372</td>
<td>Non-ferrous metals</td>
<td>11.547</td>
<td>0.703</td>
<td>0.097</td>
<td>0.010</td>
<td>0.160</td>
</tr>
<tr>
<td>322</td>
<td>Wearing apparel, except footwear</td>
<td>10.193</td>
<td>0.511</td>
<td>0.051</td>
<td>0.030</td>
<td>0.745</td>
</tr>
<tr>
<td>353</td>
<td>Petroleum refineries</td>
<td>13.204</td>
<td>0.873</td>
<td>0.250</td>
<td>0.040</td>
<td>0.058</td>
</tr>
<tr>
<td>369</td>
<td>Other non-metallic mineral products</td>
<td>11.655</td>
<td>0.678</td>
<td>0.145</td>
<td>0.060</td>
<td>0.377</td>
</tr>
<tr>
<td>313</td>
<td>Beverages</td>
<td>11.967</td>
<td>0.738</td>
<td>0.131</td>
<td>0.080</td>
<td>0.713</td>
</tr>
<tr>
<td>371</td>
<td>Iron and steel</td>
<td>11.425</td>
<td>0.696</td>
<td>0.083</td>
<td>0.090</td>
<td>0.242</td>
</tr>
<tr>
<td>311</td>
<td>Food products</td>
<td>11.259</td>
<td>0.656</td>
<td>0.097</td>
<td>0.140</td>
<td>0.331</td>
</tr>
<tr>
<td>341</td>
<td>Paper and products</td>
<td>11.693</td>
<td>0.727</td>
<td>0.109</td>
<td>0.170</td>
<td>0.348</td>
</tr>
<tr>
<td>321</td>
<td>Textiles</td>
<td>10.397</td>
<td>0.516</td>
<td>0.059</td>
<td>0.190</td>
<td>0.376</td>
</tr>
<tr>
<td>342</td>
<td>Printing and publishing</td>
<td>12.792</td>
<td>0.839</td>
<td>0.200</td>
<td>0.200</td>
<td>0.713</td>
</tr>
<tr>
<td>355</td>
<td>Rubber products</td>
<td>11.730</td>
<td>0.743</td>
<td>0.079</td>
<td>0.230</td>
<td>0.407</td>
</tr>
<tr>
<td>332</td>
<td>Furniture, except metal</td>
<td>10.760</td>
<td>0.583</td>
<td>0.071</td>
<td>0.240</td>
<td>0.568</td>
</tr>
<tr>
<td>381</td>
<td>Fabricated metal products</td>
<td>11.577</td>
<td>0.699</td>
<td>0.097</td>
<td>0.240</td>
<td>0.435</td>
</tr>
<tr>
<td>351</td>
<td>Industrial chemicals</td>
<td>12.704</td>
<td>0.815</td>
<td>0.217</td>
<td>0.250</td>
<td>0.240</td>
</tr>
<tr>
<td>333</td>
<td>Wood products, except furniture</td>
<td>10.787</td>
<td>0.593</td>
<td>0.071</td>
<td>0.280</td>
<td>0.516</td>
</tr>
<tr>
<td>354</td>
<td>Misc. petroleum and coal products</td>
<td>11.921</td>
<td>0.691</td>
<td>0.141</td>
<td>0.330</td>
<td>0.395</td>
</tr>
<tr>
<td>384</td>
<td>Transport equipment</td>
<td>12.346</td>
<td>0.780</td>
<td>0.159</td>
<td>0.360</td>
<td>0.859</td>
</tr>
<tr>
<td>390</td>
<td>Other manufactured products</td>
<td>11.354</td>
<td>0.651</td>
<td>0.119</td>
<td>0.470</td>
<td>0.547</td>
</tr>
<tr>
<td>382</td>
<td>Glass and glass products</td>
<td>11.484</td>
<td>0.691</td>
<td>0.087</td>
<td>0.530</td>
<td>0.557</td>
</tr>
<tr>
<td>382</td>
<td>Machinery, except electrical</td>
<td>12.266</td>
<td>0.789</td>
<td>0.139</td>
<td>0.600</td>
<td>0.764</td>
</tr>
<tr>
<td>352</td>
<td>Chemicals, other</td>
<td>13.031</td>
<td>0.821</td>
<td>0.270</td>
<td>0.750</td>
<td>0.490</td>
</tr>
<tr>
<td>383</td>
<td>Machinery, electric</td>
<td>12.357</td>
<td>0.781</td>
<td>0.163</td>
<td>0.950</td>
<td>0.740</td>
</tr>
<tr>
<td>385</td>
<td>Professional &amp; scientific equipment</td>
<td>12.518</td>
<td>0.793</td>
<td>0.185</td>
<td>0.960</td>
<td>0.785</td>
</tr>
<tr>
<td>356</td>
<td>Plastic products</td>
<td>11.678</td>
<td>0.715</td>
<td>0.102</td>
<td>1.140</td>
<td>0.400</td>
</tr>
</tbody>
</table>

C. Country Level

Our benchmark measure of country-level human capital is average years of schooling of the population from the latest update of the Barro and Lee (2001) database. In our sensitivity analysis we also use proxies of human capital that are based on the share of the population with a completed secondary education and the Hanushek and Kimko (2000) schooling quality indicator.

Our other country-level controls come from standard sources. Financial development is measured as the share of private credit to GDP.12 Real per capita GDP and the capital-output ratio come from the Penn World Tables and Klenow and Rodríguez-Clare (2005) respectively. Data on trade openness are taken from Wacziarg and Welch (2003), who extend and update Sachs and Warner’s (1995) trade openness indicator. The rule of law indicator comes from the International Country Risk Guide database (see Knack & Keefer, 1995) and the measure of property rights institutions from the Polity IV database (we use executive constraints, following Acemoglu & Johnson, 2005). All specifications use the value of the country-level variables in 1980, the beginning of the period we examine, except the
We first examine whether countries with high initial skill-biased technical change during the 1980–1999 period, characterized by pervasive improvements in country-level schooling and skills at the country-level, have lower levels of schooling in the subsample of countries that were open to international trade since 1970.

### A. Initial Education Levels and Industry Growth

The estimation equation used for examining the link between initial education levels and value-added employment growth in schooling-intensive industries is

\[
\Delta \ln(V_{A,s,c}) = \lambda + \mu + \Sigma SCH_{c} \times HCINT_{s} + \epsilon_{s,c,1980–1999},
\]

where the dependent variable is the annualized growth rate in country-industry level schooling and value-added or employment (ln(VA)), and the country fixed effect captures factors that determine the schooling intensity of countries and the country-level schooling in 1980 ($SCH_{c}$). The product terms account for other determinants of industry growth discussed in the literature by using the relevant specifications. We examine the link between improvements in country-level schooling and shifts in the production structure toward schooling-intensive industries. We conclude by examining the relationship between schooling and industry growth in the subsample of economies that were open to international trade since 1970.

### IV. Main Results

<table>
<thead>
<tr>
<th>Table 2: Benchmark Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unconditional Estimates</strong></td>
</tr>
<tr>
<td><strong>Physical Capital</strong></td>
</tr>
<tr>
<td><strong>Rule of Law</strong></td>
</tr>
<tr>
<td><strong>Finance</strong></td>
</tr>
<tr>
<td><strong>All Controls</strong></td>
</tr>
<tr>
<td>VAGR OLS (1)</td>
</tr>
<tr>
<td>Initial schooling interaction</td>
</tr>
<tr>
<td>$SCH \times HCINT$</td>
</tr>
<tr>
<td>Physical capital interaction</td>
</tr>
<tr>
<td>$K/Y \times CAPINT$</td>
</tr>
<tr>
<td>Rule of law interaction</td>
</tr>
<tr>
<td>$PRIV \times EXFIN$</td>
</tr>
<tr>
<td>Initial conditions</td>
</tr>
<tr>
<td>$ln(V_{A,s,c})/ln(EMP_{s,c})$</td>
</tr>
<tr>
<td>Adjusted R²</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Countries</td>
</tr>
<tr>
<td>Country fixed effects</td>
</tr>
<tr>
<td>Industry fixed effects</td>
</tr>
</tbody>
</table>

The coefficient \(\Delta \ln(V_{A,s,c})\) is always negative and highly significant. But since this control does not emerge from our theoretical framework, we also estimate models without it. This does not affect the results (only lowered coefficients).

All value-added models include the initial log of value added (VA) and all employment growth models include the initial log employment (EMP) at the country-industry level. The initial schooling interaction is country-level average years of schooling in 1980 ($SCH_{c}$) multiplied by industry-level schooling intensity ($HCINT_{s}$). The physical capital interaction is the product of industry physical capital intensity ($CAPINT_{s}$) and country-level physical capital to output ratio in 1980 ($K/Y_{c}$). The rule of law interaction is the product of industry contract intensity ($CONTRACT_{s}$) and a country-level measure of rule of law in 1984 ($PRIV_{c}$). The finance interaction is the product of industry-level dependence on external finance ($EXFIN_{s}$) and country-level financial development in 1980 ($PRIV_{c}$). Columns 1, 3, 6–12 report OLS coefficient estimates. Columns 2 and 4 report instrumental variable (IV) coefficient estimates where we use the 1970 value of country-level average schooling as instrument for the 1980 value. All specifications also include country fixed effects (coefficients not reported). Absolute values of \(t\)-statistics based on robust (heteroskedasticity-adjusted) standard errors are reported in parentheses below the coefficients. The data appendix gives detailed variable definitions and data sources.
industries (5). In columns 1 and 2, we measure industry growth using value-added data, while in columns 3 and 4 we use employment data. Odd columns report ordinary least squares (OLS) estimates. Even columns report instrumental variables (IV) results, with 1970 schooling levels as instruments for 1980 schooling, to reduce concerns regarding endogeneity and measurement error. The coefficient on the initial schooling interaction is 0.0015 and statistically significant at the 5% level. It implies an annual growth differential of 0.75% between the industry at the 75th percentile (electric machinery) and the 25th percentile (pottery) of schooling intensity in a country with schooling at the 75th percentile (such as the United Kingdom with 8.17 years) compared with a country at the 25th percentile (such as Singapore with 3.65 years). The IV estimates in column 2 are very similar in size and level of statistical significance. When we measure changes in the production structure using industry employment growth, the effect of initial schooling on subsequent growth of schooling-intensive industries becomes stronger. The coefficient on the initial schooling interaction is now 0.002 and statistically significant at the 1% level. This estimate implies that the growth differential between the industry with schooling at the 75th and the 25th percentile is around 1.0%–1.3% higher in a country with average years of schooling at the 75th percentile compared with a country at the 25th percentile.

Controlling for other determinants of industry growth. In columns 5–12 of table 2 we investigate the robustness of our results to alternative determinants of industry growth emphasized in the finance and industry growth literature and recent work on international specialization.

Physical capital. We first examine whether the positive impact of initial schooling levels on growth in schooling-intensive industries is sensitive to controls for the role of physical capital. Country-level growth effects of physical capital are captured by country fixed effects in our difference-in-difference framework. Physical capital could still affect our findings however because it may interact with the physical capital intensity of industries, which could be correlated with their schooling intensity. In columns 5 and 6 we check on this possibility by adding an interaction between industry capital intensity ($K_{i}/Y_{i}$) and the country-level capital-output ratio in 1980 ($K_{c}/Y_{c}$). The physical capital interaction enters with a statistically insignificant coefficient in our value-added models (column 5) and our employment growth models (column 6). The size and significance level of the coefficient on the initial schooling interaction remains very similar to the unconditional models.

Property rights. Empirical work by Levchenko (2007) and Nunn (2007) shows that countries with good contract enforcement (property rights) institutions specialize in complex, contract-intensive industries. In columns 7 and 8, we therefore augment our specifications by an interaction between Nunn’s measure of industry contract intensity ($CONTRACT_{i}$) and a country-level rule of law index ($RLAW_{c}$). This interaction enters always positively, indicating that countries with greater rule of law saw faster growth in more complex industries, but is never significant at the 5% level. The coefficient on the initial schooling interaction continues to be very similar to previous specifications in terms of both size and statistical significance. This applies whether we examine the value-added growth model (in column 7) or the employment growth model (in column 8).

Financial development. Rajan and Zingales (1998) show that external-finance-dependent industries experience faster growth in financially developed countries. Countries with high levels of human capital tend to have developed financial markets (see supplementary appendix table A-IV). Moreover, the external finance dependence of industries is significantly positively correlated with schooling intensity (see supplementary appendix table A-V). Our previous estimates might therefore be partly capturing the effects of finance. To take this into account, we augment our specifications by an interaction between industry external finance dependence ($EXTFIN_{i}$) and country-level financial development ($PRIV_{c}$). Columns 9 and 10 show that the $EXTFIN_{i} \times PRIV_{c}$ interaction enters with a positive and statistically significant coefficient in both value-added and employment specifications. This is in line with the empirical findings of the finance and industry growth literature. The initial schooling interaction continues to be positive and significant at standard confidence levels in all specifications.

---

14 Bils and Klenow (2000) show that the positive cross-country correlation between school enrollment and subsequent growth can partly be explained by schooling decision reacting to expected growth. Note that country-level growth trends are captured by country fixed effects in our empirical framework. Schooling decision could be responding to expected industry growth in schooling-intensive industries, however. This is unlikely to have an important effect on our results, however, as 1980 (1970) schooling levels are largely determined by schooling decisions made during the 1960s and early 1970s (1950s and early 1960s).

15 In the IV models we lose China because of data unavailability. The results are similar when we instrument 1980 schooling by schooling in 1960. We check on this possibility by adding an interaction between Nunn’s measure of industry contract intensity ($CONTRACT_{i}$) and a country-level rule of law index ($RLAW_{c}$). This interaction enters always positively, indicating that countries with greater rule of law saw faster growth in more complex industries, but is never significant at the 5% level. The coefficient on the initial schooling interaction continues to be very similar to previous specifications in terms of both size and statistical significance. This applies whether we examine the value-added growth model (in column 7) or the employment growth model (in column 8).

18 Claessens and Laeven (2003) show that property rights protection is particularly beneficial for the growth of intangible asset–intensive sectors. In an earlier version of this paper (Ciccone & Papaioannou, 2005) we also estimated models interacting Rajan and Zingales’s investment intensity measure (defined as investment over capital stock) with country-level capital per worker and again found similar results.

19 Fisman and Love (2007) and Ciccone and Papaioannou (2006) argue that financial development leads to rapid growth in industries with good growth prospects. To check the robustness of our findings to this link between financial development and industry growth, we also estimated similar results when experimenting with other measures of industry capital intensity, such as capital stock over employment and 1 minus the labor share in value added. In an earlier version of this paper (Ciccone & Papaioannou, 2005) we also estimated models interacting Rajan and Zingales’s investment intensity measure (defined as investment over capital stock) with country-level capital per worker and again found similar results.

16 We found similar results when experimenting with other measures of industry capital intensity, such as capital stock over employment and 1 minus the labor share in value added. In an earlier version of this paper (Ciccone & Papaioannou, 2005) we also estimated models interacting Rajan and Zingales’s investment intensity measure (defined as investment over capital stock) with country-level capital per worker and again found similar results.

17 Consistent with Nunn’s results, we find that the rule of law interaction with contract intensity is positive and highly significant when we analyze the determinants of the pattern of production (rather than changes in the pattern of production).
The effects of human capital on value-added and employment growth in industries (proxied by industry sales or capital growth in the United States). Models interacting financial development with industry growth opportunities (proxy by industry sales or capital growth in the United States). The effects of human capital on value-added and employment growth in human-capital-intensive industries remain positive, statistically significant, and similar in magnitude to the estimates in table 2.

B. Improvements in Schooling and Industry Growth

So far, our specifications do not account for the possibility that faster growth in schooling-intensive industries might be driven by improvements in country-level schooling, as suggested by the neoclassical theory of international specialization. To allow for this additional channel we augment our estimating equation by an interaction between the country-level increase in average years of schooling over the 1980–1999 period, $\Delta SCH_{1980-1999}$, and the industry schooling intensity, $HCINT_i$.

$$\ln y_{i,c,1980-1999} = \lambda_c + \mu_s$$

$$+ \delta(SCH_{c,1980} \times HCINT_i)$$

$$+ \theta(\Delta SCH_{c,1980-1999} \times HCINT_i)$$

$$+ \gamma Z_i + \lambda \ln y_{i,c,1980} + \epsilon_{i,c}$$

models interacting financial development with industry growth opportunities (proxy by industry sales or capital growth in the United States). There is a human capital accumulation effect on growth in human-capital-intensive industries if $\theta > 0$.

Table 3 columns 1–4 report the results for value-added growth models (columns 1 and 2) and for employment growth models (columns 3 and 4). Odd columns report unconditional specifications while even columns report the results controlling for the physical capital interaction, the rule of law interaction, and the financial development interaction (analogously to columns 11 and 12 of table 2). The positive and statistically significant estimate of $\theta$ indicates that value-added and employment growth in schooling-intensive industries was faster in countries with greater improvements in schooling. To get a sense for the size of this effect, consider the comparison between a country with an improvement in schooling at the 5th percentile (such as China with an improvement of 2.1 years) and a country at the 25th percentile (such as El Salvador with an improvement of 1.1 years). Our estimates imply an annual growth gap between the industry at the 75th and the industry at the 25th percentile of schooling intensity of 0.5%. This evidence fits well with Romalis’s (2004) work. Romalis’s theoretical framework yields that the impact of human capital accumulation on industry value-added and export growth is increasing in the industry’s schooling intensity (a result he refers to as the quasi-Rybczynski prediction). He examines the export growth prediction using data on U.S. imports by industry and country of origin for the 1972–1998 period and finds that imports from countries experiencing rapid human capital accumulation did in fact grow most in human-capital-intensive industries.20

20 Romalis’s model also yields that human-capital–abundant countries specialize in human-capital-intensive industries (the quasi-Heckscher-Ohlin prediction). He finds that this prediction is also supported by U.S.
The results in columns 1–4 continue to yield empirical support for the initial schooling effect. The interaction between initial schooling and industry schooling intensity enters positively and significantly at the 1% level in all specifications. Moreover, point estimates are larger than in the previous specifications. The coefficient on the initial schooling level interaction is now 0.0024, approximately 25% greater than in the analogous specification in table 2. The strength of the initial schooling effect also increases in the employment growth models (by 30%–35%). Hence, higher initial schooling went together with faster growth in schooling industries during the 1980–1999 period, even when improvements in schooling are accounted for.

C. The Effects of Human Capital in Open Economies

For countries to specialize in production they must be open to international trade. We therefore redo our empirical analysis in countries that were open to international trade. Focusing on open economies also serves as a robustness check. During the 1980s and especially the 1990s, many countries reduced trade tariffs, quotas, and other trade barriers. Such trade liberalization policies may have allowed human-capital-abundant countries to specialize (further) in human-capital-intensive industries. In this case, the human-capital-level effect could partly reflect adjustments of the pattern of specialization in economies that opened to trade during the 1980–1999 period.

Table 3 columns 5–8 summarize the results of reestimating the specifications in columns 1–4 after restricting the sample to those countries that have been open to international trade since 1970—well before the 1980–1999 period we examine.\(^{21}\) It can be seen that the coefficient on the initial schooling interaction increases across all specifications; the estimate also continues to be significant at the 1% level. For example, while the effect of initial levels of schooling was 0.002 when we controlled for physical capital, rule of law, and financial development (in column 2), it is now 0.0043 (in column 6). This estimate implies an annual growth gap of 0.9% between the industry at the 75th and the 25th percentile of schooling intensity in a country with an improvement in schooling over the 1980–1999 period at the 75th percentile (such as Cyprus with an improvement of 2.2 years) and a country at the 25th percentile (such as the Netherlands with 1.25 years). The estimates in columns 7 and 8 show that the effect of schooling levels and improvements on employment growth of schooling-intensive sectors is also greater in open economies than in the whole sample (columns 3 and 4).

V. Further Evidence and Sensitivity Analysis

We start by examining whether the initial human capital effect partly captures other interaction of country-level schooling with industry characteristics. We also examine whether industry schooling intensity interacts with country characteristics other than schooling. Then we explore the sensitivity of our results to alternative measures of human capital. We conclude by estimating the effect of schooling on growth in schooling-intensive industries during alternative sample periods.\(^{22}\)

A. Human Capital and Other Industry Characteristics

Columns 1 and 2 in table 4 examine whether initial schooling continues to have an effect on growth in schooling-intensive industries when it is also interacted with the physical capital intensity of industries. The results show that the effect of the schooling-level interaction changes little in size and statistical significance. The interaction between initial human capital and industry physical capital intensity is only significant among open economies. These results are confirmed by the analogous employment growth regressions in columns 7 and 8.

In columns 3 and 4 we explore whether the initial schooling-level effect could be partly standing in for growth effects of schooling that work through the complexity of industries as measured by Nunn’s (2007) CONTRACT index.\(^{23}\) The initial schooling-level interaction changes little in size and statistical significance when we include the interaction between initial schooling and industry contract intensity. This is also the case when we analyze employment growth in columns 9 and 10.

---

\(^{21}\) The countries in our sample that were already open to international trade in 1970 are Australia, Austria, Belgium, Canada, Cyprus, Finland, France, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mauritius, the Netherlands, Norway, Portugal, Singapore, Spain, Sweden, and the United Kingdom. Cutoff years other than 1970 (such as 1975, 1980) yielded similar results.

\(^{22}\) We also performed additional sensitivity checks. In the working-paper version, for example, we estimated models expressing human capital in logs and also used the Cohen and Soto (2007) schooling statistics to account for measurement error. The results appear very robust (see Ciccone & Papaioannou, 2005).

\(^{23}\) In our sample of 28 manufacturing industries there is zero correlation between schooling and contract intensity. In Nunn’s sample of 342 industries there is a positive and significant correlation, however.
### Table 4—Cross-Industry Interactions

<table>
<thead>
<tr>
<th></th>
<th>Value-Added Growth</th>
<th>Employment Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Capital Intensity</td>
<td>Contract Intensity</td>
</tr>
<tr>
<td></td>
<td>All (1) Open (2)</td>
<td>All (3) Open (4)</td>
</tr>
<tr>
<td>Initial schooling interaction &amp; [SCH × HCINT]</td>
<td>0.0023 (2.89) 0.0039 (4.62)</td>
<td>0.0022 (2.74) 0.0043 (4.92)</td>
</tr>
<tr>
<td>Schooling accumulation &amp; [ΔSCH × HCINT]</td>
<td>0.0795 (4.71) 0.1672 (2.46)</td>
<td>0.0805 (4.64) 0.1667 (4.64)</td>
</tr>
<tr>
<td>Initial schooling level × industry capital intensity</td>
<td>-0.0007 (0.99) 0.0024 (2.90)</td>
<td>-0.0056 (1.24) -0.0051 (1.76)</td>
</tr>
<tr>
<td>Initial schooling level × industry contract intensity</td>
<td>-0.0007 (2.79) 0.0024 (1.76)</td>
<td>-0.0056 (1.24) -0.0051 (1.76)</td>
</tr>
<tr>
<td>Initial schooling level × industry finance dependence</td>
<td>-0.0007 (2.79) 0.0024 (1.76)</td>
<td>-0.0056 (1.24) -0.0051 (1.76)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Countries</td>
<td>0.461 (2.45) 0.5738 (2.45)</td>
<td>0.463 (2.45) 0.569 (2.45)</td>
</tr>
<tr>
<td>Observations</td>
<td>1.049 (523) 1.049 (523)</td>
<td>1.049 (523) 1.049 (523)</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Country fixed effects</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
</tr>
</tbody>
</table>

The dependent variable in columns 1–6 is the annual growth rate of value added at the country-industry level for the period 1980–1999. The dependent variable in columns 7–12 is the annual growth rate of employment over the same period. All value-added growth models include the initial log of value added and all employment growth models include the initial log employment at the country-industry level (coefficients not reported). Models in odd columns are estimated for the largest possible sample. Models in even columns restrict estimation to countries that have been open to international trade since 1970, according to the Sachs and Warner (1995) criterion of openness as updated and extended by Wacziarg and Welch (2003). The initial schooling interaction is country-level average years of schooling in 1980 (SCH80) multiplied by industry-level schooling intensity (HCINT). The schooling accumulation interaction is the product of industry-level schooling intensity with the annual country-level change in average years of schooling over the 1980–1999 period. In columns 1–2 and 7–8, we add an interaction between initial schooling (SCH80) and industry physical capital intensity (CAPINT). In columns 3–4 and 9–10, we add an interaction between initial schooling (SCH80) and industry contract intensity (CONTRACT). In columns 5–6 and 11–12, we add an interaction between initial schooling (SCH80) and industry external finance dependence (EXTFIN). All specifications also include country and industry fixed effects (coefficients not reported). Absolute values of t-statistics based on robust standard errors are reported in parentheses. The data appendix gives detailed variable definitions and sources.
Columns 5–6 and 11–12 add an interaction term between initial schooling level and industry external finance dependence. In the full sample, the initial schooling effect is nearly unchanged in the employment growth regressions (in columns 11 and 12) but becomes somewhat weaker in the value-added growth regressions (in columns 5 and 6). In the sample of open economies, the initial schooling-level effect changes little in size and statistical significance in both value-added and employment models, while the interaction between initial human capital and external finance dependence is insignificant.24

The effect of improvements in schooling on value-added and employment growth in schooling-intensive industries (the “quasi-Rybczynski” effect) continues to be significant, economically and statistically. This is the case when we examine its robustness by including interactions between country-level schooling improvements and other industry characteristics (see supplementary appendix table A-VI, which is analogous to table 4).

B. Country Characteristics

In panels A and B of table 5 we check the robustness of our results by allowing industry schooling intensity to interact with country characteristics other than schooling.

In columns 1 and 2 we add an interaction between the capital-output ratio and industry schooling intensity (\(K_c/ Y_c \times HCINT_c\)). This allows us to see whether industry schooling intensity interacts with physical rather than human capital. The results show that the initial schooling interaction remains a positive and highly statistically significant determinant of value-added growth (panel A) and employment growth (panel B) in schooling-intensive industries.

In columns 3 and 4 we augment the empirical model by an interaction term between industry schooling intensity and country-level financial development (\(PRIV_c \times HCINT_c\)). The interaction of schooling with industry schooling intensity continues to be statistically significant and of similar magnitude than in our benchmark estimates. The coefficient on the interaction between financial development and industry schooling is significant in the employment models in the full sample (panel B, column 3), but insignificant in the sample of open economies (panel B, column 4). The estimate is also insignificant in the value-added models, both in the full sample and in the sample of economies open to international trade (panel A, columns 3 and 4).

In columns 5 and 6 we address the question of whether the initial schooling interaction is capturing higher growth in schooling-intensive industries in countries with good contracting institutions. This is done by adding an interaction between the rule of law index and industry schooling intensity (\(RLAW_c \times HCINT_c\)). In the sample including open and closed economies, both the initial schooling interaction and the interaction between industry schooling and rule of law are insignificant (column 5, panel A). But the initial schooling interaction remains significant in the large sample when we measure changes in production structure using industry employment growth (column 5, panel B). And the initial schooling interaction is significant in both the value-added and employment models when we focus on open economies (column 6, panels A and B).

As a further robustness check, we examine whether the initial schooling effect reflects differences in property rights institutions by adding an interaction between industry schooling intensity and the Polity Project measure of executive constraints (\(PROP_c\); see the data appendix for details) in columns 7 and 8. The results show that schooling remains a significant determinant of the growth of schooling-intensive sectors.

In columns 9 and 10 we include an interaction between industry schooling intensity and country-level income per capita (\(Y_c \times HCINT_c\)). These specifications have to be interpreted with caution because human capital is a major determinant of aggregate productivity, and GDP could actually be a better proxy for human capital than our indicators of schooling (both because human capital is broader than formal schooling and because schooling is observed with error).25 In the sample including both open and closed economies, the initial schooling interaction is significant in the employment growth regressions (panel B, column 9), but not the value-added growth regressions (panel A, column 9). Among open economies, the initial schooling-level effect remains positive and statistically significant in the value-added growth regressions and in the employment growth regressions (column 10, panels A and B).

C. Alternative Measures of Human Capital

Secondary education split. Columns 1–4 in table 6 estimate the effects of schooling on value-added and employment growth in schooling-intensive industries using the share of the population with a completed secondary education (\(SEC_c\)) as a proxy for country-level schooling. Improvements in schooling are measured as the increase in the share of the population with a secondary education over the 1980–1999 period. The industry schooling intensity is proxied by the share of workers with a completed secondary education (\(HCINT(SEC)\)). The initial schooling-level interaction and the schooling improvements interaction are therefore \(SEC_c \times HCINT(SEC)\) and \(ΔSEC_c \times HCINT(SEC)\) respectively. The results show that both interactions enter positively and statistically significantly in our country-industry growth regressions. Hence, our results are robust to

24 The initial schooling interaction also remains unaffected when we add an interaction between initial schooling and Claessens and Laeven’s (2003) industry asset-intangibility measure.

25 Human capital comprises education (quantity and quality) in and out of the classroom, on-the-job learning and training, and health (Kartini Shastry & Weil, 2003). Manuelli and Seshadri (2005) show in a calibrated model that aggregate productivity is closely related to properly measured human capital.
measuring country-level schooling by the population share with secondary schooling.

In columns 5–8 we repeat the estimation using the population with a completed secondary education relative to the population with less than secondary schooling (SECREATIO,) to measure country-level schooling. Our empirical results continue to yield support for the human-capital–level and the human capital accumulation effect.

Labor force quality. In table 6, columns 9–12, we use the Hanushek-Kimko (2000) labor force quality index (LFQUALc) as a proxy for the initial level of human capital.
This index is based on internationally administrated tests in mathematics and sciences. The labor force quality interaction with the industry schooling intensity enters positively and significantly in all models. This indicates that countries with greater schooling quality experienced faster growth in schooling-intensive industries. The estimate in model 9 implies that the annual growth differential between the industry at the 75th percentile and the 25th percentile of schooling intensity is 0.5% higher in a country with schooling quality at the 75th percentile (such as Austria) than in a country with schooling quality at the 25th percentile (such as Peru). The effect of schooling quality is considerably stronger in economies open to international trade (models 10 and 12). We also estimated models interacting industry schooling intensity with average years schooling as well as labor force quality. The schooling quantity interaction is significant in all specifications. When we measure changes in the production structure using industry employment growth, the schooling quantity and the schooling quality interactions are both significant.

D. Alternative Sample Periods

Coverage of the UNIDO database starts deteriorating in the early 1990s and worsens considerably after 1996, which is why most empirical studies of the determinants of industry growth focus on the 1980s (for example, Claessens & Laeven, 2003; Beck et al., 2007; Fisman & Love, 2007). We therefore reestimate all specifications in two alternative samples. Table 7 reports our benchmark specifications for the 1980–1995 period (columns 1–6) and the 1980–1989 period (columns 7–12).26 Relative to the 1980–1999 period, coverage increases by more than 30% when we consider the 1980–1995 period and by 50% when we consider the 1980s. We report unconditional estimates and results controlling simultaneously for all the determinants of industry growth considered in table 4 (models 2, 5, 8, and 11 are analogous to models 10–12 in table 4). We also report estimates in the group of countries that were open to international trade since 1970. The initial schooling interaction is positive and highly significant in all cases, and the size of the effect is quite stable across samples. The link between schooling improvements and growth in schooling-intensive industries also continues to be positive and significant.

VI. Conclusion

One way to progress in our understanding of the effects of human capital on economic growth is to examine channels through which such effects could work. If high levels of human capital facilitate technology adoption, better-educated countries should have been quicker in adopting the skilled-labor-augmenting technologies becoming available since the 1970s. Better-educated countries should therefore have experienced faster shifts toward schooling-intensive industries. We therefore use data for 28 manufacturing industries.
industries in a large cross section of countries to examine whether higher initial schooling was associated with faster value-added and employment growth in schooling-intensive industries in the 1980s and 1990s. Theories of international specialization point to human capital accumulation as another important determinant of growth in schooling-intensive industries. Hence, we also examine the link between improvements in education and growth in schooling-intensive industries.

We find that value-added and employment growth in schooling-intensive industries was significantly faster in economies with higher initial levels of schooling. Moreover, the link becomes stronger when we focus on economies that were open to international trade. The link between initial schooling and subsequent shifts of the production structure toward schooling-intensive industries is robust to controls for physical capital endowments, for financial development, for indicators of rule of law, property rights institutions, and initial levels of income. The effect prevails when we use different proxies for schooling and when we consider schooling quality. We also find that countries that saw greater improvements in schooling experienced faster shifts in production toward schooling-intensive industries.

### DATA APPENDIX

#### Variable Definitions and Sources

1. **Country-Industry-Specific**

   - **VAGR**: Annual logarithmic growth rate of value added in industry \( s \) in country \( c \) over the 1980–1999 period (and alternatively the 1980–1989 and the 1980–1995 periods). We use all countries with data on human capital, but we exclude countries with fewer than ten industry observations and country-industries with fewer than five observations in the 1980s, and fewer than five observations in the 1990s. Source: United Nations Industrial Development Organization (UNIDO) Statistics, 2005.
   - **EMPR**: Annual logarithmic growth rate of employment in industry \( s \) in country \( c \) over the 1980–1999 period (and alternatively the 1980–1989 and the 1980–1995 periods). We use all countries with data on human capital, but we exclude countries with fewer than ten industry observations and country-industries with fewer than five observations in the 1980s, and fewer than five observations in the 1990s. Source: United Nations Industrial Development Organization (UNIDO) Statistics, 2005.
   - **HCINT**: Average years of schooling at the industry level in 1980. This variable is based on data from the 1980 Integrated Public Use Microdata Series. We extract two series: (i) hours worked by industry and years of education; and (ii) number of employees by industry and education. Our calculations are based on eight groups of educational attainment: (i) zero years of schooling; (ii) one to four years of schooling; (iii) five to eight years of schooling; (iv) nine to eleven years of schooling; (v) twelve years of schooling; (vi) thirteen to fifteen years of schooling; (vii) sixteen years of schooling; and (viii) more than sixteen years of schooling. Average years of schooling in each industry is obtained by multiplying the share of employees in each educational attainment group by 0, 1, 6, 10, 12, 14, 16, and 18, respectively. We also calculate two additional industry-level schooling intensity indicators. The ratio of hours worked by employees with at least twelve years of schooling to total hours worked by all employees in each industry, \( HCINT(SEC) \). The ratio of hours worked by employees with at least sixteen years of education to total hours worked in each industry, \( HCINT(COLL) \). Source: Integrated Public Use Microdata Series.

2. **Industry-Specific**

   - **PRIV**: Private value-added and employment growth in schooling-intensive industries in a large cross section of countries to examine whether higher initial schooling was associated with faster value-added and employment growth in schooling-intensive industries in the 1980s and 1990s. Theories of international specialization point to human capital accumulation as another important determinant of growth in schooling-intensive industries. Hence, we also examine the link between improvements in education and growth in schooling-intensive industries.

### Table 7.—Alternative Sample Periods

<table>
<thead>
<tr>
<th></th>
<th>Value-Added Growth</th>
<th>Employment Growth</th>
<th>Value-Added Growth</th>
<th>Employment Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
<td>(5) (6)</td>
<td>(7) (8)</td>
</tr>
<tr>
<td></td>
<td>(9) (10)</td>
<td>(11) (12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td><strong>Open</strong></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td><strong>Adjusted R²</strong></td>
<td>0.457</td>
<td>0.463</td>
<td>0.495</td>
<td>0.510</td>
</tr>
<tr>
<td></td>
<td>0.510</td>
<td>0.682</td>
<td>0.359</td>
<td>0.373</td>
</tr>
<tr>
<td></td>
<td>0.407</td>
<td>0.364</td>
<td>0.394</td>
<td>0.498</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1,340</td>
<td>1,192</td>
<td>557</td>
<td>1,457</td>
</tr>
<tr>
<td></td>
<td>1,310</td>
<td>1,362</td>
<td>614</td>
<td>1,634</td>
</tr>
<tr>
<td><strong>Countries</strong></td>
<td>56</td>
<td>49</td>
<td>22</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>53</td>
<td>53</td>
<td>23</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>23</td>
<td>23</td>
<td>66</td>
</tr>
<tr>
<td><strong>Country fixed effects</strong></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td><strong>Industry fixed effects</strong></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

All specifications also include country fixed effects and industry fixed effects (coefficients not reported). Absolute values of |-statistics based on robust (heteroskedasticity-adjusted) standard errors are reported in parentheses below the coefficients. The data appendix gives detailed variable definitions and data sources.
REFERENCES


Durlauf, Steven N., Paul A. Johnson, and Jonathan Temple, “Growth Econometrics,” in Philippe Aghion and Steven Durlauf (Eds.), *The
Handbook of Economic Growth (Amsterdam: North-Holland, 2005).