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What is Needed for Convergence? The Role of Capital and Finance

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ABSTRACT: What is needed for poor countries to catch up with rich ones? This paper first documents the role of human capital, physical capital, and financial development in convergence in manufacturing labor productivity across countries, and then examines the influence of economic structure and financial development at the aggregate level. Using industry-level data from manufacturing industries in a large set of countries over the period 1980-2022, we show that manufacturing industries exhibit strong unconditional convergence over time, but there is variation in the pace of convergence: Greater reliance on human capital in an industry is linked to faster convergence, whereas dependence on physical capital has no bearing. Instead, industries with a greater dependence on physical capital see convergence only if there is sufficient financial development. At the country level, we find that convergence tends to be faster as countries shift away from agriculture (which typically requires less human capital), and towards industrial production or services. Furthermore, poorer countries that initially have a higher share of agriculture in their GDP have been shifting away from agriculture at a faster rate, which may have contributed to the observed aggregate convergence. Greater financial development is also linked to faster convergence at the country level.

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WORKING PAPERS

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Prepared by Bryan Hardy and Can Sever[1]

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1. Introduction

Economists have long sought to understand what makes countries poor or rich, and how poor countries can grow. Out of this analysis sprang an important prediction: Poor countries have high returns to investment, and so if capital is allocated efficiently across countries, we should see poor countries grow faster than rich ones (Solow 1956). This "unconditional convergence" – whereby poor, low capital countries with high returns to capital grow faster than rich ones, capital abundant countries with low returns to additional capital – was the subject of considerable debate thereafter. Evidence came in for and against, qualifications were made (i.e., conditional convergence), and conclusions varied (Barro and Sala-i-Martin 1992, Mankiw et al. 1992, Pritchett 1997, Easterly and Levine 2001). Despite the disagreement on the path thus far, the growth of poor countries in absolute terms, to join the ranks of rich countries, remains a key concern.

Evidence on unconditional convergence in manufacturing industries was more recently documented by Rodrik (2013) and Bénétrix et al. (2015). Rodrik argues that the lack of convergence in non-manufacturing sectors suggests that convergence occurs in only the "modern" parts of the economy; and the small size of the manufacturing sector and modest pace of labor reallocation to manufacturing imply that aggregate convergence was not to be seen. However, some recent evidence suggests that convergence has reignited in recent decades (Kremer et al. 2021, Klein and Crafts 2023).

The resurgence of aggregate convergence suggests that underlying factors that foster convergence are changing. However, it is still not clear what drives convergence in the manufacturing sector and what the key ingredients are to spur the convergence process and how these might contribute to aggregate convergence. Easterly and Levine (2001) suggest that productivity is the key separator for growth, not factor accumulation. Good quality institutions seem to be a precondition (Acemoglu et al. 2005).[2] Further, the theoretical literature – in addition to describing the role of capital accumulation – predicts that financial development and accumulation of human capital are key inputs that greatly affect productivity and the path of economic growth (Mankiw et al. 1992, Aghion et al. 2005, De Gregorio 1996, Morales 2003). Hardy and Sever (2023) show that patenting rates are converging across countries and industries, implying that research and knowledge accumulation can act as a possible driver of manufacturing productivity convergence.

This paper empirically examines the role of (physical and human) capital and finance in the convergence process. It first focuses on labor productivity in manufacturing industries at the cross-country level. It finds that manufacturing industries that rely more on human capital are the ones driving

[2] For instance, Alfaro et al. (2008) show that institutional quality is the key explanation for why capital flows from poor to rich countries, and not the other way around as would be consistent with convergence and investment in high marginal productivity of capital countries.

unconditional convergence in labor productivity, i.e., manufacturing industries with higher human capital intensity see faster convergence. Physical capital intensity does not correlate with the pace of convergence. However, greater financial development speeds up the convergence process for industries with higher physical capital intensity, deepening the link shown in Aghion et al. (2005) between financial development and aggregate convergence.

The analysis then turns to country-level data and explore how these results relate to overall macroeconomic convergence. The analysis of per capita GDP shows that unconditional convergence across countries over time is faster when the economy is composed more of activities that need more human capital, i.e., industrial production and services (more “modern” parts of the economy as noted by Rodrik 2013), rather than agriculture (more traditional production). Moreover, we observe that poorer countries which initially have a higher share of agriculture in their GDP tend to shift toward non-agricultural activities (requiring greater human capital) faster, which has possibly played an underlying role in convergence of per capita GDP, considering that the positive role of human capital in convergence (as found by this paper). Finally, we show that greater financial development is also linked to faster convergence of GDP per capita across countries over time. The faster shift by poorer activities toward non-agricultural activities and improvements in financial development are suggestive of continued convergence moving forward.

We follow the empirical framework proposed by Rodrik (2013), and use industry-level data from the UNIDO database to examine unconditional convergence in labor productivity (as an equivalent to GDP per capita at the aggregate level) across countries and industries over time. The analysis is based on 2-digit manufacturing industries (ISIC Rev. 3, 15-36) in 99 developing, emerging market, and advanced economies over the period 1980-2022. In line with the standard approach in the convergence literature, data is transformed into four 10-year non-overlapping periods to smooth out annual variations while maintaining variation within industries over time. In particular, we examine the association between the beginning-of-period level of industry labor productivity and its average growth during the subsequent decade.

We start by showing evidence on unconditional convergence in labor productivity across countries and manufacturing industries, consistent with the findings by Rodrik (2013). The estimated rate of convergence in our sample suggests that a 2-digit manufacturing industry which is initially the 25^{th} percentile of the labor productivity distribution across the sample (a relatively low productivity industry) sees a boost in labor productivity growth of about 3 percentage points annually, on average over the subsequent decade, compared to its peer at the 75^{th} percentile of the sample (a relatively high productivity industry). This is economically large considering that the average annual growth of labor productivity in the sample is 4 percent.

Next, we examine whether this convergence process is linked to industries’ dependence on different types of capital. To test this phenomenon, we extend the specification by adopting an empirical strategy in the spirit of Rajan and Zingales (1998). In particular, we test differences in convergence patterns by exploiting within-country variation in the reliance on human and physical capital across 2-digit manufacturing industries. In the baseline, the measures of human and physical capital intensity for each industry are calculated using data from a benchmark country, such as the US, with highly developed financial markets and a relatively frictionless labor market to ensure that those industry-level measures of dependence on different sorts of capital likely reflect the differences in the production processes or technologies (rather than being driven by financing or labor market frictions).

Another advantage of benchmarking these industry-level measures using data from the US is that they are not affected by the country-specific shocks in the sample, which could otherwise lead to endogeneity issues. To the degree that industries' reliance on human and physical capital, as calculated from the US, carries over to other countries and across years, industry-level data allows us to identify the differences in convergence patterns by exploiting these (within-country) differences across industries.

Based on the data from the US industries, human capital intensity (HCI) is defined as the share of workers in each industry with at least a high school degree, while physical capital intensity (PCI) is the ratio of total real capital stock to value added in each industry (both are adopted from Erman and Kaat 2019).

The results show that labor productivity convergence is linked to industries' dependence on human capital: Cross-country cross-industry convergence is faster for industries that rely on human capital more intensely. The findings show that, for instance, an industry at the 25th percentile of HCI (wood products) converges with a rate of 1.1 percent, whereas an industry the 75th percentile of HCI (machinery) converges with a rate of 1.6 percent. This difference in the convergence rates implies that a machinery industry in a country that is initially at the 25th percentile of the industry labor productivity distribution in the sample exhibits a 2.7 percentage points additional growth per annum (on average, during the subsequent decade) coming from convergence, compared to a machinery industry in another country that is initially at the 75th percentile of the labor productivity distribution. A similarly estimated convergence boost remains 1.9 percentage points in an industry with low HCI (i.e., wood). Thus, the differential convergence boost to the growth rate, based on the differences in HCI across these two industries, is 0.8 percentage points. By contrast, convergence does not appear to be linked to industries' dependence on physical capital. These findings stay similar when we test convergence conditional on country-specific factors.

In the next step, we explore the role of the availability of finance in this process. We find that industries with greater dependence on physical capital start to converge only when the level of financial development exceeds a threshold, which is consistent with the macro-level findings by Aghion et al. (2005).

In the second part of the analysis, we aim to link these results to convergence dynamics at the macro-level. First, we focus on the link between convergence and the reliance on human capital at the country-level. We assume that as the economies shift from traditional activities (i.e., agriculture) to more modern production (i.e., broad sectors encompassing industrial production and services) in the process of structural transformation, they rely more on human capital.[3] If this is the case, and if the patterns observed at the industry-level hold at the macro-level, one can expect that per capita GDP convergence should be faster for countries and periods with a higher share of non-agricultural activities in GDP. We indeed find that a higher share of industrial production and services predict faster cross-country convergence in per capita GDP. Next, we document that poorer countries which initially have greater agricultural contribution in their GDP tend to shift toward non-agricultural production faster (compared to richer ones), which likely has positive implications for per capita GDP convergence.

Finally, we test the role of finance in convergence at the macro-level. We show that per capita GDP convergence is stronger for countries and periods with greater financial development, consistent with the industry-level findings above.

This paper builds directly on the literature examining convergence in manufacturing industries. Most notable of these is Rodrik (2013), which documents absolute (unconditional) convergence in manufacturing labor productivity among a wide sample of countries. Klein and Crafts (2023) similarly find unconditional convergence in manufacturing labor productivity within the US over 1880-2007, with manufacturing driving overall productivity convergence in the economy. Bénétrix et al. (2015) show convergence in industrial output as a whole from 1890-1972.[4] Madsen and Timol (2011) document that manufacturing productivity has been (unconditionally) converging for OECD countries, and that R&D plays a key role. Hardy and Sever (2023) show that patenting rates show convergence across countries and industries, implying an important role for human capital and R&D in the ongoing convergence.

Our paper sets itself apart from these on two key dimensions. First, we show that the type of capital used in the industry matters for its observed convergence. Specifically, human capital-intensive industries drive convergence. This provides direct evidence of the conjecture that "modernity" in an economy is somehow linked to convergence. Second, we document where the role of finance comes in. Specifically, financial development contributes to convergence in industries where physical capital plays a larger role. This highlights the how financial constraints may prevent convergence in industries where production is highly dependent on physical capital.

We also contribute to the debate about the existence of convergence and whether convergence has resurged in recent years, discussed above. We show that, with a sample including recent years, GDP per capita shows (unconditional) convergence. Further, we show that this is driven by countries with a larger share of the economy in services or industrial production (rather than agriculture), and boosted by greater financial development.

[3] See Miles (2008) for some evidence on this.

[4] In contrast to those papers, Bernard and Jones (1996) find evidence for convergence in services but not manufacturing, using less granular and not recent data.

We also shed light on the underlying drivers of economic growth and convergence. For instance, King and Levine (1993), Levine (1997), Beck et al. (2000) and Aghion et al. (2005) point to financial development as a key factor.[5] Financial development is linked to both productivity improvements and physical capital accumulation, and efficiency in allocation of physical capital. Lucas (1988) and Galor and Weil (2000) provide theoretical foundations to connect human capital development to long-run economic growth, setting it as a key driver of productivity improvements and technological progress. Ciccone et al. (2009) and Gennaioli et al. (2013) substantiate the importance of human capital accumulation empirically. Our paper provides further nuance and context to when these factors matter and how they interact in patterns of growth convergence.[6]

Some of the literature on economic growth focuses on technological diffusion.[7] While our results do not speak directly to this, they can be informative because human capital is viewed as a key factor to whether technological developments from abroad can be absorbed in the receiving country (Xu 2000, Benhabib and Spiegel 2005, Perez-Trujillo and Lacalle-Calderon 2020). Our analysis shows that industries that typically use more human capital converge faster across countries. This appears to be consistent with easier technological transfer in high human capital industries facilitating convergence in those industries.

Finally, we contribute to the literature on structural transformation. Kuznets (1996) documents the main empirical patterns in this transformation, including a shift from agriculture to industry and services, and noted its link to productivity growth and increased urbanization. Gollin et al. (2002) argue that increases in agricultural productivity enable the structural transformation by freeing up labor for other sectors. Herrendorf et al. (2014) provide a review of the literature and suggest that multisector growth models are key to understand growth and structural transformation as they capture reallocation of inputs across sectors. Duarte and Restuccia (2010) suggest that the reallocation of labor across industries (i.e., to more productive industries) drives growth, and that productivity catch-up in the industrial sector explains much of the aggregate productivity gains. We contribute to this extensive literature by showing further evidence that faster convergence is linked to a higher share of the economy in more human capital-intensive industries like manufacturing and services. But, we further show that the shift to a higher share of non-agricultural activities is faster for poorer countries with initially low shares of such production in their GDP, linking this shift directly to convergence patterns.

The remainder of this paper is organized as follows. Section 2 explains the data. Section 3 introduces the empirical methodology. Section 4 illustrates the results. Finally, Section 5 concludes.

[5] Hardy and Sever (2021) show in the context of financial crises that access to finance is a key driver of productive innovation, a crucial input for growth.

[6] Acemoglu and Molina (2022) and Fatás and Mihov (2013), among others, highlight the role of institutions, an angle that we do not explore in this paper.

[7] For instance, Eaton and Kortum (1999), Keller (2002), Comin and Hobijn (2010), and De Visscher and Everaert (2020).

2. Data

2.1. Industry-level variables

We use the number of employees, value added and output for 2-digit (ISIC Rev. 3, 15-36) manufacturing industries from the UNIDO database. We calculate our baseline measure of nominal labor productivity as the ratio of value added (in USD) to the number of employees. We also adopt the ratio of output to the number of employees in robustness. We calculate labor productivity growth as log difference of these ratios each year, and winsorize it at the 1st and 99th percentiles to reduce the influence of outliers. We also calculate the industry value added share in each country's manufacturing sector (to be used as a control variable in robustness checks). Table A1 in the Appendix provides the data sources and summary statistics for the industry-level variables.

To test whether industries exhibit different degrees of convergence based on their innate differences in the use of human and physical capital, we need proxies for those which should reflect underlying differences across industries' production processes or technologies. For this purpose, we follow an approach that is similar to Rajan and Zingales (1998). In their seminal work, Rajan and Zingales (1998) argue that some industries need more external finance than others and use a proxy for industries' dependence on external finance, as calculated using data from the US. Similarly, we adopt measures of industries' dependence on human and physical capital based on the US, and test convergence across industries by exploiting the cross-industry (within-country) variation in these measures.

The first reason why we adopt measures of industries' use of human and physical capital is rather practical: Detailed historical data to calculate these measures for 2-digit manufacturing industries is not available for the vast majority of countries in the sample. However, even if data were available, calculating these measures using data from each country in the sample would lead to endogeneity. In particular, human and physical capital decisions in a given economy can be driven by country-specific factors (such as labor market and financial frictions), rather than reflecting underlying differences in industries' production processes and technological needs, which would undermine our identification. Therefore, it is sensible to calculate industry-specific measures of human and physical capital intensity based on data from a benchmark country. In this regard, a common practice in the literature pioneered by Rajan and Zingales (1998) is to use the US as the benchmark to calculate proxies for industry-level characteristics.

In our context, since the US has highly developed financial markets and less labor market frictions, relative to many other countries, it is reasonable to assume that the measures of industries' human and physical capital intensity as calculated from the US likely reflect industry characteristics (i.e., different production processes and technological needs). However, this does not necessarily mean that those measures represent the "correct" value for each industry, but instead, they are likely to be reasonable proxies for the extent of the need for human and physical capital across industries, driven by some innate factors (rather than by financial or labor market frictions).

A possible concern about benchmarking industries' need for different types of capital can be that industry-specific values for these measures may differ across countries, to the extent that the production processes or technologies change based on local conditions. However, this is not likely to alter our results, as long as the ordering of industries regarding these measures remains similar across countries. For instance, if production of electrical machinery requires a relatively high-skilled workforce compared to textile products, or production of metals needs more physical capital compared to tobacco industry (in line with the orderings in the US, see below), this phenomenon does not generate a significant bias in the estimation.

Human capital intensity (HCI) is defined as the share of workers in each industry with at least a high school degree. It is calculated using the March supplement of the 1980 Current Population Survey which provides information on employees' schooling. Similar to Nunn (2007) and Ciccone and Papaioannou (2009), physical capital intensity (PCI) is calculated as the ratio of total real capital stock to value added in each industry based on the NBER manufacturing database in 1980. We adopt these measures from Erman and Kaat (2019).

Table 1 shows the measures of HCI and PCI in 2-digit manufacturing industries. Textiles, tobacco and apparel products are the industries with the lowest HCI, whereas refined petroleum, chemicals and communication equipment products industries have the highest. Wearing apparel, leather and computing machinery products industries have the smallest PCI, whereas basic metals, minerals and refined petroleum industries have the largest. We note that the correlation between HCI and PCI is low (0.12), avoiding potential problems due to low number of degrees of freedom, and thereby allowing a reasonable differentiation across industries.

Two assumptions remain important for our identification, similar to the literature pioneered by Rajan and Zingales (1998). First, the relative differences across the US industries are representative of those in other countries in the sample. For instance, if the production of communication equipment relies more human capital relative textiles in the US, this relationship should stay similar in other countries. Second, the ordering of human and physical capital intensity across industries should not change much over time.[8]

We adopt four alternative approaches to proxy for HCI as robustness. First, to alleviate any concerns about drawing inferences from the exact values calculated for HCI and PCI, we run our analysis using dummy variables which categorize industries with high and low HCI and PCI based on the median values of these measures, as shown in Table A1. Second, we adopt the average years of schooling for workers in each industry as an alternative measure of HCI, based on the data from the US in the same year (adopted from Ciccone and Papaioannou 2009).

[8] A possible caveat for HCI may be the variation in education quality across countries, which is not captured by this measure.

Next, to address concerns that the US might not be an appropriate benchmark, we compute measures of HCI based on European data. Labor outcomes from Europe can also provide a reasonable benchmark for industry characteristics, since financial frictions are likely to be lower compared to less developed economies, and wide-spread access to public education alleviates the frictions in the supply of human capital. In particular, we adopt the industry-level employment share of high-skilled workers in 1988 in seven European countries (Belgium, Denmark, France, Germany, Netherlands, Spain, UK) from Erman and Kaat (2019).[9] High correlation between the baseline measure of HCI (from the US) and HCI based on European data (0.85) suggests that industries' reliance on human capital are indeed similar across these countries, which is reassuring for our identification assumption.

Finally, to further mitigate any concerns on benchmarking HCI using data from relatively advanced countries, we adopt a measure of HCI from a broader sample, half of which are low- and middle-income countries. For this purpose, we use the estimates of factor shares for different types of workers based on data from 21 countries in the World Bank Enterprise Surveys (WBES) during the first half of 2000s, adopted from Shikher (2014). We define HCI as the ratio of value added by workers with secondary and tertiary education to total labor value added in each industry. The correlation between the baseline measure of HCI (from the US) and this measure also remains high (0.81).

[9] We thank Daniel Marcel te Kaat and Lisardo Erman for sharing the series with us.

Table 1: Industry human and physical capital intensity

Industry	ISIC	Human capital intensity (HCI)	Physical capital intensity (PCI)
Food and beverages	**15**	0.63	1.81
Tobacco products	**16**	0.52	0.86
Textiles	**17**	0.51	1.95
Wearing apparel, fur	**18**	0.52	0.49
Leather, leather products, footwear	**19**	0.54	0.61
Wood products (excl. furniture)	**20**	0.55	2.08
Paper and paper products	**21**	0.74	2.23
Printing and publishing	**22**	0.61	1.00
Coke, refined petroleum, nuclear fuel	**23**	0.86	2.42
Chemicals and chemical products	**24**	0.81	2.31
Rubber and plastics products	**25**	0.69	2.14
Non-metallic mineral products	**26**	0.64	2.63
Basic metals	**27**	0.63	3.35
Fabricated metal products	**28**	0.68	1.36
Machinery and equipment n.e.c.	**29**	0.78	1.39
Office, accounting, computing machinery	**30**	0.79	0.62
Electrical machinery and apparatus	**31**	0.78	1.04
Radio, TV, communication equipment	**32**	0.81	1.01
Medical, precision, optical instruments	**33**	0.78	0.69
Motor vehicles, trailers, semi-trailers	**34**	0.74	2.28
Other transport equipment	**35**	0.74	0.81
Furniture; manufacturing n.e.c.	**36**	0.55	0.97

Notes: This table is adopted from Erman and Kaat (2019). Human capital intensity (HCI) is the share of employees with at least high school degree. Physical capital intensity (PCI) is the total real capital stock as share of value added.

2.2. Country-level variables

We adopt different proxies for financial development. The first is the IMF's composite index, which accounts for the multifaceted nature of financial development by incorporating rich information on financial markets and institutions regarding depth, access and efficiency. Financial institutions include banks, mutual funds, insurance companies and pension funds. Financial markets include bond and stock markets. It is defined as a combination of depth (size and liquidity of markets), access (ability of individuals and firms to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the degree of activity of capital markets). The index is constructed based on a principal component analysis of the underlying series (as described by Svirydzenka 2016). It is between 0 and 1, higher values indicating greater financial development. As a second proxy, we use bank credit to the private sector by banks (as share of GDP) from the World Bank's World Development Indicators (WDI) database.

To examine the broad structure of the economy, we use the value added shares (in percent of GDP) of different sectors, including agriculture (including agriculture, forestry, and fishing), industry (including mining, manufacturing, construction, electricity, water, and gas) and services (including wholesale and retail trade, hotels and restaurants, transport, and government, financial, professional, and personal services such as education, health care, and real estate services) from the WDI database.

Lastly, we obtain data on nominal exchange rate (local currency vis-a-vis USD), consumer price inflation (CPI), GDP (constant in 2015 USD) and GDP per capita (constant in 2015 USD) from the WDI database; and data on producer price index from the World Bank (pulled from Ha et al. 2023).[10]

2.3. Sample

Our industry-level sample covers 22 manufacturing industries (in 2-digit ISIC, as listed in Table 1) across 99 countries (where 38 of them are advanced economies) over the period 1980-2022. Following the literature on convergence, annual data is transformed into four non-overlapping 10-year periods to calculate growth rates of labor productivity over the periods of 1981-1990, 1991-2000, 2001-2010, and 2011-2022 (where the last period has 12 years).[11] The average annual growth rate of labor productivity in each 2-digit industry is calculated within each of these periods (in percent). We apply two restrictions: We drop country-industry pairs with only one (10-year) period observation to maintain within industry variation; and a small number of countries with less than 20 country-industry-period observations to ensure within country variation. However, we also show that these steps do not change the results. The list of countries in the industry sample is in the Appendix.

In the second part of the analysis, we focus on country-level convergence focusing on per capita GDP. Annual data is similarly transformed into non-overlapping 10-year periods. The average annual growth rate of real per capita GDP is calculated within each of these periods (as log change and in percent). We use a global sample with all available data over the period 1980-2022, but by dropping countries with only one (10-year) period observation to maintain within country variation.

[10] We calculate real exchange rate, to be used in a robustness check, based on nominal exchange rate vis-à-vis USD, and inflation based on producer prices in the US and based on consumer prices elsewhere.

[11] We also present the results based on annual data, as robustness.

3. Methodology

3.1. Convergence at the industry-level

Our goal is to examine heterogeneity in the uncondotional convergence of manufacturing labor productivity and what factors contribute to it, particularly regarding industries' reliance on human and physical capital and the role of finance. Specifically, we explore whether (i) manufacturing industries with initially lower labor productivity exhibit higher labor productivity growth, implying β-convergence across countries and industries over time; and (ii) manufacturing industries that are more human or physical capital intensive show any difference in this convergence process, and whether financial development plays a role.

Our main analysis collapses the annual data to four non-overlapping 10-year periods, as discussed above. There are two main reasons why this approach has been widely used in examining convergence. First, it helps maintain the within-country-industry variation over time while smoothing out annual variations. Second, it captures the medium-run dynamics in growth. Nevertheless, we also examine results based on annual data.

Following Rodrik (2013), we start with the basic convergence estimation, as follows:

$$\Delta \log(LP)_{c,i,p} \ = \ \beta_1 \log(LP)_{c,i,t} + \theta_i + \ \theta_p + \theta_{i,p} + \epsilon_{c,i,p} \qquad \textbf{(1)}$$

where c, i, and t stand for country, 2-digit manufacturing industry, and year, respectively. A 10-year period p has its initial year represented by the t subscript. $\Delta \log(LP)_{c,i,p}$ is the average annual change in labor productivity over a 10-year period p (i.e., average of annual growth rates over the years $t+1$, $t+2, \ldots, t+10$). For each period p, $\log(LP)_t$ is the initial level of log labor productivity for that period (i.e., at year t). Standard errors are clustered at the country-level.

The specification above includes industry, period and industry-period fixed effects, θ_i, θ_p and $\theta_{i,p}$, respectively. Assuming that each 2-digit industry faces a global USD inflation rate, industry-period fixed effects isolate the underlying variation in labor productivity arising from inflationary effects (Rodrik 2013). In addition, these fixed effects soak the impact of all common annual shocks or developments on labor productivity dynamics in each industry (such as global growth opportunities or global demand). Last but not least, they also isolate the underlying variation in growth arising from industry-specific global trends.[12]

Our main focus in this paper is the so-called unconditional convergence, which does not include country fixed effects, using the regression setup proposed by Rodrik (2013). However, we also show for the results for conditional convergence by controlling for country fixed effects in a separate regression.

[12] We note that Nickell (1981) bias can be a potential caveat in this estimation (as industry fixed effects are included). However, we also show that the results remain similar when tested at annual frequency, where a longer panel likely alleviates this issue.

Country fixed effects absorb the impact of all country-specific time-invariant factors on industry labor productivity growth.

In this setup, convergence in labor productivity is captured by β_1. If convergence exists, β_1 must be negative, suggesting that labor productivity grows faster in countries, industries, and periods where it is initially lower (i.e., cross-country cross-industry β-convergence). On the other side, $\beta_1 \approx 0$ indicates that differences in labor productivity do not narrow across countries and industries over time. Finally, a positive estimate for β_1 suggests labor productivity divergence (i.e., widening gaps in labor productivity across industries and countries). We expect to find evidence for convergence as in Rodrik (2013), i.e., a negative estimate for β_1.

To examine heterogeneity in convergence, we first test convergence in each 2-digit manufacturing industry across countries separately. For this purpose, we run the regression in equation (1) for each industry i to estimate industry-specific coefficients (β_1^i). Once we run this test for each industry i, we also look at how the coefficient estimates (β_1^i) are associated with our measures of HCI and PCI. This test serves three goals. First, industry-specific analysis allows us to observe whether (and to what extent) individual industries converge to their own global labor productivity frontier (i.e., within-industry convergence across countries). Next, if this convergence is widespread, it will confirm that cross-country cross-industry results based on equation (1) are not driven by a few industries. Third, we can compare the convergence rates (β_1^i) for each industry with measures of HCI (PCI), where a higher correlation between them will imply that industries that rely more on human (physical) capital tend to converge faster.

We then extend the specification in equation (1) to more formally explore the link between convergence heterogeneity and industries' human and physical capital intensity. To this end, we add the interactions of HCI and PCI with the initial labor productivity:

$$\Delta \log(LP)_{c,i,p} = \beta_1 \log(LP)_{c,i,t} + \beta_2 \log(LP)_{c,i,t} \times HCI_i + \beta_3 \log(LP)_{c,i,t} \times PCI_i + \theta_i + \theta_p + \theta_{i,p} + \epsilon_{c,i,p} \quad \textbf{(2)}$$

where HCI_i and PCI_i stand for human and physical capital intensity in each industry, respectively. In this setup, the extent of convergence is captured by a convergence parameter $\lambda_i = \beta_1 + \beta_2 HCI_i + \beta_3 PCI_i$, where β_2 and β_3 will gauge the extent to which convergence depends on HCI_i and PCI_i, respectively. In a case where β_1 is estimated to be negative, if β_2 (β_3) is negative, it would mean that industries' human (physical) capital intensity is linked to faster convergence. On the other side, if β_2 (β_3) is positive, it would indicate that industries' reliance on human (physical) capital hinders the convergence process.

We reiterate that, for our identification to hold, we make two implicit assumptions aligned with the empirical literature pioneered by Rajan and Zingales (1998). First, we assume that some industries inherently and persistently rely more on human (or physical) capital than their peers, mainly driven by differences in their production processes or technologies. Second, these inherent differences carry over to other countries, so that an industry's human and physical capital intensity as calculated using the data from the US serves as a reasonable proxy for its dependence on those types of capital in general.

Finally, given the key role that finance plays for the accumulation of capital, we explore the association between financial development and convergence in different industries:

$$\begin{aligned}\Delta \log(LP)_{c,i,p} \; = \; & \beta_1 \log(LP)_{c,i,t} + \beta_2 \log(LP)_{c,i,t} \times HCI_i + \beta_3 \log(LP)_{c,i,t} \times PCI_i \\ & + \beta_4 \log(LP)_{c,i,t} \times FD_{c,t} + \; \beta_5 HCI_i \times FD_{c,t} + \beta_6 PCI_i \times FD_{c,t} \\ & + \beta_7 \log(LP)_{c,i,t} \times HCI_i \times FD_{c,t} + \; \beta_8 \log(LP)_{c,i,t} \times PCI_i \times FD_{c,t} \\ & + \beta_9 FD_{c,t} + \theta_i + \; \theta_p + \theta_{i,p} + \epsilon_{c,i,p} \qquad \textbf{(3)}\end{aligned}$$

where $FD_{c,t}$ is a proxy for financial development adopted from the initial year t for each period p. In this specification, β_4 captures the role of financial development in convergence on average, whereas β_7 and β_8 examine whether its role changes based on industries' HCI and PCI, respectively. We also control for the role of financial development in labor productivity growth on average (captured by β_9), and also based on HCI and PCI (captured by β_5 and β_6, respectively) to avoid omitted variable bias.

3.2. Convergence at the country-level

Next, we connect our industry-level results to country-level outcomes. We first establish a baseline of unconditional convergence of per capita GDP across countries, as follows:

$$\Delta \log(GDP\ per\ capita)_{c,p} \; = \; \beta_1 \log(GDP\ per\ capita)_{c,t} + \; \theta_p + \epsilon_{c,p} \qquad \textbf{(4)}$$

where c and t stand for country and year, respectively. As above, we use 10-year non-overlapping periods in these tests. A 10-year period p has the initial year marked by the subscript t. In particular, $\Delta \log(GDP\ per\ capita)_{c,p}$ is the average annual change in log real GDP per capita over a 10-year period p (i.e., average of annual growth rates over the years $t+1$, $t+2, \ldots$, $t+10$). For each period p, $\log(GDP\ per\ capita)_{c,t}$ is the beginning-of-period level for that specific period (i.e., at year t). Period fixed effects (θ_p) control for the impact of global common shocks on growth. Standard errors are clustered at the country-level.

In this setup, a negative estimate for β_1 would mean that countries with relatively lower per capita GDP levels to begin with exhibit a higher growth rate in the subsequent 10-year period, pointing to β-convergence.

We then aim to provide some suggestive evidence on the link between convergence and countries' reliance on human capital-intensive sectors. For this purpose, we focus on the shares of broad sectors in the economic activity. We assume that, in the process of structural transformation (i.e., shifting from agriculture to other sectors), countries typically need more human capital. We use the following specification to examine whether this phenomenon predicts a different degree of convergence:

$$\begin{aligned}\Delta \log(GDP\ per\ capita)_{c,p} = {} & \beta_1 \log(GDP\ per\ capita)_{c,t} + \beta_2 \log(GDP\ per\ capita)_{c,t} \times Agriculture_{c,t} \\ & + \beta_3 \log(GDP\ per\ capita)_{c,t} \times Industry_{c,t} + \beta_4 \log(GDP\ per\ capita)_{c,t} \times Services_{c,t} \\ & + \beta_5 Agriculture_{c,t} + \beta_6 Industry_{c,t} + \beta_7 Services_{c,t} + \theta_p + \epsilon_{c,p} \end{aligned} \quad \textbf{(5)}$$

where $Agriculture_{c,t}$, $Industry_{c,t}$ $Services_{c,t}$ are the beginning-of-period values for value added share in GDP for agricultural sector, industry, and services (including manufacturing), respectively. Similar to the industry-level analysis, convergence in this estimation is captured by a parameter that includes $\beta_1, \beta_2, \beta_3$, and β_4. The coefficient estimates of the double interactions gauge the degree to which those sectoral shares play a role in convergence. For instance, if the coefficient estimate of β_4 is negative, it will mean that GDP per capita in countries with a higher share of services in GDP tends to converge faster. In this estimation, we interpret the sectoral shares apart from agriculture as proxies for countries' reliance on human capital.

We lastly explore the role of financial development in the convergence process of GDP per capita, using the following specification:

$$\begin{aligned}\Delta \log(GDP\ per\ capita)_{c,p} = {} & \beta_1 \log(GDP\ per\ capita)_{c,t} + \beta_2 \log(GDP\ per\ capita)_{c,t} \times FD_{c,t} \\ & + \beta_3 FD_{c,t} + \theta_p + \epsilon_{c,p} \end{aligned} \quad \textbf{(6)}$$

where $FD_{c,t}$ is a measure of financial development. We expect β_2 to be negative, if higher financial development fosters convergence across countries.

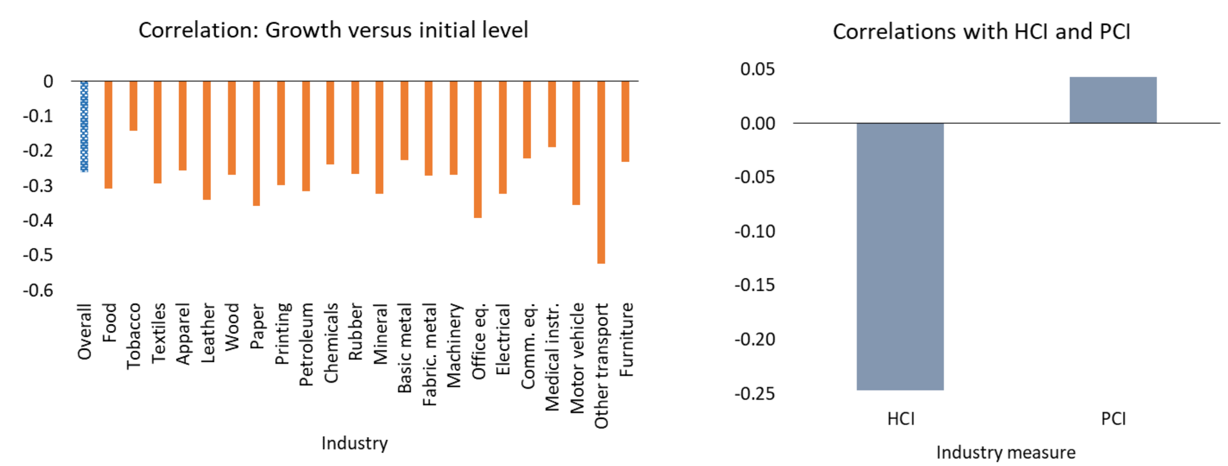
4. Stylized Facts

We begin by illustrating the basic relationships in the data, to motivate our more formal analysis. We first calculate for each industry the correlation between the initial level of industry labor productivity and its growth rate (net of industry, period and industry-period fixed effects), averaged over the subsequent 10-year period. A negative association between the initial level and subsequent growth would mean that industries with initially lower labor productivity exhibit higher growth in the next 10 years on average, thereby converging to its own frontier (i.e., β-convergence), while a positive relationship will point to divergence.

The left-hand panel in Figure 1 illustrates that labor productivity across industries tends to converge, and there is heterogeneity in the degree of convergence across industries. The first (dashed) bar shows that the association between initial labor productivity and its growth remains negative (-0.26) in the overall sample (including all 2-digit industries), thereby suggesting that labor productivity converges across countries and industries.[13] The negative values for each industry (the remaining solid bars) indicate that this convergence process is also prevalent within industries across countries, suggesting that each 2-digit industry tends to converge its own global frontier over time. However, there seems to be variation across industries, with (i) this correlation being largest in size (-0.52) for other transportation equipment (ISIC 35) and lowest (-0.14) for tobacco products (ISIC 16), and (ii) the mean value of industry-specific correlations being -0.29 with a standard deviation of 0.08.

The right-hand panel in Figure 1 calculates the correlations of the estimated convergence (as shown by the solid bars in the left-hand side panel) with our industry-specific measures of HCI and PCI. The correlation with HCI is negative (-0.25) while it is 0.04 in the case of PCI. This suggests that industries with higher HCI show stronger convergence (i.e., more negative associations between initial labor productivity and its subsequent growth). In the next section, we start scrutinizing this pattern in a formal setting.

Figure 1: Industry labor productivity: Associations between initial level and subsequent growth



Notes: Left-hand side chart reports the correlations between the initial level of industry labor productivity and its growth rate averaged over the subsequent 10-year period for the overall sample and for each industry separately. The analysis is based on non-overlapping 10-year periods in line with the regression analysis. Industry growth rates are net of industry, period, and industry-year fixed effects (in line with the regression analysis). Right-hand side chart reports the correlations of the industry-specific associations (i.e., the correlations as shown by the industry-specific bars in the left-hand side chart) and industry-level measures of human (HCI) and physical capital intensity (PCI).

[13] We note that the average annual growth rate of labor productivity (net of industry, period and industry-period fixed effects) is -1.23 (1.23) percent for industries with an initial labor productivity level above (below) the sample median.

5. Results

5.1. Main Results

Table 2 illustrates the main results on industry labor productivity convergence based on 10-year non-overlapping periods. Columns 1-2 test unconditional convergence, the main focus of this study, whereas columns 3-4 add country fixed effects to examine conditional convergence.

The rate of convergence is about 1.75 percent in the first column. This convergence rate suggests that a 2-digit industry which is initially at the 25th percentile of the labor productivity distribution across the sample (a relatively low productivity industry) sees a boost in labor productivity growth of about 3 percentage points annually ($1.75 \times \ln(5.5)$), compared to its peer at the 75th percentile (a relatively high productivity industry, with a labor productivity about 5.5 times that of the former). This is economically large considering that the average annual growth of industry labor productivity in the sample is 4 percent.

However, when we account for the role of HCI and PCI in this convergence process (column 2), we observe that convergence mainly comes from industries that rely more on human capital. The coefficient estimate of initial labor productivity is much lower compared to the first column, and becomes statistically insignificant. The interaction term between initial labor productivity and HCI implies a convergence rate of 2.05 percent, and it is statistically significant at the 1 percent level. This suggests that an industry at the 25th percentile of HCI (wood) converges with a rate of 1.1 percent, whereas an industry the 75th percentile of HCI (machinery) converges with a rate of 1.6 percent. This difference in the convergence rates implies that a high HCI industry like machinery in a country that is at the 25th percentile of the labor productivity distribution in the sample exhibits a 2.7 percentage points additional growth per annum coming from convergence ($1.6 \times \ln(5.5)$), compared to the 75th percentile of the sample. A similarly estimated convergence boost remains 1.9 percentage points in a low HCI industry like wood ($1.1 \times \ln(5.5)$). On the other side, we do not see a statistically significant link between the rate of convergence and industries' PCI.

A possible concern for our findings can be whether labor productivity is systemically different across industries with high and low HCI. In particular, if labor productivity levels tend to be somehow lower for industries with high HCI, this can be the driving force of a higher growth in those industries (i.e., convergence). Importantly, we do not observe large differences in the level of labor productivity across industries with low and high HCI (or PCI). If anything, such a relationship works against our main finding. Industries that depend more on human capital (i.e., above the median HCI) have a 4.1 percent higher labor productivity level on average, compared to their peers with relatively low HCI. This pattern, if it has any affect, should weaken the convergence process in the former group with high HCI, by predicting lower growth in those industries, since they start from a somewhat higher level of labor productivity. We also note that industries with higher PCI (based on the median value of this measure) have 3.1 percent higher labor productivity compared their peers with low PCI, on average.

While our main focus in this paper is unconditional convergence, we also show that conditional convergence points to a similar pattern (column 4). The convergence rate (based on a joint evaluation of β_1 and β_2 in this case, given that β_1 is also statistically significant) is 2.8 percent for the machinery (75th percentile of HCI) industry, while it is 2.5 percent for the wood industry (25th percentile of HCI). Convergence boosts in labor productivity growth, similarly calculated as above, become 4.8 and 4.2 percentage points per annum for machinery and wood industries, respectively. PCI does not appear to affect the convergence process. The results are also similar when the analysis is done at annual frequency, instead of 10-year non-overlapping periods (Appendix Table A2).[14]

Table 2: Labor productivity convergence

	Unconditional		Conditional	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
$log(LP)$	-1.753***	-0.268	-2.861***	-1.830**
	(0.231)	(0.500)	(0.791)	(0.765)
$log(LP) \times HCI$		-2.054***		-1.249**
		(0.645)		(0.585)
$log(LP) \times PCI$		-0.068		-0.112
		(0.100)		(0.110)
Industry F.E.	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes	Yes
Country F.E.	No	No	Yes	Yes
Observations	5,560	5,560	5,560	5,560
R-squared	0.151	0.152	0.286	0.287

Notes: Results are based on equation 1 and 2. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. Tests in the last 2 columns include country fixed effects as well. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

5.2. Robustness to industry-level variables

We test the robustness of the results to using alternative variables, as well as to accounting for industry size. Table 3 illustrates the results. We first focus on the measures of HCI and PCI. In column 1, we adopt dummy variables representing the half of the industries that have relatively high HCI and PCI, instead of using the exact values of those measures. This approach mitigates possible concerns about our identification assumptions. For instance, HCI and PCI in textiles and automobiles may change over time or across countries, due to some underlying factors. However, as long as textiles industry remains with a lower

[14] We note that R-squared tends to be lower when convergence is tested at annual frequency due to increased variation, while country fixed effects (Table 2) increase it markedly.

dependence on human capital than automobiles (over time or in different countries), the classification based on the dummy variables would stay the same. Next, in column 2, we adopt an alternative measure of HCI based on the average years of schooling for the workers in each industry, rather than the share of workers with at least high school degree. In column 3, we use the measure of HCI based on data from the European industries, instead of the US. The results are similar.

In column 4, we adopt a measure of HCI based on data from a broader sample (adopted from Shikher 2014). The previous findings stay similar. We note that the coefficient estimate of the initial labor productivity turns to be positive (and statistically significant) in this estimation. However, a joint evaluation of the coefficient estimates of initial labor productivity and its interaction with HCI yields a negative convergence parameter (being statistically significant at the 1 percent level) even for the 2-digit industry with the lowest value with this measure of HCI (which is 0.87). Thus, similar to the findings above, we observe convergence across all country-industry pairs, while this process is faster for industries with greater reliance on human capital.[15]

We then employ several tests focusing on labor productivity. Column 5 calculates labor productivity (both level and growth) based on industry output, rather than value added. Column 6 explicitly corrects for the changes in real exchange rates, aimed at alleviating any concerns about a possible bias in the estimation (Rodrik 2013). In particular, while the changes in domestic costs including wages are offset by depreciation of the local currency, thereby keeping the USD value similar, this may not apply in some cases, such as the periods of enduring movements in the real exchange rate. To account for any bias from such cases, we deflate labor productivity growth with (one plus) the rate of appreciation in the real exchange rate.

In column 7, we use the level and growth rate of labor productivity relative to the same industry in the US in the corresponding time (dropping the US from the sample). Therefore, this test asks a slightly different questions, i.e., whether industry labor productivity tends to grow faster (particularly in the industries with higher HCI or PCI) compared to the growth rate of the same industry in the US when it is initially farther away from it. The finding is consistent with the previous patterns.

In the last two columns we focus on industry size. In column 8, we test the results with weighted regressions where the weights are industries' beginning-of-period values for value added (in log) to make sure that it is not the smaller industries driving the results. Finally, we control for the beginning-of-period value added share of each industry in total manufacturing in the last column (column 9). Industries that are relatively smaller to begin with may have less resources for innovative activities, thereby hindering labor productivity growth. On the other side, smaller industries can be more dynamic, and there may be more room to increase labor productivity. To the extent that these potential channels interact with industries

[15] We also note that lower cross-industry variation in this measure of HCI (with a mean value of 0.93 and standard deviation of 0.03, as shown in Table A1) is the main driver of relatively larger coefficient estimates in this test.

dependence on human capital, there can be a concern whether these may be a channel driving our baseline results. However, our results stay similar in this test.

Table 3: Robustness

Variable	Dummy variable	HCI: average years	HCI: Europe	HCI: Broader sample	LP: output	Exchange rate	Relative to the US	Weighted	Controlling for VA share
$log(LP)$	-1.483***	0.625	-1.276***	4.989**	-0.316	1.624	-0.429	0.088	-0.289
	(0.228)	(0.881)	(0.346)	(1.997)	(0.400)	(1.556)	(0.519)	(0.583)	(0.494)
$log(LP) \times HCI$	-0.499***	-0.187***	-2.312**	-7.082***	-1.938***	-2.283**	-1.781***	-2.524***	-2.017***
	(0.159)	(0.070)	(1.141)	(2.122)	(0.740)	(1.111)	(0.648)	(0.687)	(0.638)
$log(LP) \times PCI$	-0.116	0.134	-0.138	-0.117	0.151*	-0.55	-0.096	-0.121	-0.069
	(0.137)	(0.108)	(0.109)	(0.105)	(0.086)	(0.192)	(0.099)	(0.114)	(0.019)
$VA\ share$									-0.006
									(0.019)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,560	5,560	5,560	5,560	5,515	5,320	5,429	5,560	5,560
R-squared	0.152	0.152	0.151	0.152	0.167	0.044	0.190	0.138	0.152

Notes: Results are based on equation 2. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. Column 1 adopts dummy variables indicating high HCI and PCI (based on the median value for each measure). Column 2 uses an alternative measure of HCI based on average years of schooling in each industry. Column 3 uses an alternative measure of HCI based on data from European countries. Column 4 adopts an alternative measure of HCI based on a broader sample. Column 5 adopts an alternative measure of labor productivity based on output. Column 5 deflates labor productivity growth with (one plus) the rate of appreciation in real exchange rate. Column 7 defines labor productivity (both growth rate and level) relative to the same industry in the US for each industry. Column 8 uses industry (beginning-of period) value added as weights. Column 9 controls for the beginning-of-period value of value-added share for each industry in the manufacturing sector in its country. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

5.3. Robustness to the sample

In this section, we test the robustness of the results to the sample. Table A3 in the Appendix focuses on the industry composition, and shows that the previous pattern still holds when we drop (i) the four industries with minimum and maximum values of HCI and PCI (column 1); (ii) exclude several country-industry pairs with high and low labor productivity growth over the sample period (column 2); (iii) drop several country-industry pairs with high and low labor productivity level over the sample period (column 3); (iv) drop the 2-digit industry with the highest coefficient estimate in industry-specific regressions (ISIC 32, as shown in Table 4 below) (column 4), to make sure that those are not the ones driving the results. In column 5, we use data only from the continuous sample (by restricting the sample to the country-industry pairs with available data in all 4 periods) to confirm that the changing industry composition over time (due to data availability) does not drive the findings. Finally, we extend the sample by adding the country-industry pairs with available data only for one period to the sample (column 6). The results remain similar.

Table A4 in the Appendix checks the robustness of the results to the country sample and illustrates that the previous results remain similar. In column 1, we drop the US to address any concerns about endogeneity given that HCI and PCI are adopted based on the US data. In column 2, we exclude G7 economies to make sure that those large, advanced economies do not drive the results. In column 3 (column 4), we exclude several richer and poorer (smaller and larger) economies to make sure they are not driving the findings. Finally, we extend the sample by including all countries, instead of dropping the ones with few observations (column 5).

Finally, we confirm that these patterns are not driven by the Covid-19 period. Table A5 in the Appendix shows the results when the period of the analysis is restricted to 2019.

5.4. Industry-specific convergence

Next, we examine convergence within each industry across countries by running the specification in equation (1) for each 2-digit manufacturing industry separately. Our goal is three-fold. First, we want to observe whether each 2-digit industry converges to its own global labor productivity frontier over time (within-industry cross-country convergence). Second, we aim to further establish that convergence is not driven by a few industries in the sample, but widespread. Finally, and more importantly in our context, we aim to observe whether industries that are more human capital intensive tend to converge faster in line with the previous findings. We employ a simple exercise for this purpose: We obtain the convergence rates from industry-specific regressions and examine the correlation between the magnitudes of those estimates with HCI and PCI.

Table 4 shows the findings when convergence is tested in each individual industries across countries. We find that labor productivity in all 2-digit manufacturing industries converge to its own global frontier. This confirms that the previous findings are not driven by a few industries. We also note some variation across industries, where the mean value of the coefficient estimates is -1.96 with a standard deviation of 0.77.

Next, we report the correlations between the industries' convergence coefficients and our measures of HCI and PCI. The correlation between the coefficient estimates and HCI is negative and large (-0.49), while this correlation is small and positive for PCI. This is consistent with our previous finding that industries with higher HCI tend to converge faster, whereas PCI does not make much difference in this convergence process.

Table 4: Industry-specific convergence

ISIC	β_1^i	Std. error	Observations	R-squared
15	-1.662***	(0.164)	317	0.186
16	-0.828***	(0.290)	214	0.057
17	-1.785***	(0.394)	315	0.135
18	-1.610***	(0.404)	302	0.161
19	-2.023***	(0.560)	132	0.202
20	-1.317***	(0.222)	318	0.142
21	-2.005***	(0.315)	315	0.207
22	-1.627***	(0.221)	305	0.142
23	-2.394***	(0.421)	225	0.149
24	-1.312***	(0.202)	309	0.128
25	-1.528***	(0.269)	304	0.165
26	-1.941***	(0.442)	318	0.186
27	-1.824***	(0.444)	294	0.132
28	-1.452***	(0.241)	311	0.177
29	-1.638***	(0.393)	293	0.178
30	-2.574***	(0.626)	100	0.169
31	-1.789***	(0.308)	282	0.184
32	-4.147***	(1.235)	24	0.208
33	-1.765***	(0.594)	167	0.058
34	-2.785***	(0.850)	294	0.168
35	-3.729***	(0.764)	110	0.473
36	-1.461***	(0.251)	312	0.122
Correlation with HCI	*-0.49*			
Correlation with PCI	*0.12*			

Notes: Results are based on equation 1. The regression is run for each industry separately. Industry, period and industry-period fixed effects are included in all regressions. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

5.5. Role of financial development

We next investigate the role of financial development in convergence based on industries' reliance on human and physical capital. Table 5 illustrates the results. In column 1, we adopt a composite index accounting for the multifaceted nature of financial development. Our main results are again evident: Manufacturing convergence is stronger in industries with higher HCI (second row). Interestingly, industries with higher PCI appear to diverge in particularly low levels of financial development, while financial development reverts this process and catalyzes convergence in those industries higher PCI (as implied by the coefficient estimates in third and eighth rows). Specifically, a joint evaluation of the coefficient estimates on those two columns suggests that industries with higher PCI (statistically significantly) diverge for cases where the index on financial development is below 0.17 (representing about 26 percent of the observations), whereas it starts to converge once financial development surpasses 0.61 (representing about 17 percent of the observations). When the index on financial development is between those two thresholds, PCI does not play a role in industry convergence (i.e., the joint evaluation of the coefficient estimates yields statistically insignificant results). This finding is consistent with the findings of Aghion et al. (2005) that convergence is observed above after a critical threshold of financial development.

Moreover, the positive and statistically significant coefficient estimate of the interaction between FD and PCI suggests that greater financial development is associated with higher labor productivity growth in industries with higher PCI (sixth row). Finally, statistically insignificant coefficient estimates on the fifth and seventh rows suggest that financial development does not seem to have a differential role in neither growth nor convergence of industries with higher HCI. Thus, our results reveal a key insight: While human capital-intensive industries converge in productivity, physical capital-intensive industries require a high degree of financial development in order to converge.

We adopt two different proxies for financial development to check the robustness of these findings. First, a possible concern can be whether financial development can simply be a proxy for economic development or other slow-moving variables. To address this, we first regress the index on financial development on (log) real per capita GDP, and country and year fixed effects, and adopt the residual from this regression as a proxy for financial development (column 2). Thus, we use the component of the financial development index that is orthogonal to per capita GDP, time-invariant country-specific features, or annual (global) developments affecting countries similarly. Finally, we use credit to the private sector narrowly focusing on the role of the banking sector (column 3). The results on the differential role of financial development in convergence of industries with higher PCI remain broadly similar.

Table 5: Role of financial development

Variable	FD index	FD index (residual)	Credit
$log(LP)$	-0.643	-0.231	-1.103
	(0.967)	(0.579)	(0.708)
$log(LP) \times HCI$	-3.015**	-2.356***	-1.932**
	(1.159)	(0.657)	(0.903)
$log(LP) \times PCI$	0.400**	0.001	0.278**
	(0.161)	(0.113)	(0.132)
$\log(LP) \times FD$	-0.451	-1.285	-0.001
	(2.561)	(7.561)	(0.014)
$HCI \times FD$	-27.051	-122.989	-0.225
	(34.433)	(123.834)	(0.248)
$PCI \times FD$	12.440**	30.779**	0.099*
	(6.155)	(12.842)	(0.056)
$\log(LP) \times HCI \times FD$	3.035	13.358	0.020
	(3.200)	(11.886)	(0.022)
$\log(LP) \times PCI \times FD$	-1.316**	-3.149**	-0.010**
	(0.565)	(1.283)	(0.005)
FD	8.866	-2.982	0.053
	(26.781)	(77.713)	(0.153)
Industry F.E.	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes
Observations	5,467	5,387	4,044
R-squared	0.164	0.165	0.154

Notes: Results are based on equation 3. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. FD index is a composite index for financial development. FD index residual is the FD index net of (log) real GDP per capita and country and year fixed effects. Credit is credit to the private sector by banks, as share of GDP. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

5.6. Country-level implications: Role of structural transformation and finance

We now turn to macro-data and test unconditional convergence at the country-level. Specifically, we want to confirm the role of human capital and financial development for aggregate convergence and better understand how the industry-level results contribute to macro convergence patterns.

To examine the role of human capital in aggregate convergence, we first test cross-country convergence in GDP per capita over time. We then focus on the role of structural transformation in this process. Specifically, we look at the transition away from less human capital intensive sectors like agriculture to higher ones like industry and services.[16]

Table 6 depicts the results. In column 1, we observe that real per capita GDP tends to converge across countries over time. In the next column, we find that the composition of production matters in this process. In particular, per capita GDP convergence is faster when countries are less intensive in the agriculture sector. We focus on the coefficient estimate of the corresponding interaction terms, since the estimate for β_1 is statistically insignificant in this test. Convergence turns to be stronger in countries with a higher share of industry in its overall GDP (third row), and partly with a higher share of services (fourth row). The convergence rate becomes 0.67 percent for a country at the 25th percentile of GDP share of industry (20.2 percent), while it becomes 1.10 percent for a country at the 75th percentile of the sample (33.3 percent). These suggest that a country with high industry share (i.e., 33.3 percent of GDP) will experience a convergence boost in per capita GDP growth 2.3 percentage points per annum if it is located at the 25th percentile of per capita GDP, compared to a country at the 75th percentile of per capita GDP ($1.1 \times ln(8.4)$).[17] This convergence boost would be about 1.4 percentage points for a country with low industry share (i.e., 20.2 percent of GDP) ($0.67 \times ln(8.4)$).

A similar pattern is observed for countries with a larger service sector, while the coefficient estimate of the corresponding interaction term is statistically significant only at the 10 percent level.

[16] Returns to human capital tend to be higher in the industry and services sector, so these sectors naturally accumulate more human capital than agriculture, and human capital accumulation itself can cause the sector shift (Tamura 2002). The transition from agriculture to industry is consistent with a coincident rise in productivity and the demand for human capital (Galor 2005).

[17] The ratio of per capita GDP levels in those percentiles of the sample is 8.4.

Table 6: Per capita GDP convergence

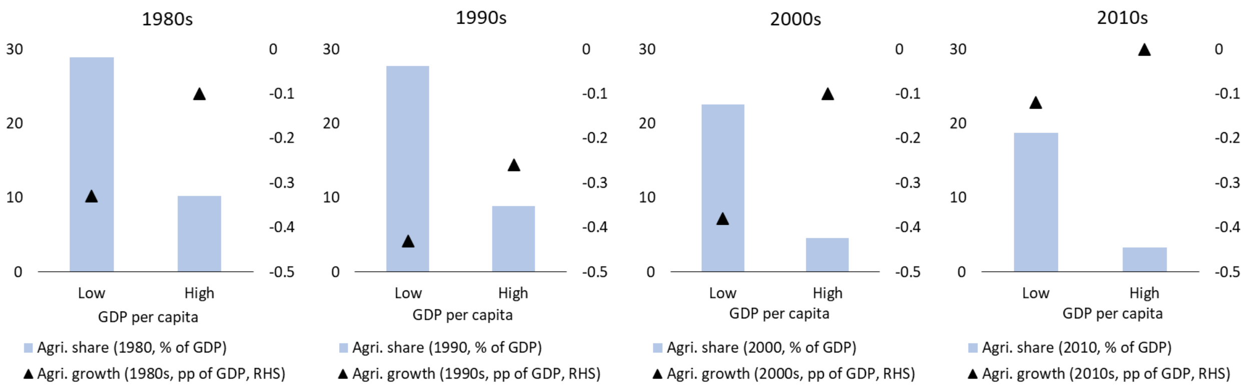
Variable	(1)	(2)
$\log(GDP\ per\ capita)$	-0.266***	1.869
	(0.091)	(1.209)
$\log(GDP\ per\ capita) \times Agriculture$		-0.028
		(0.018)
$\log(GDP\ per\ capita) \times Industry$		-0.033**
		(0.015)
$\log(GDP\ per\ capita) \times Services$		-0.025*
		(0.013)
$Agriculture$		0.145
		(0.135)
$Industry$		0.234*
		(0.140)
$Services$		0.183
		(0.115)
Period F.E.	Yes	Yes
Observations	541	541
R-squared	0.083	0.135

Notes: Results are based on equation 4 and 5. Agriculture, industry and services are value added shares in GDP (in percent). Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

Given the above evidence for faster convergence when the economy is tilted more towards non-agricultural activities (i.e., services and especially broader industry), we explore whether poorer economies tend to shift from agriculture faster, which would have positive implications for per capita GDP convergence. Figure 2 shows some suggestive evidence. In each period, the charts report the initial share of agriculture in GDP and the average growth rate of this share (in percentage points of GDP) over the decade in two subsamples based on the median value of initial per capita GDP (i.e., dividing the sample into poorer and richer countries based on the per capita GDP levels at the beginning of that period). We observe a clear pattern: Poorer countries have larger shares of agriculture in their GDP to start with, but they tend to shift away from it faster.[18] This suggests that the shift to the sectors that tend to be more dependent on human capital (non-agriculture) has been more pronounced in poorer economies, which has a positive bearing on continued convergence at the aggregate level.

[18] We note that a similar pattern is also observed when the same analysis is done using data on employment in agriculture (as share of total employment), i.e., poorer countries tend to employ a higher share of population in agriculture, while their employment shifts away from agriculture faster.

Figure 2: Shift from agriculture over time



Notes: The charts use aggregate data (for all countries with available data points in each decade) over the period 1980-2022, and report the beginning-of-period GDP share of agriculture value added and its growth rate in the subsequent decade (in percentage points of GDP) in two subsamples with low and high levels of the beginning-of-period values of real GDP per capita. The first chart divides the sample into 2 subsamples based on the median level of GDP per capita in 1980. It documents the mean share of agriculture value added (as percent of GDP) in each subsample in 1980 (shown by the bars). It also uses the average growth rate in agriculture value added share (in percentage points of GDP) over the 1980s (average of the growth rates in 1981, 1982, …, 1990), and reports the mean value of the growth rates across countries (shown by the black triangles, right-hand side axis). The rest of the charts follows the same procedure for the remaining 10-year periods.

We finally examine the role of financial development in convergence. Table 7 shows the results. In column 1, we observe that real per capita GDP converges across countries over time in this sample (consistent with the result above). In the next column, we show that greater financial development predicts a faster convergence, again consistent with the literature, notably Aghion et al. (2005). The joint evolution of β_1 and β_2 suggests that a country with high financial development (e.g., at the 75th percentile of this sample, where the index is about 0.34) exhibits a convergence rate of 1.01 percent. Thus, it will experience a convergence boost in per capita GDP growth 2.3 percentage points per annum if it is located at the 25th percentile of per capita GDP, compared to a country at the 75th percentile of per capita GDP ($1.01 \times ln(9.5)$).[19] The convergence rate is about 0.49 percent for a country with low financial development (i.e., where the index is about 0.10 at the 25th percentile of the sample), which implies that a similarly calculated convergence boost in growth will be about 1.1 percentage points per annum in this case ($0.49 \times ln(9.5)$).

[19] The ratio of per capita GDP levels in those percentiles of the sample is 9.5.

Table 7: Role of financial development

Variable	(1)	(2)
$\log(GDP\ per\ capita)$	-0.193**	-0.276*
	(0.098)	(0.142)
$\log(GDP\ per\ capita) \times FD$		-2.196***
		(0.457)
FD		25.963***
		(4.891)
Period F.E.	Yes	Yes
Observations	684	684
R-squared	0.064	0.140

Notes: Results are based on equation 4 and 6. FD is the composite index for financial development. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion

The composition of the economy matters for convergence, as well as for which factors can accelerate that convergence. Within manufacturing, labor productivity converges faster across countries and industries when there is a high reliance on human capital. For those industries that rely on physical capital, convergence is only observed with sufficient financial development in the country. At the aggregate level, a higher share of sectors which require more human capital (i.e., non-agriculture) predicts faster per capita GDP convergence across countries over time. Moreover, countries have generally been shifting from agriculture towards industry- and services-oriented economies, and this shift is occurring faster in poorer countries which initially have a higher share of agriculture in their GDP. These factors combined help explain the observed aggregate growth convergence, which is aided by financial development.

The results have important implications for our understanding of economic growth and policy priorities in poorer economies. First, it reinforces the view that the sectoral composition of the economy matters, both in the aggregate as well as the composition of the manufacturing sector. Aggregate convergence is driven by both within manufacturing (but to different degrees across manufacturing industries) and by composition shift from agriculture to industry and services. Thus, structural and macroeconomic policies enabling reallocation of resources from production activities that do not exhibit much convergence to the ones that can reap growth benefits from convergence matter. Second, the role of human capital is crucial, pointing to both the need to invest in human capital accumulation (such as through schooling), but also to implement policies conducive to industries that can utilize such capital. Finally, physical capital accumulation can help contribute to convergence, but likely only when financial development is sufficiently high, calling for efforts to deepen domestic financial markets. Overall, financial development, accumulation of human capital, and fostering high human capital industries remain key elements to help growth in developing countries converge faster towards their advanced economy peers.

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Appendix

The list of countries

Countries included in the industry-level analysis are as follows: Albania, Australia, Austria, Belgium, Bangladesh, Bulgaria, Bosnia and Herzegovina, Bermuda, Bolivia, Brazil, Barbados, Canada, Switzerland, Chile, China, Cameroon, Colombia, Costa Rica, Cyprus, Czechia, Germany, Denmark, Ecuador, Egypt, Eritrea, Spain, Estonia, Ethiopia, Finland, Fiji, France, United Kingdom, Georgia, Ghana, Greece, China - Hong Kong SAR, Croatia, Hungary, Indonesia, India, Ireland, Iran (Islamic Republic of), Iceland, Israel, Italy, Jordan, Japan, Kenya, Kyrgyzstan, Korea, Kuwait, Lao, Sri Lanka, Lithuania, Luxembourg, Latvia, China - Macao SAR, Morocco, Moldova, Mexico, North Macedonia, Malta, Mongolia, Mauritius, Malawi, Malaysia, Netherlands, Norway, New Zealand, Oman, Pakistan, Panama, Peru, Philippines, Papua New Guinea, Poland, Portugal, Qatar, Romania, Russia, Senegal, Singapore, Slovakia, Slovenia, Sweden, Syria, Thailand, Trinidad and Tobago, Tunisia, Türkiye, Taiwan Province of China, Tanzania, Uruguay, USA, Venezuela, Vietnam, Yemen, South Africa, Zambia.

Tables

Table A1: Industry-level variables: Data sources and summary statistics

Variable	Source	25th ptile	Mean	75th ptile	Std. dev.
Human capital intensity (baseline)	Erman and Kaat (2019)	0.55	0.68	0.78	0.11
Human capital intensity (Europe)	Erman and Kaat (2019)	0.07	0.11	0.16	0.05
Human capital intensity (average years)	Ciccone and Papaioannou (2009)	11.00	11.64	12.43	0.96
Physical capital intensity	Erman and Kaat (2019)	0.86	1.55	2.23	0.80
Human capital intensity (broader sample)	Shikher (2014)	0.90	0.93	0.95	0.03
Labor productivity (log)	Based on UNIDO	8.96	9.76	10.66	1.54
Labor productivity growth (percent)	Based on UNIDO	0.26	4.04	7.54	8.91
Labor productivity (based on output, log)	Based on UNIDO	10.01	10.85	11.73	1.57
Labor productivity growth (based on output, percent)	Based on UNIDO	0.68	4.42	7.83	7.72
Value added share (percent)	Based on UNIDO	1.59	5.69	6.92	7.25

Table A2: Labor productivity convergence (annual frequency)

	Unconditional		Conditional	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
$log(LP)$	-4.124***	-0.296	-9.027***	-6.871***
	(0.354)	(0.977)	(0.868)	(1.112)
$log(LP) \times HCI$		-5.339***		-2.838**
		(1.255)		(1.263)
$log(LP) \times PCI$		-0.154		-0.141
		(0.151)		(0.185)
Industry F.E.	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes	Yes
Country F.E.	No	No	Yes	Yes
Observations	66,620	66,620	66,620	66,620
R-squared	0.086	0.086	0.124	0.124

Notes: Results are based on equation 1 and 2, but at the annual frequency (where labor productivity level is included with 1-year lag). LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. Tests in the last 2 columns include country fixed effects as well. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Industry composition

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$log(LP)$	0.025	-0.407	-0.274	-0.326	-0.169	0.100
	(0.584)	(0.367)	(0.521)	(0.502)	(0.504)	(0.662)
$log(LP) \times HCI$	-2.473***	-1.784***	-1.904**	-1.908***	-1.670**	-2.857***
	(0.889)	(0.514)	(0.788)	(0.628)	(0.724)	(0.985)
$log(LP) \times PCI$	-0.038	-0.005	-0.119	-0.085	-0.007	-0.032
	(0.136)	(0.068)	(0.092)	(0.099)	(0.057)	(0.109)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,424	5,354	5,322	5,450	3,056	5,848
R-squared	0.152	0.185	0.157	0.148	0.164	0.123

Notes: Results are based on equation 2. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. Column 1 drops 4 industries with the maximum and minimum values of HCI and PCI (ISIC 17, 23, 18, 27). Column 2 drops a few country-industry pairs with high and low labor productivity growth (below 2.5th and above 97.5th percentiles of the distribution in the sample). Column 3 drops a few country-industry pairs with high and low labor productivity level (below 2.5th and above 97.5th percentiles of the distribution in the sample). Column 4 excludes ISIC 32. Column 5 restricts the sample to country-industry pairs with available data in all 4 periods. Columns 6 extends the sample by including data from country-industry pairs with only one observation. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Country composition

Variable	(1)	(2)	(3)	(4)	(5)
$log(LP)$	-0.315	-0.479	-0.217	-0.241	-0.390
	(0.507)	(0.528)	(0.521)	(0.507)	(0.483)
$log(LP) \times HCI$	-2.059***	-1.953***	-2.106***	-2.083***	-1.948***
	(0.659)	(0.665)	(0.663)	(0.662)	(0.637)
$log(LP) \times PCI$	-0.063	-0.056	-0.083	-0.077	-0.045
	(0.102)	(0.108)	(0.104)	(0.102)	(0.098)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes
Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Observations	5,483	5,085	5,350	5,373	5,646
R-squared	0.154	0.158	0.156	0.157	0.149

Notes: Results are based on equation 2. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. Columns 1 and 2 drop the US and G7 economies, respectively. Column 3 drops a few richer or poorer countries (below 2.5^{th} and above 97.5^{th} percentiles of the real per capita GDP distribution in the sample). Column 4 drops a few smaller and larger countries that are (below 2.5^{th} and above 97.5^{th} percentiles of the real GDP distribution in the sample). Column 5 extends the sample by including data from countries with a few observations. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Labor productivity convergence - excluding the Covid-19 period

Variable	(1)	(2)
$log(LP)$	-1.718***	-0.196
	(0.221)	(0.496)
$log(LP) \times HCI$		-2.066***
		(0.665)
$log(LP) \times PCI$		-0.085
		(0.101)
Industry F.E.	Yes	Yes
Period F.E.	Yes	Yes
Industry-period F.E.	Yes	Yes
Observations	5,560	5,560
R-squared	0.157	0.158

Notes: Results are based on equation 1 and 2. LP, HCI and PCI are labor productivity, human capital intensity and physical capital intensity, respectively. The period of the analysis is 1980-2019. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1.

PUBLICATIONS

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